THE IMPACT OF AUDIO CLASSIFICATION ON DETECTING SEIZURES AND PSYCHOGENIC NON-EPILEPTIC SEIZURES

By

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CHAPTER I INTRODUCTION

Epilepsy is one of the four most common neurological health problems in the US. Patients suffering from epilepsy go through difficult times whenever a seizure event occurs. The recurrence of such events affects patients' psychological aspects negatively facilitating the introduction of psychiatric disorders including, but not limited to, depression and stress as well as difficulties in conducting regular daily activities such as driving and working, depending on severity and frequency of seizures. Correct diagnosis of seizures helps patients experience a better life-style.

Multiple clinical efforts are in place already to identify seizures. Physicians have identified multiple features to help them draw an accurate diagnosis. However, limited use of computer-aided programs is observed. There is a good chance that a few computer-aided detection methods can be added to the diagnosis practice.

The other problem physicians are facing is related to misdiagnoses of psychogenic non-epileptic seizures as being organic seizures. Such misdiagnosis may increase patients' suffering due to the consumption of unneeded drugs which might cause patients to experience side effects. Some patients might consume the wrong medication for a long period that extends to 16 years or more prior to correctly diagnosing their problem. The current methods of diagnosing seizures, video-EEG, diagnostic questionnaire, interactional features, and serum parameters, are still not enough to facilitate a correct diagnosis on a timely basis. Some of the methods experience limited availability (i.e., video-EEG) while others depend primarily on how experienced the physician is (i.e., interactional features). There is still some room to introduce simple and efficient computer-aided detection equipment and/or programs.

In this study we will try to focus on features and techniques that haven't been studied in the past. Fortunately, there were some elements that are not covered fully by previous studies/products which could bring hope to patients to ease their recurrent struggle. Our study will cover few of the untapped areas primarily focusing on vocalization related to seizures to understand how computer-aided signal processing can support the correct identification of seizures. The impact will not only be achieving a better life style for patients but also more efficient utilization of resources, financial and manpower, by care providers, whether at home or at hospitals. Good results could also increase the safety of seizure patients since it could lead to enhancing the technique in the future so that real-time alarms occur when a patient is undergoing a seizure.

The study was based on track proven methodologies, albeit not related directly to epilepsy, to provide a good jump start for continuous future efforts. Multiple sources were reviewed to understand seizures and their features as well as understanding the best techniques for handling seizure vocalizations properly. The size of the dataset was kept relatively low over the course of this study to allow for a meaningful manipulation of applied techniques to achieve desired results before generalizing the techniques to larger datasets combined with additional improvements.

The study was conducted with the help of the Neurology Department at the Vanderbilt University Medical Center. Patient audio samples and understanding of current practices were coordinated with the Neurology Department. Results will also be discussed with the Neurology Department upon completion.

The remainder of the document is divided into four chapters. Chapter 2 will primarily focus on background material covering epilepsy seizures and psychogenic non-epileptic seizures. It will also define the main problem this study is concerned about. Chapter 3 will discuss the methodology proposed to solve the main problem. It will detail the necessary steps as well as their scientific basis concretely. Chapter 4 will discuss and comment on the results achieved highlighting the most relevant observations. Conclusion and ideas for future research will be included in chapter 5. Additional information such as references used, programming code, and additional less relevant results will be included in the appendices.

CHAPTER II BACKGROUND AND SIGNIFICANCE

An epilepsy seizure is a temporary loss of control, often with abnormal movements, unconsciousness, or both. Epilepsy seizures are caused by sudden abnormal electrical discharges in the brain [7]. Seizures fall into three groups: focal – they start in one area of the brain and can extend to other regions, generalized – they involve both hemispheres of the brain, and unknown – they cannot be diagnosed as focal or generalized [9]. The term "seizure" will refer to an epilepsy seizure in the remaining of this document.

Psychogenic **N**on-**E**pileptic **S**eizures (PNESs) are behavioral events that mimic epilepsy seizures, however, they are not credited with abnormal electric brain discharge [6,7]. Nagaraajan [6] and Benbadis [7], also, suggest that PNESs are most often related to personal emotional conflicts. PNESs are also sometimes called pseudo-seizures, non-epileptic seizures, or psychogenic seizures [5,6,7,8]. We will use the term **P**sychogenic **N**on-**E**pileptic **S**eizure (PNES) throughout this study which eliminates the "fakeness" aspect connoted by the word "pseudo" since patients do not fake the seizure, however, its causes are different from epileptic seizures [6,7,8].

The Epilepsy Foundation and the Institute of Medicine [3,4] state that prevalence of active epilepsy in the US (people who have epilepsy, both old and new cases) is 7.1 out of 1,000, equivalent to 2.2 million patients, while the number of people who are reported to have epilepsy at some point in their life increases to 16.5 out of 1,000. Additionally, the incidence of epilepsy in the US (new cases each year) is 48 out of 100,000, a total of 150,000 patients. Children and older adults are the fastest growing segments of the population with new cases of epilepsy. It has been estimated, also, that epilepsy is the fourth most common neurological disorder in the US. The mortality rate among people with epilepsy is estimated to be 2-3 times higher than the general population.

There are multiple features, motor (movement related – voluntary and involuntary), sensory, and visceral (e.g., vomiting, diarrhea, and urination) that are used in clinical practice to distinguish between seizures and PNESs. PNESs, for example, mainly occur when the patient is surrounded by others, in a physician waiting room, and while the patient is awake (not likely in sleep) in comparison to epilepsy seizures which can occur at any time even if the person is sleeping. Complete loss of awareness, convulsion, urinary incontinence, tongue biting and self-injury are common in epilepsy seizures, however, they are usually absent in PNESs. Table 2.1 below details further the most common features distinguishing epilepsy seizures from PNESs [5,6,7,8].

Table 2.1. Common features distinguishing epilepsy seizures and PNESs.

Sign	Epilepsy seizures	Psychogenic Non-Epileptic Seizures
Duration	Usually brief – 20-70 seconds	Variable – often longer than 2 minutes
Eyes	Eyes usually open during event	Eyes often closed – forced eye closure suggests PNES
Motor activity	Stereotyped Synchronized Build, progress	Variable Forward pelvic thrusting, rolling side to side, opisthotonus Wax and wane
Vocalization	Uncommon – especially during convulsion	May occur
Prolonged ictal atonia	Very rare	May occur
Incontinence	Common in convulsion seizures	Less common
Autonomic signs	Cyanosis, tachycardia common with major convulsion	Uncommon
Post-ictal symptoms	Usually confused, drowsy Headache common	May rapidly awaken and reorient Headache rare

EEG-Video monitoring which records three main elements, namely brain electricity through electrodes connected to the head, movements and sounds produced using an A/V recorder, is the most common equipment used to correctly diagnose epilepsy seizures. The EEG-video monitoring will record patients' activities continuously for 24 hours or more until a seizure event is recorded. The treating physician will then review the recording to determine whether the event is an epilepsy seizure or PNES [7]. However, the main issue associated with EEG-video monitoring is accessibility, only a few physicians (epileptologists) have access to this technology.

Although table 2.1 details the most common discriminant features, it is generally difficult to decide whether an event is an epilepsy seizure or PNES. Studies suggest that complex partial seizures of frontal origin, for example, might present similar characteristics with PNES and could be confused with the latter [6,7]. Also, out-patient EEG readings sometimes might misdiagnose PNESs as organic seizures [7].

One of the features listed in table 2.1 is vocalization. The sound patients produce when undergoing a seizure or PNES differs clearly in most of the times. Seizure ictal cry is best described as a characteristic, clonic-tonic, fragmented, guttural utterance caused by a tonic diaphragm forcing air against tonic or clonic vocal cords [1]. It is strongly associated with epilepsy seizures. PNES sounds, on the other hand, are behavioral and can be either moaning, weeping, snorting, crying, stuttering and/or coughing [1]. Elzawahry, Do, Lin, and Benbadis [1] states that ictal cry happens due to the contraction of the axial, trunk, and abdominal muscles, which causes the diaphragm to slowly force air through the vocal cords. Hence, ictal cry can be difficult to produce without a generic seizure due to the combinations of muscles involved.

Bruijne, Sommen, and Aarts et al. [2] have conducted audio classification analysis of sounds related to epilepsy seizures. The features used were average band-energy ratios, pitch and its strength, spectral flatness of the residual after linear prediction, temporal behavior of the spectral centroids, and temporal behavior of the first linear production coefficient. These features were extracted out of the following set of audio events:

- Screams.
- Smacking of the lips.
- Movements of the bed due to shaking of patients during the seizures.
- Noises due to bronchial secretion.

Significant results were obtained in relation to the accuracy of the sound system to pick up the sounds during and after the seizure. However, a limited dataset was used. Their study was only focused on epilepsy seizures and not on PNESs.

Unlike other research conducted in this field (e.g., [2]), our study will focus only on the cry (scream), however, both seizures and PNESs will be included. The main goal will be to understand how accurately can a computer-aided audio classification system determine whether a cry (scream) is seizure or PNES related. Also, the study would reveal which audio signal features produces best results.

One might ask why would it make a difference if seizures and PNES are classified correctly? The answer relates to the following:

- Avoid unneeded intervention (i.e., anti-epileptic drugs to PNES patients since the drugs are associated with potential morbidity and side-effects).
- Reduce patient's burden associated with managing epilepsy (i.e., less frequent hospitalization and taking the right medication).
- Increase efficiency of care givers (i.e., the nursing station can prioritize at difficult times if the case is PNES in certain occasions and reduce costs).
- Availability of treatment for both cases, epilepsy seizures and PNESs.

The technique followed in this study is similar to previous studies conducted at Vanderbilt University to classify suicidal, depressed, and remitted patients correctly by the means of computer-aided audio classification. France, Salisbury, Ozdas, Yingthawornsuk, Keskinpala, and Nik Hashim [10,11,12,13,14,15] presented excellent results in their audio classification studies.

CHAPTER III METHODOLOGY

3.1 Introduction

In this section, the aim is to explain how the data of this research has been collected, manipulated and processed to achieve desired results. In general, data samples were collected from 28 patients by recording their sound while undergoing a seizure or PNES; each patient's sound will be referred to as a "sample" proceeding forward in the document. Each sample has been initially identified as seizure or PNES by the Department of Neurology, hence providing a basis to represent results in a meaningful way. Additionally, multiple features have been extracted from each sample to allow for proper processing, comparison, and classification. The features included power spectral density (PSD), maximum of the envelope, average of the maximum of envelopes, and mel-frequency cepstral coefficients (MFCCs). In section 3.2, data collection will be explained in detail followed by techniques of feature extraction in section 3.3. The final section in this chapter, section 3.4, discusses feature analysis and classification.

3.2 Data Collection

As stated above, 28 data samples have been collected for the purpose of this study. Two different recording devices have been used to capture the sounds made by patients when undergoing a seizure or a PNES. Sixteen out of the twenty eight patients were undergoing a seizure while the remaining twelve were undergoing a PNES. The identification of the samples as seizure or PNES was done by the physicians at the Department of Neurology at Vanderbilt Medical Center using clinically proven methods. The differences in gender, age, or any other biological/pathological aspects were not considered in this study since the main purpose is to determine whether the classification of seizures and PNESs is possible. Although the number of samples is not large, it represents a good starting point as an initial look to determine whether such a problem is solvable.

The recorded samples had sampling frequencies as follows:

- Seizure sounds
    - 10 out of 16 with a sample frequency of 44.1kHz.
    - 6 out of 16 with a sample frequency of 48kHz.
- PNES sounds
    - 11 out of 12 with a sample frequency of 44.1kHz.
    - 1 out of 12 with a sample frequency of 48kHz.

The variation in the sample frequency is due to using two different recording devices to obtain the samples. This issue has been considered when processing the sound files. The frequency has been normalized whenever there was a need for a unified frequency, for example the samples were resampled at 10.0kHz before extracting MFCCs. Each sample was then stored in the mp3 audio format. The durations of the recorded sounds were as follows:

- Seizure sounds
    - 1 second: 1 sample.
    - 2 seconds: 5 samples.
    - 3 seconds: 2 sample.
    - 5 seconds: 1 sample.
    - 6 seconds: 1 sample.
    - 8 seconds: 1 sample.
    - 10 seconds: 2 samples.
    - 11 seconds: 1 sample.

    - 12 seconds: 1 sample.
    - 16 seconds: 1 sample.
- PNES sounds
    - 1 second: 1 sample.
    - 2 seconds: 1 sample.
    - 3 seconds: 2 samples.
    - 5 seconds: 1 sample.
    - 6 seconds: 1 sample.
    - 7 seconds: 1 sample.
    - 8 seconds: 1 sample.
    - 12 seconds: 1 sample.
    - 13 seconds: 1 sample.
    - 14 seconds: 1 sample.
    - 29 seconds: 1 sample.

Clearly, there is a variation in the duration of each file, mainly due to the period along which the seizure or PNES happens being different. One patient might produce a sound that lasts for 1 second while another would produce a sound that lasts for 29 seconds. It indicates that the duration of the sample could be studied in more detail in future research. Additionally, since PNESs by definition are not true seizures, patients tend to produce a sound for a longer duration compared to true seizure patients who do not have control over the produced sound. Approximately 58% of PNESs lasted more than 6 seconds while 62% of seizures lasted for less than 6 seconds.

To overcome variations in the duration of recorded sounds, a "rolling window" technique was utilized to extract the different features and then find the mean of all the windows related to each sample to conduct the desired analysis whenever required. Additionally, a low-pass filter has been used in certain occasions to lower the noise associated with the collected samples leaving a much clearer sample with features extracted more accurately.

3.3 Feature Extraction

The approach followed in processing the samples included in this study consisted of four introductory feature extraction steps, namely:

1. Applying a low pass filter to reduce the background noise and mainly focus on the seizure/PNES sounds.
2. Estimating the maximum of the waveform envelope and the mean maximum envelope.
3. Estimating the power spectral density for the lower frequencies, 0 – 3kHz.
4. Calculating Mel-Frequency Cepstral Coefficients (MFCCs).

Once the above features were collected, a classifier exercise was applied to determine whether the data was separable or not. Supervised classification was applied through two steps:

a. Equal test classification, where all the samples were tested against themselves, i.e., all the data was used in both training the classifier and testing. This mainly illustrates the potential for separability.
b. Supervised cross-validation, where the samples were divided into a test dataset and a training dataset. The test dataset was then tested and classified against the training dataset. This provides a more realistic evaluation of classifier performance.

The aim of the first step was to determine whether it is possible to distinguish the different extracted features and to understand the possibility of clustering the samples into two distinct groups, i.e., seizure sounds and PNES sounds. While the second step facilitated the identification of the best possible classifier that can be applied to place the different samples into their respective group, i.e., seizures or PNESs, given the availability of a reference for each group, i.e., training dataset tagged initially to be either seizures or PNESs.

Figure 3.1 below illustrates the overall approach followed in this study.

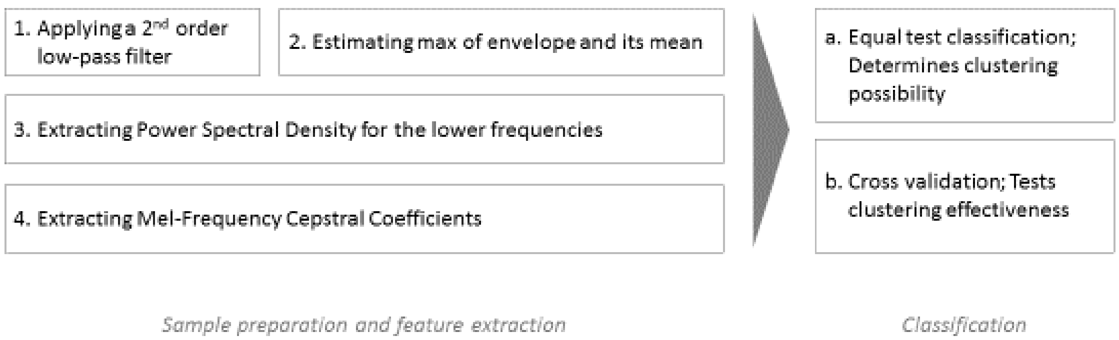


Figure 3.1. Chart illustrating the overall approach followed in this study.

The said approach relies heavily on an approach that was followed by a Vanderbilt research study that was ongoing for almost 20 years and has its validity to classify sound samples of depressed, remitted, and high risk subjects into their respective group. France, Salisbury, Ozdas, Yingthawornsuk, Keskinpala, and Nik Hashim [10,11,12,13,14,15] have followed a similar approach to classify such patients.

3.3.1 Noise Reduction by the Means of Applying a Low-Pass Filter

Each recorded sound had some sort of noise associated with it. For example, some of the recordings had a silence interval either at the beginning or at the end of the recorded sample. While other files had some background noise of people walking or talking while the recording is ongoing. To reduce the noise level at each sample, a simple low-pass filter was applied. This step was particularly important when estimating samples' maximum of the envelope and mean of the maximum of the envelope. The low-pass filter helps terminate any outlier non-real maximum amplitudes that might have resulted from the background noise, e.g., sudden impulsive noise. The low-pass filter used in this study was a 2nd order butterworth low-pass filter with a normalized cut-off frequency, f_c, of 4.41kHz when the sampling frequency, f_S, is 44.1kHz and 4.80kHz when f_S is 48.0kHz. f_c needs to be less than half of the sampling frequency [16]. It is also described as the frequency which determines an attenuation of the magnitude by 3dB. In an ideal low-pass filter, all frequencies above the f_c would be removed. However, this state cannot be realized in reality and hence the use of butterworth low-pass filter which approximates the functionality of an ideal low-pass filter. It is also worth noting that the filter used is a soft one which doesn't skew the samples aggressively due to the fact that the recording environment had, in general, a low noise level. Knowing the design parameters of the butterworth filter, Matlab was used to pass each sample through it before extracting maximum of the envelope and mean maximum of the envelope. Figure 3.2 below shows the 2nd order butterworth filter described in this section.

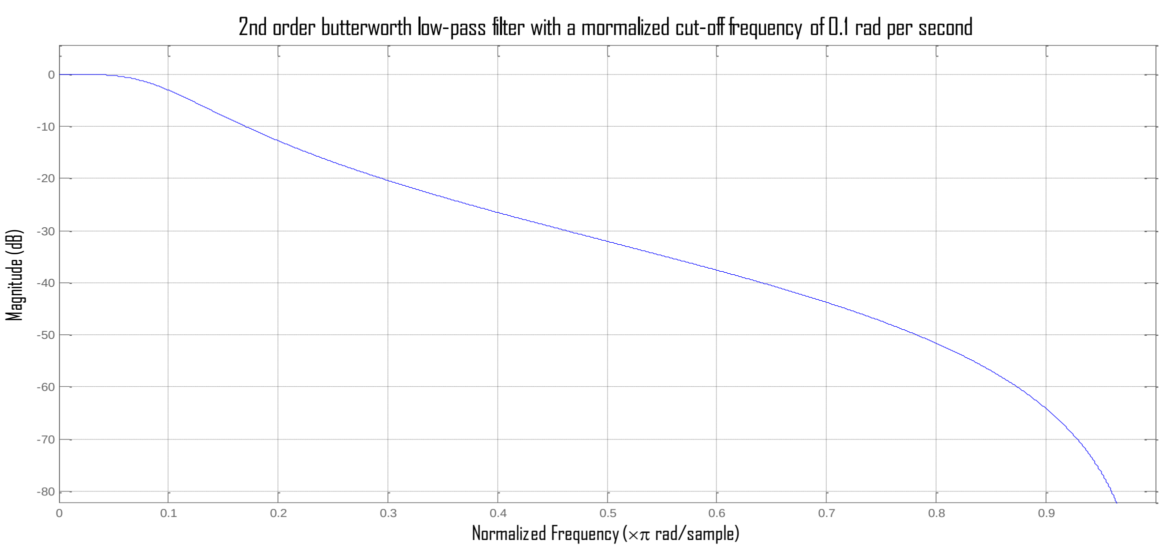
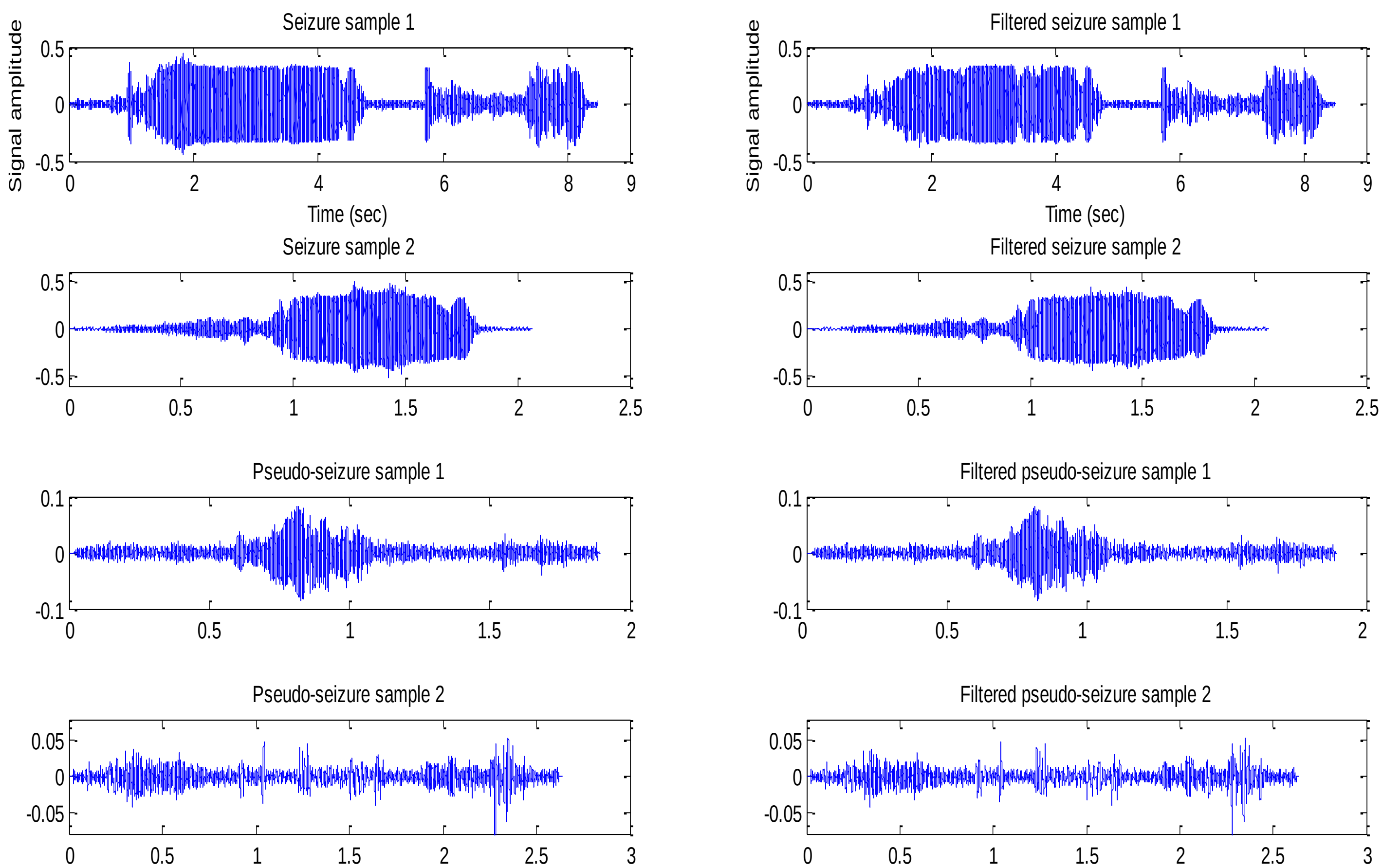


Figure 3.2. 2nd order butterworth low-pass filter with a cut-off frequency of 0.1 rad/s.

As an illustration, figure 3.3 below shows a few samples before and after applying the butterworth low-pass filter. As shown in the figure below, the low-pass filter didn't significantly alter the signal, however it suppressed the outlier noise in each signal.



(a) Before *(b) After*

Figure 3.3. Impact of applying butterworth low-pass filter on few samples.
The left side (a) represents the samples before applying the filter while the right had side (b) shows the filtration effect of the samples. Please note that the x-axis represents time in seconds while the y-axis represents signal amplitude in acoustic pressure.

3.3.2 Maximum of the Envelope and Mean Maximum of the Envelope Estimation

The envelope of a signal contains the amplitude information of the signal. It is obtained by taking the absolute value of the signal followed by passing the signal through a low-pass filter. Consequently, the maximum of the envelope is related to how loud the signal is. In order to determine the maximum of the envelope, the samples had to be passed through a low-pass filter, please read section 3.3.1 for more details on the low-pass filter. Once the samples were filtered, two approaches were followed to estimate the maximum of the envelope feature. The first approach was to take the absolute maximum of the envelope for the overall sample. While the second approach was to extract the mean of the maximum of the envelope following below steps:

a. Each sample was divided into small windows of 15ms each.
b. The maximum of the envelope of each window was then determined.
c. The mean of all windows' maximum of the envelope was then calculated.

The two approaches were followed to indicate which of the two would present a better classifier. Sometimes, following the first approach only might result in poorer results because of the fact that there might be noise in the sample. The algorithm might end up choosing an outlier maximum of the envelope associated with background noise or a non-patient related sound (e.g., falling of an object on the ground). Hence, adding the second approach of calculating the mean of the maximum of envelope of the windows comprising the sample would minimize the error associated with the first approach. It will also provide an additional classifier feature which may provide a better classification of the samples.

3.3.3 Power Spectral Density (PSD) Estimation

The total energy in a signal $\boldsymbol{f}$(t) is equal to the area under the square of the magnitude of its Fourier transform [17,18]. Eq 3.1 is the mathematical representation of the total energy.

$$E = \int_{-1/2}^{1/2} |F(f)|^2 df \qquad \text{(Eq. 3.1)}$$

where $F(f)$ is the DTFT of the signal f(t). The term $|F(f)|^2$ is called the **P**ower **S**pectral **D**ensity (**PSD**). There are multiple techniques available to estimate the PSD of a signal. A periodogram is one of the estimators commonly used for obtaining the PSD of a signal. Eq. 3.2 below is called the periodogram [17,18].

$$S_{FF}(f) = \frac{1}{N}|F(f)|^2 \qquad \text{(Eq. 3.2)}$$

In this study, the PSD was estimated by applying a window w(n) to the sample before calculating its periodogram, a technique called spectral estimation by averaging modified periodograms, following the below steps [17]:

- Divide the data sequence into L segments.
- Multiply each segment by an appropriate window.
- Take the FFT of the product.
- Multiply the FFT by its conjugate to obtain the spectral density of the segment.
- Repeat steps 2-4 for each segment so that the average of these periodogram estimates produces the PSD estimate.

In this study the focus was primarily on the lower frequencies, 2kHz and 3kHz ranges, since the National Center for Voice and Speech [19] suggests that most of the human speech energy is stored in the lower frequencies. The PSD for multiple sub-frequencies was calculated in each frequency range. The ratio between the PSD at each sub-frequency and the total PSD in its respective frequency range was then used in the classification exercise. Table 3.1 below illustrates a detailed description of the frequency ranges and their respective sub-frequencies.

Table 3.1. The frequency and sub-frequency ranges at which Power Spectral Density (PSD) was estimated.

Frequency range	PSD band	Sub-frequency range
0 – 2.0kHz	PSD_0	0 – 250Hz
	PSD_1	0 – 500Hz
	PSD_2	500Hz – 1.0kHz
	PSD_3	1.0kHz – 1.5kHz
	PSD_4	1.5kHz – 2.0kHz
	PSD_{Total}	0 – 2.0kHz
0 – 2.0kHz	PSD_1	0 – 333Hz
	PSD_2	333Hz – 666Hz
	PSD_3	666Hz – 1.0kHz
	PSD_4	1.0kHz – 1.33kHz
	PSD_5	1.33kHz – 1.66kHz
	PSD_6	1.66kHz – 2.0kHz
	PSD_{Total}	0 – 2.0kHz
0 – 2.0kHz	PSD_1	0 – 250Hz
	PSD_2	250Hz – 500Hz
	PSD_3	500Hz – 750Hz
	PSD_4	750Hz – 1.0kHz
	PSD_5	1.0kHz – 1.25kHz
	PSD_6	1.25kHz – 1.5kHz
	PSD_7	1.5kHz – 1.75kHz
	PSD_8	1.75kHz – 2.0kHz
	PSD_{Total}	0 – 2.0kHz
0 – 3.0kHz	PSD_0	0 – 250Hz
	PSD_1	0 – 500Hz
	PSD_2	500Hz – 1.0kHz
	PSD_3	1.0kHz – 1.5kHz
	PSD_4	1.5kHz – 2.0kHz
	PSD_5	2.0kHz – 2.5kHz
	PSD_6	2.5kHz – 3.0kHz
	PSD_{Total}	0 – 3.0kHz
0 – 3.0kHz	PSD_1	0 – 333Hz
	PSD_2	333Hz – 666Hz
	PSD_3	666Hz – 1.0kHz
	PSD_4	1.0kHz – 1.33kHz
	PSD_5	1.33kHz – 1.66kHz
	PSD_6	1.66kHz – 2.0kHz
	PSD_7	2.0kHz – 2.33kHz
	PSD_8	2.33kHz – 2.66kHz
	PSD_9	2.66kHz – 3.0kHz
	PSD_{Total}	0 – 3.0kHz
0 – 3.0kHz	PSD_1	0 – 250Hz
	PSD_2	250Hz – 500Hz
	PSD_3	500Hz – 750Hz

PSD_4	750Hz – 1.0kHz
PSD_5	1.0kHz – 1.25kHz
PSD_6	1.25kHz – 1.5kHz
PSD_7	1.5kHz – 1.75kHz
PSD_8	1.75kHz – 2.0kHz
PSD_9	2.0kHz – 2.25kHz
PSD_{10}	2.25kHz – 2.5kHz
PSD_{11}	2.5kHz – 2.75kHz
PSD_{12}	2.75kHz – 3.0kHz
PSD_{Total}	0 – 3.0kHz

For the purpose of calculating the Power Spectral Density (PSD), the Nik Hashim [20] approach was followed. Periodogram based PSD estimation [17,18], described at the beginning of 3.3.3, was used to obtain the different PSD features detailed in table 3.1 following the below approach:

- Each sample was divided into multiple frames using a non-overlapping window of 15ms.
- The desired FFT-based PSDs were obtained for each frame according to table 3.1 frequency and sub-frequency ranges.
- The PSDs of each sub-frequency as well as that of the respective frequency range were summed up from all the frames.
- The ratio of each sub-frequency's PSD out of the total PSD in its respective frequency range was then calculated and stored as a feature for the classification exercise.

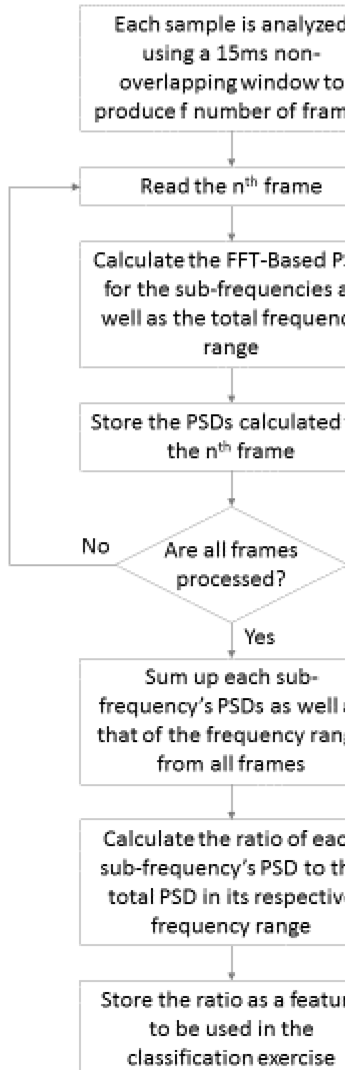


Figure 3.4. Steps followed to extract the PSD feature related to each sample.

It is worth noting that in this study the decision was to include a higher frequency range, up to 3kHz, compared to Nik Hashim's [20] range, up to 2kHz, due to the fact that in her study the focus was only on human speech. In this study, patients undergoing seizures might produce sounds that are not in the human speech range since these sounds are produced unconsciously. It will show later in this document that it was effective to expand the frequency range to 3kHz.

3.3.4 Mel-Frequency Cepstral Coefficients (MFCCs) Extraction

MFCCs have extensive use in speech signal processing from speech classification (ASR, speaker identification, emotion recognition, etc.) to music information retrieval (instrument recognition, singer identification, etc.) as well as others (speech pathology classification, identification of cell phone models, etc.) [21]. MFCCs are based on human hearing perception where multiple filters are applied to mimic how the human ears perceive sounds. It comprises two types of filters that are spaced linearly at low frequencies, below 1kHz, and spaced exponentially at higher frequencies above 1kHz, figure 3.5 illustrates MFCC filters spacing. Slaney's Matlab Auditory Toolbox [22] was used to extract the MFCCs for each sample. Each sample is first framed into frames of 15ms. Each frame is then weighted by a hamming window. Then FFT is applied to get the magnitude spectrum of the windowed frame in frequency domain. The resulting magnitude spectrum is then passed through the filter bank in the mel scale using 27 triangular filters. The Mel frequencies are calculated using Eq. 3.3 to decide the location of the center of the filters [21,23,24].

$$f_{Mel} = 2595 \times \log_{10}\left(1 + \frac{f}{700}\right) \qquad \text{(Eq. 3.3)}$$

The following step was to perform the natural logarithm the purpose of which is to act as a smoothing function. The log is computed following Eq. 3.4 [21,23,24].

$$S(m) = 20\log_{10}\left(\sum_{k=0}^{N-1} |X(k)|H(k)\right), \quad 0 < m < M \qquad \text{(Eq. 3.4)}$$

where M is the number of Mel filters, 27 in this study, X(k) is the N-point FFT of the specific window frame, and H(k) is the Mel filter transfer function. The last step was to perform a Discrete Cosine Transform (DCT) which encodes the mel logarithmic magnitude spectrum into the Mel-Frequency Cpestral Coefficients (MFCCs). The number of MFCCs extracted was set to 13. The cpestral coefficient are obtained using Eq. 3.5 [21,23,24]. The block diagram in figure 3.6 shows the steps followed to extract MFCCs.

$$c(n) = \sum_{m=0}^{M-1} S(m) cos\left(\frac{\pi n\left(m-\frac{1}{2}\right)}{M}\right) \quad \text{(Eq. 3.5)}$$

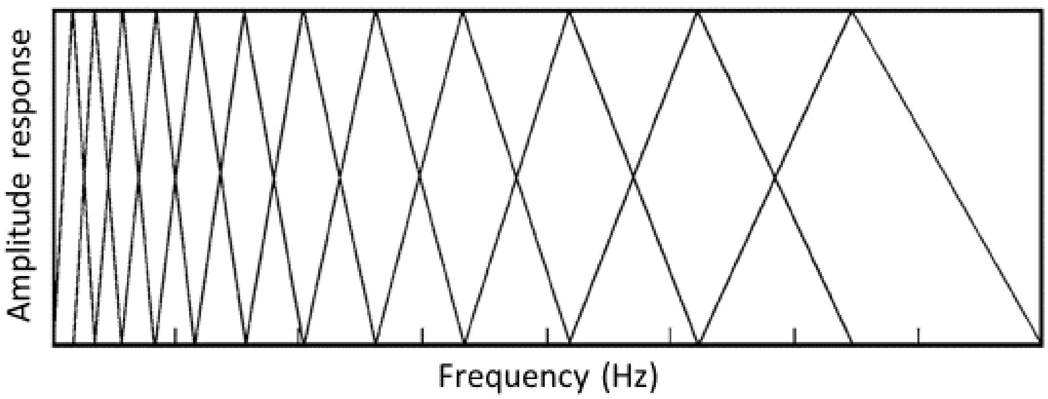


Figure 3.5. Mel-scale filter banks used to extract MFCCs (Illustrative).

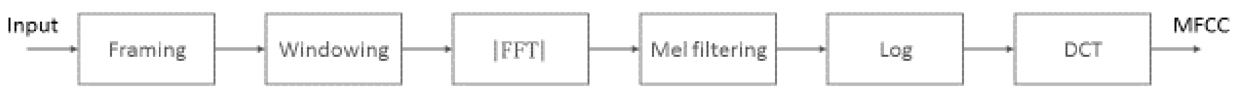


Figure 3.6. Steps of MFCC evaluation algorithm.

Following the approach described above, a matrix of 13×N was created at the end of the MFCCs extraction exercise where 13 represents the number of coefficients and N represents the number of 15ms frames in each sample. In other words, each frame resulted in 13 MFCCs. A mean operation was applied to the matrix to produce a 13×1 vector, called MFCCs mean, where each i^{th} row represents the mean of the values included in that row in the 13×N matrix. The MFCCs mean vector was then used as a feature in the classification exercise. Also, each sample has been resampled at 10kHz before extracting MFCCs. The reason to resample is due to the fact that most of the energy in human speech lies in the lower frequencies. This resampling will facilitate efficient computational cost.

3.4 Feature Analysis and Classification

Upon extraction of the features, steps 3.3.1 – 3.3.4, the next task will be to first classify the features and then ensure the robustness of the classification. Three classification techniques were tested in this study namely linear classifier, quadratic classifier, and support vector machine classifier. To ensure the applicability of the classifiers, two validation techniques were utilized: a) Equal test-train, and b) Cross-validation. More details on each task is presented in the last section of this chapter.

3.4.1 Linear Classifier

Linear **D**iscriminant **A**nalysis (LDA) is a commonly used approach to data classification and dimensionality reduction [25,26,27,28]. A Gaussian LDA was used in this study. It is considered a specific instant of the Gaussian distribution function, explained in detail in section 3.4.2 below. The linear discriminant function can be defined as [28]

$$g_i(\boldsymbol{x}) = \boldsymbol{\omega}_i^T \boldsymbol{x} + \omega_{i0} \qquad \text{(Eq. 3.6)}$$

where,

$$\boldsymbol{\omega}_i = \Sigma^{-1} \boldsymbol{\mu_i} \qquad \text{(Eq. 3.7)}$$

and,

$$\omega_{i0} = \ln P(\omega_i) - \frac{1}{2} \boldsymbol{\mu}_i^T \Sigma^{-1} \boldsymbol{\mu_i} \qquad \text{(Eq. 3.8)}$$

The command “classify” in Matlab has been used to classify the data using LDA. One of the problems associated with LDA is the “small sample size” problem where the size of the training set, N, is smaller than the dimensionality, m, of the original feature space. It is also called the singularity problem [28]. To avoid this issue, the number of features tested in the equal test-train and cross validation had always been chosen to be smaller than the number of training dataset.

3.4.2 Quadratic Classifier

Quadratic **D**iscriminant **A**nalysis (QDA) follows a Gaussian distribution. A multivariate generalization of the Gaussian probability density function (pdf) is given by

$$p(\boldsymbol{x}|\omega_i) = \frac{1}{(2\pi)^{l/2}|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu_i})^T\Sigma_i^{-1}(\boldsymbol{x}-\boldsymbol{\mu_i})\right) \quad \text{(Eq. 3.9)}$$

where l is the dimensional space, $\boldsymbol{\mu}$ is the mean value, Σ is the covariance matrix, and $|\Sigma|$ is the determinant of Σ [28,29]. QDA assumes that the covariance matrices of the classes are not identical. Hence the quadratic discriminant function can be formulated as

$$g_i(\boldsymbol{x}) = \ln(p(x|\omega_i)P(\omega_i) = -\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu_i})^T\Sigma_i^{-1}(\boldsymbol{x}-\boldsymbol{\mu_i}) + lnP(\omega_i) + c_i \quad \text{(Eq. 3.10)}$$

where the constant $c_i = -\left(l/_2\right)ln2\pi - \left(1/_2\right)ln|\Sigma_i|$. The largest $g_i(\boldsymbol{x})$ corresponds to the class ω_i to which $\boldsymbol{x}$ belongs [28,29]. The case when the covariance matrices of the different classes are identical represents LDA [28]. Figure 3.7 below illustrates the graphical differences between LDA and QDA.

Unlike LDA which draws linear boundaries between the different classes in the data set, QDA provides more flexibility by drawing curved boundaries [28,29]. QDA has more predictability power than LDA, however, it needs to estimate the covariance matrix for all classes in the data set. The "classify" function in Matlab was also used to perform QDA on the data set.

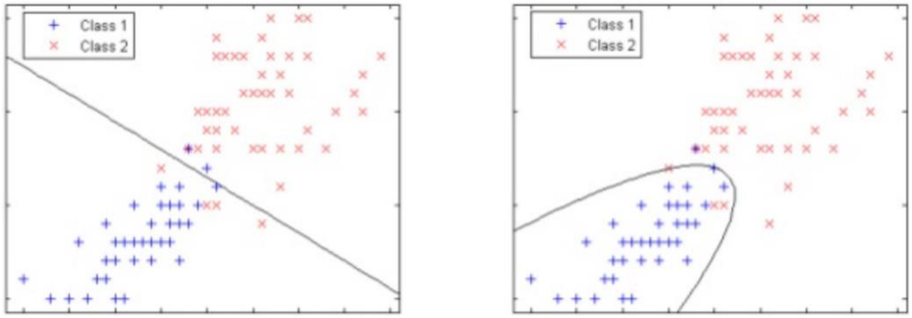


Figure 3.7. LDA draws a line to separate the two classes (the left side of the figure) compared to QDA which presents a better classification of the data sets using curves (the right side of the figure).

3.4.3 Support Vector Machine Classifier

Support **V**ector **M**achines (SVM) as a classifier was first introduced in the Seventies by Vapnik [30]. It was originally introduced as a linear classifier and then was adopted to create non-linear SVM classifiers in the Nineties by Boser, Guyon, and Vapnik [31]. The idea of linear SVM classifier is to maximize the margin separating two category of classes, figure 3.8 and 3.9 below illustrate how SVM works. If we assume D to be a training set of n points so that

$$D = \left\{(\boldsymbol{x}_i, y_i) \middle| \boldsymbol{x}_i \in \mathbb{R}^p, y_i \in \{+1, -1\}\right\}_{i=1}^{n} \qquad \text{(Eq. 3.11)}$$

where $\boldsymbol{x}_i$ is a p-dimensional real vector, y_i is the either +1 or -1 indicating the class to which $\boldsymbol{x}_i$ belongs [28,30,32,33]. A hyperplane with a set of points $\boldsymbol{x}$ that lies on it can be written as

$$\boldsymbol{w} \cdot \boldsymbol{x} + b = 0 \qquad \text{(Eq. 3.12)}$$

where $\boldsymbol{w}$ is normal to the hyperplane, $\cdot$ is the dot product, $b/\|\boldsymbol{w}\|$ is the perpendicular distance from the hyperplane to the origin, and $\|\boldsymbol{w}\|$ is the Euclidean norm of $\boldsymbol{w}$ [28,30,32,33]. If d_1 is the shortest distance from the hyperplane to the first class and d_2 is the shortest distance from the hyperplane to the second class, $d_1 + d_2$ is called the margin, then for a linearly separable case, it requires that

$$\boldsymbol{x_i} \cdot \boldsymbol{w} + b \geq +1 \qquad for\ y_i = +1 \qquad \text{(Eq. 3.13)}$$
$$\boldsymbol{x_i} \cdot \boldsymbol{w} + b \leq -1 \qquad for\ y_i = -1 \qquad \text{(Eq. 3.14)}$$

which means there will be two hyperplanes $\boldsymbol{x_i} \cdot \boldsymbol{w} + b = +1$ and $\boldsymbol{x_i} \cdot \boldsymbol{w} + b = -1$ separating the classes and $d_1 = d_2 = {}^{1}/_{\|\boldsymbol{w}\|}$. The task will be to maximize the margin between the two hyperplanes which is equivalent to minimizing $\frac{1}{2}\|\boldsymbol{w}\|^2$, since it is a quadratic optimization task, while at the same time meeting the following constraint [28,30,32,33]

$$y_i(\boldsymbol{x_i} \cdot \boldsymbol{w} + b) \geq +1 \qquad \forall i \qquad \text{(Eq. 3.15)}$$

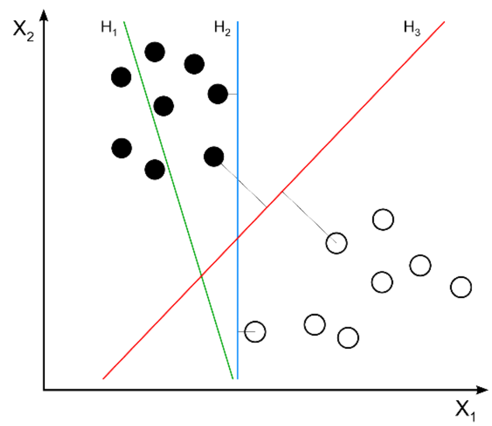


Figure 3.8. SVM's task is to determine which hyperplane results in the maximum margin between the hyperplane and each of the classes, H3 in this figure although H2 fully separates the classes as well.

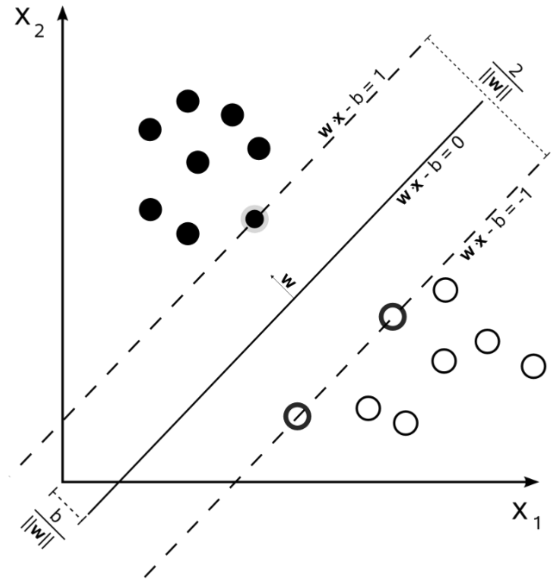


Figure 3.9. SVM's task is to maximize the margin between the two classes (the white and the black circles) which can be achieved by minimizing $\frac{1}{2}\|\boldsymbol{w}\|^2$.

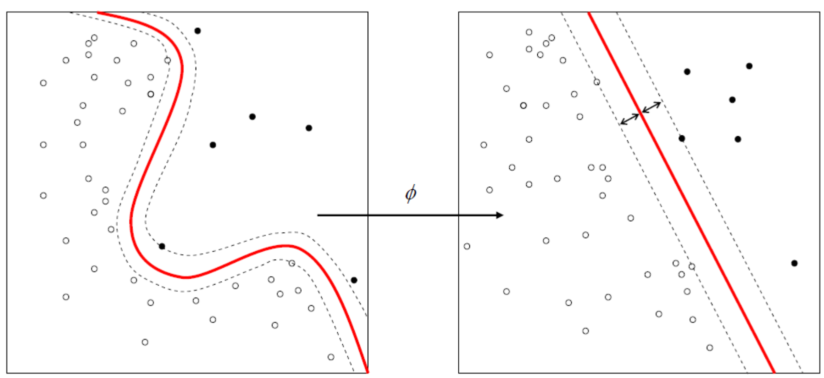


Figure 3.10. The SVM kernel function transforms linearly non-separable classes to linearly separable classes using a function $\boldsymbol{\phi}$.

The above primarily applies to the linearly separable classes. What about the linearly non-separable classes? The kernel function trick can be utilized to transform the non-separable classes into linearly separable classes. The Polynomial Learning Machine and Gaussian Radial-Basis Functions (rbfs) are examples of kernel functions that can be used to transform the linearly non-separable classes to separable ones. Figure 3.10 above illustrates how the kernel function works.

In this study, a Gaussian Radial-Basis Function (rbf) has been used to classify the data. A variable σ was set to 0.5 after several trials to determine the value that produces best results since rbf is given by [28,30,32,33]

$$\exp\left(-\frac{1}{2\sigma^2}\|\boldsymbol{x}-\boldsymbol{x_i}\|^2\right) \qquad \text{(Eq. 3.16)}$$

Matlab's "*svmtrain*" and "*svmclassify*" functions were used to implement the SVM classification.

3.4.4 Equal Test-Train

In equal test-train, the main task was to understand the separability of the available samples. The classifier was first trained with all available samples and then the same samples were used for testing. Obviously this is overly optimistic, since a good classifier will be able to correctly identify the class of the test samples since they are a duplicate of the training set.

Using Matlab and the three classification methods described above, the following steps were executed to understand classification possibility of the seizure and PNES samples:

1. Extract the features indicated in section 3.3 for all the samples.
2. Choose a maximum of 5 features at a time. A maximum of 5 is chosen to try to avoid overmodeling. The number of selected features ranges from 1-5 features at each trial.
3. Train the classifier on available features for all samples indicating to which class they belong. A more detailed description of the features split is provided later in this section.
4. Test each sample against the training data set from step 2 above.

5. Record the following results:

    a. *overall accuracy* = % all correctly classified samples.

    b. *true positive* = % correctly classified seizures = $\frac{\text{\# correctly classified seizures}}{\text{Total number of seizures}}$.

    c. *true negative* = % correctly classified PNESs = $\frac{\text{\# correctly classified pesudo−seizures}}{\text{Total number of pesudo−seizures}}$.

    d. *miss* = % misclassified seizures = 1 – *true positive*.

    e. *robustness* = *true positive* – (1 – *true negative*).

6. Repeat steps 2-5 for all possible combinations of features.

The steps above were repeated for each classification method, namely LDA, QDA, and SVM. The best features are the ones that score best *true positive* and *robustness* results simultaneously, a target of more than 90% is set for both when performing equal test-train. The choice of *true positive* as an indicator of good feature is due to the nature of the main problem, namely how to identify seizures and PNESs correctly. The classification method should identify all seizures correctly because patients with seizures harm themselves unconsciously which could result in their death. Alerting someone staying close to a seizure patient at the right time could save his life. Additionally, *robustness* is an indicator that combines how much false is associated with the classification related to the set of features used. It shows the difference between *true positive* and *false alarm* which gives an idea of how reliable are the set of features tested. It lowers the accuracy of seizures detected correctly by PNESs that are misclassified as seizures. t*rue positive* and *robustness* will be the main focus of equal test-train results section below, section 4.2.

The equal test-train was performed on the following features separately to figure out which set of features provides the most desirable results. The features with best results were then used in the cross-validation exercise described in the final section of this chapter. The set of features upon which the equal test-train was performed are:

- PSD bands in the different frequency ranges indicated in table 3.1 – total of 69 trials.
- Maximum of the envelope and mean maximum of the envelope – total of 9 trials.
- 13 MFCCs – total of 12 trials.

A total of 8 equal test-train trials have been performed. More information on the features that produce best results, and subsequently used for cross-validation, will be presented in the next chapter.

3.4.5 Cross-Validation

In cross-validation, a similar approach to the one presented in equal test-train was followed, however, with one main difference. The task in this exercise is to validate the results obtained in equal test-train (i.e., the best features that can separate seizures from PNESs properly). Hence, the training set had to be different than the testing set. The following steps were performed to execute the cross-validation:

1. All desired features are uploaded to Matlab as one big matrix containing 28 samples. Another matrix was loaded which included class label for each sample.
2. Maximum of 5 features are selected at each trial. The number of features was either 4 or 5 depending on the overall number of features available.
3. The samples are divided into two groups, namely training and test data sets. 30% of the samples from each group, seizures and PNESs, were chosen randomly and used as a testing data set (5 seizures and 4 PNESs) while the remaining 70% were used as a training data set (11 seizures and 8 PNESs).

4. Number of iterations was set to 500 to ensure a rich set of combinations of the "30% testing – 70% training" are tested. A small number of iterations might not result in sufficient combinations being tested.
5. Train the classifier on the 70% training data set.
6. Test the classifier with the remaining 30% testing data set.
7. Record the following results (*Note: all 500 iterations for all possible feature combinations, as indicated in step 2 above, considered*):
    a. *overall accuracy* = % correctly classified test data set = $\frac{\text{\# correctly classified test samples}}{\text{Total number of samples}}$.
    b. *true positive* = % correctly classified seizures = $\frac{\text{\# correctly classified test seizures}}{\text{Total number of seizures}}$.
    c. *true negative* = % correctly classified PNESs = $\frac{\text{\# correctly classified pesudo−seizures}}{\text{Total number of pesudo−seizures}}$.
    d. *miss* = % misclassified seizures = 1 – *true positive.*
    e. *robustness* = *true positive* – (1 – *true negative*).
8. Repeat steps 2-7 for all possible feature combinations.

The cross-validation exercise was also performed for all types of classifiers, LDA, QDA, and SVM. The number of features used in the classification was set so that optimal results are achieved with as few features as possible to reduce the computational cost. It will be chosen based on equal test-train results. For example, if best results in equal test-train are achieved using four dimensional feature space, cross-validation will start from there. The number of features could be increased if necessary.

Cross-validation top results will not follow equal test-train filtration, i.e., *true positive* and *robustness* of more than 90% simultaneously, however, it will focus on the top 10 – 20 records depending on the results. The aim is to highlight the performance of each classifier, which features contribute to the top results, and the impact of the feature space dimensionality.

CHAPTER IV ANALYSIS OF RESULTS

The main purpose of this chapter is to detail the results of the study highlighting the most significant aspects. The chapter will start with a short introduction followed by two main sections covering the equal test-train and cross-validation results.

4.1 Introduction

In order to obtain the study results, the steps in chapter 3 were followed. In this chapter, we will go over the results of the two most important exercises: 1) Equal test-train classification – section 4.2, and 2) Cross-validation analysis – section 4.3; the remainder of the chapter is arranged along these two lines. This chapter will not highlight the data related to extracted features or those that are sample-specific. In section 4.2, we will show the detailed results of the equal test-train for all the PSDs of the desired frequency ranges, max on the envelope and its mean, and MFCCs. We will highlight which features have produced the best results in terms of classifying the samples. In section 4.3, we will focus only on the features that presented best results, namely 0 – 3.00kHz PSD bands and MFCCs as will be shown below, and implement a cross-validation to confirm the separability of the samples. The results of the cross-validation will be shown in section 4.3.

4.2 Equal Test-Train Results and Remarks

Equal test-train had to deal with all available features. There was no exception. Multiple classification trials have been performed on available features as follows (according to table 3.1 and section 3.4.4):

a. PSDs in the 0 – 2.00kHz frequency range along 5 sub-frequencies; 0 – 250Hz, 0 – 500Hz, 500Hz – 1.00kHz, 1.00kHz – 1.50kHz, and 1.50kHz – 2.00kHz.

b. PSDs in the 0 – 2.00kHz frequency range along 6 sub-frequencies; 0 – 333Hz, 333Hz – 666Hz, 666Hz – 1.00kHz, 1.00kHz – 1.33kHz, 1.33kHz – 1.67kHz, and 1.67kHz – 2.00kHz.
c. PSDs in the 0-2.00kHz frequency range along 8 sub-frequencies; 0 – 250Hz, 250Hz – 500Hz, 500Hz – 750Hz, 750Hz – 1.00kHz, 1.00kHz – 1.25kHz, 1.25kHz – 1.50kHz, 1.50kHz – 1.75kHz, and 1.75kHz – 2.00kHz.
d. PSDs in the 0 – 3.00kHz frequency range along 7 sub-frequencies; 0 – 250Hz, 0 – 500Hz, 500Hz – 1.00kHz, 1.00kHz – 1.50kHz, 1.50kHz – 2.00kHz, 2.00kHz – 2.50kHz, and 2.50kHz – 3.00kHz.
e. PSDs in the 0 – 3.00kHz frequency range along 9 sub-frequencies; 0 – 333Hz, 333Hz – 666Hz, 666Hz – 1.00kHz, 1.00kHz – 1.33kHz, 1.33kHz – 1.67kHz, 1.67kHz – 2.00kHz, 2.00kHz – 2.33kHz, 2.33kHz – 2.67kHz, and 2.67kHz – 3.00kHz.
f. PSDs in the 0 – 3.00kHz frequency range along 12 sub-frequencies; 0 – 250Hz, 250Hz – 500Hz, 500Hz – 750Hz, 750Hz – 1.00kHz, 1.00kHz – 1.25kHz, 1.25kHz – 1.50kHz, 1.50kHz – 1.75kHz, 1.75kHz – 2.00kHz, 2.00kHz – 2.25kHz, 2.25kHz – 2.50kHz, 2.50kHz – 2.75kHz, and 2.75kHz – 3.00kHz.
g. Max of the envelope and mean max of the envelope
h. MFCCs

LDA, QDA, and SVM classification methods have been performed on the features described in points a-h above to obtain equal test-train results.

4.2.1 Power Spectral Densities Classification Results

In order to understand the usability and accuracy of the different features detailed in table 3.1 and earlier in section 4.2, the number of features had to be set at less than half of the available features while performing the equal test-train exercise. For example, when checking point (a) as detailed earlier at section 4.2, the number of features was chosen to be either one, two, or three at each trial. A total of 9 trials were performed by combining the method of classification (LDA, QDA, or SVM) with the number of PSD features (one, two, or three features). The reason to limit the number of features for each trial is to first avoid the singularity problem (detailed in section 3.4.1) and also to achieve good results with lower computational cost.

The results of points (a) – (f), the points are stated at the beginning of 4.2, are highlighted in this part of the study. The aim was to understand which frequency ranges of the PSDs produce the best results so that they can be used in the cross-validation exercise. The choice of the best frequency range is highlighted in the remarks section below, 4.2.4. To preserve space and focus on most important results, this section will only show a histogram of overall results with zoom-in to the top 5 results in terms of *true positive* and *robustness* simultaneously and also the top 5 most accurate results by looking into *overall accuracy*. The features corresponding to these top results will be highlighted as well. The histogram was constructed in a way to show how each category of the four most important ones, namely *overall accuracy*, *true positive*, *true negative*, and *robustness*, is distributed along seven percentage groups, namely 50% or less, 50%-60%, 60%-70%, 70%-80%, 80%-90%, 90%-99%, and 100%, without any interdependency among the four categories. For example, the histogram will show how many combinations achieved each of the percentage group values (50% or less, 50%-60%, 60%-70%, 70%-80%, 80%-90%, 90%-99%, and 100%) in *overall accuracy* regardless of the other three categories. It will handle the remaining three categories similarly.

a. <u>PSDs in the 0 – 2.00kHz frequency range along 5 sub-frequencies; 0 – 250Hz, 0 – 500Hz, 500Hz – 1.00kHz, 1.00kHz – 1.50kHz, and 1.50kHz – 2.00kHz</u>

- Equal test-train when choosing one PSD band at a time - LDA:

We had a total of 5 possible combinations when choosing one PSD band at a time. Equal test-train's LDA achieved poor results in general when choosing one PSD band. Figure 4.1 below shows the equal test-train classification results across the four categories while table 4.1 highlights the top 5 classification results sorted first by *true positive* followed by *robustness* and by *overall accuracy*.

Figure 4.1 shows that LDA classifier achieved poor results when choosing only one PSD band. Almost all results were below 70% across the four categories except for three values. One out of 5 possible combination achieved a *true positive* of more than 70% - PSD_0, one achieved a *true negative* of more than 70% - PSD_2, and one achieved an *overall accuracy* of more than 70% - PSD_0.

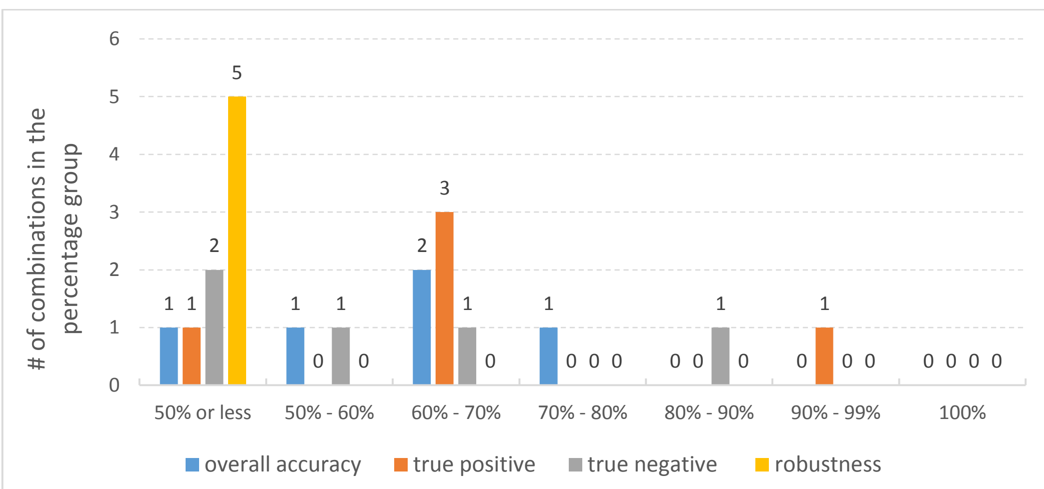


Figure 4.1. Equal test-train classification results using a LDA classifier while choosing one PSD band at a time for the frequency range detailed in point (a) above.

Table 4.1. Top 5 results of equal test-train LDA classification while choosing one PSD band at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_0
	57%	69%	42%	10%	PSD_4
	71%	63%	83%	46%	PSD_2
	61%	63%	58%	21%	PSD_1
	43%	25%	67%	-8%	PSD_3
In terms of *overall accuracy*	71%	63%	83%	46%	PSD_2
	68%	94%	33%	27%	PSD_0
	61%	63%	58%	21%	PSD_1
	57%	69%	42%	10%	PSD_4
	43%	25%	67%	-8%	PSD_3

Table 4.1 shows that PSD_0, 0-250Hz, was the best feature in terms of *true positive* followed by *robustness* when choosing one PSD band and performing a LDA classification. It missed 6% of the seizure cases only, however, it had misclassified a majority of the PNESs, 67%, as seizures. PSD_0's *robustness* was also very low but yet second highest, 27%, among the five possible combinations.

When looking into the results from another angel, PSD_2, 500Hz – 1.00kHz, achieved the most accurate results, an *overall accuracy* of 71%, followed by PSD_0 with an *overall accuracy* of 68%. PSD_3, 1.00kHz – 1.50kHz, was the least performing feature in both sorted buckets. In the remainder of the this section we will follow a similar approach of showing a histogram of the results followed by a table that highlights the top 5 results in the *true positive* followed by *robustness* and the *overall accuracy* buckets. A very brief highlight of the results will be included as well. The remarks section, 4.2.4, will summarize the findings of the PSD bands classification exercise. Table 3.1 should always be referred to for the terminologies PSD_0, PSD_1, …. , up to PSD_{12}.

- Equal test-train when choosing one band at a time – QDA:

Figure 4.2 shows the histogram of QDA classification results in a similar fashion as of figure 4.1 while table 4.2 shows the top 5 results using a QDA classifier in a similar fashion as of table 4.1.

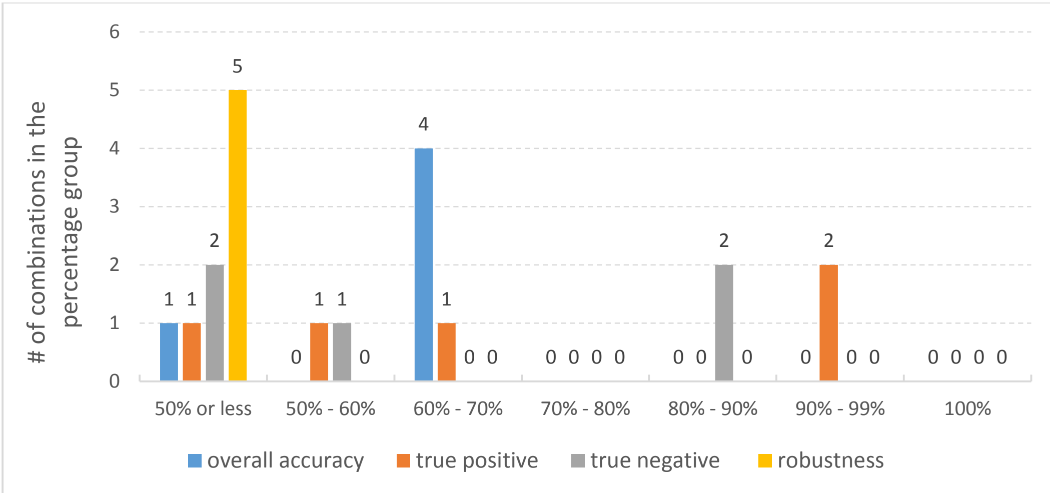


Figure 4.2. Equal test-train classification results using a QDA classifier while choosing one PSD band at a time for the frequency range detailed in point (a) above.

Table 4.2. Top 5 results of equal test-train QDA classification while choosing one PSD band at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_0
	64%	94%	25%	19%	PSD_4
	64%	69%	58%	27%	PSD_1
	68%	56%	83%	40%	PSD_2
	39%	6%	83%	-10%	PSD_3
In terms of *overall accuracy*	68%	94%	33%	27%	PSD_0
	68%	56%	83%	40%	PSD_2
	64%	94%	25%	19%	PSD_4
	64%	69%	58%	27%	PSD_1
	39%	6%	83%	-10%	PSD_3

The histogram in figure 4.2 shows that the QDA was a little better than LDA with two *true positive* values above 90% and two *true negative* values between 80% and 90%. The *overall accuracy* and *robustness* were both disappointing, below 70% and below 50% respectively. Table 4.2 shows that PSD_0 achieved the best results, however, its associated *true negative* and *robustness* indices are still very low indicating that most of the PNESs are still classified as seizures. PSD_3 was still the lowest performing feature in QDA classification with almost all samples being classified as PNESs.

- Equal test-train when choosing one band at a time – SVM:

Figure 4.3 and table 4.3 highlight the SVM classification results.

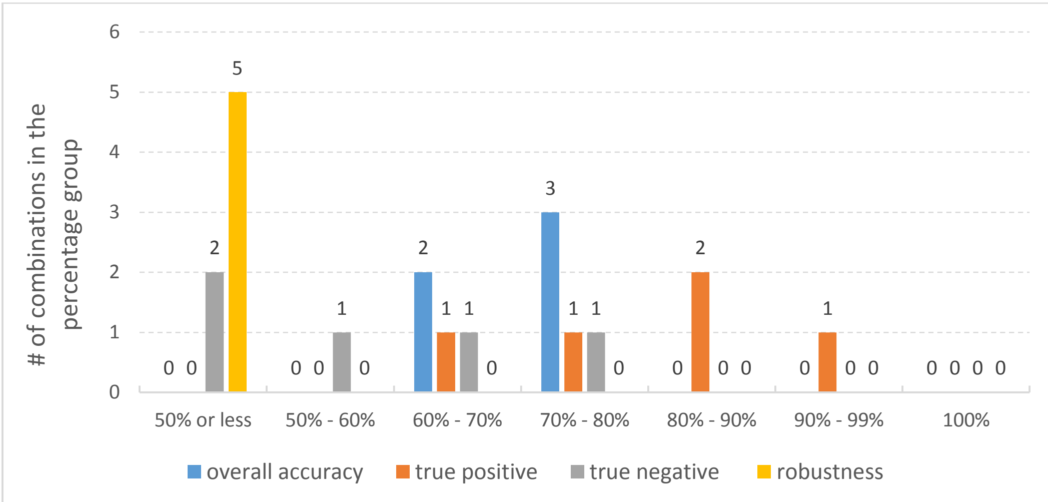


Figure 4.3. Equal test-train classification results using a SVM classifier while choosing one PSD band at a time for the frequency range detailed in point (a) above.

Table 4.3. Top 5 results of equal test-train SVM classification while choosing one PSD band at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	64%	94%	25%	19%	PSD_4
	71%	88%	50%	38%	PSD_0
	71%	81%	58%	40%	PSD_1
	75%	75%	75%	50%	PSD_2
	64%	63%	67%	29%	PSD_3
In terms of *overall accuracy*	75%	75%	75%	50%	PSD_2
	71%	88%	50%	38%	PSD_0
	71%	81%	58%	40%	PSD_1
	64%	94%	25%	19%	PSD_4
	64%	63%	67%	29%	PSD_3

The histogram shows that the SVM classifier performed better classification with 6 values exceeding 70%, yet it is still not sufficient as a classifier. The *robustness* index which is one of the most important two indices is still below 50% for all the combinations. Table 4.3 shows that PSD_4 was the best performing in the first bucket that focuses on *true positive* and *robustness* while PSD_2 was the most accurate achieving an *overall accuracy* of 75%. It is worth noting that PSD_0 was second best performing in both buckets.

The SVM classifier was the best performing when choosing only one feature at a time in the frequency range 0-2.00kHz divided into 5 sub-frequencies. The best *overall accuracy* reached 75% while the best *true positive* reached 94%, however, *robustness* never exceeded 50%.

- Equal test-train when choosing a combination of two bands at a time – LDA:

Figure 4.4 and table 4.4. below highlight the LDA classification results for the frequency range detailed in point (a) at the beginning of this section, 4.2.1, but with each feature combination containing two PSD bands. The number of possible combinations is 10. The classifier has tested all possible combinations.

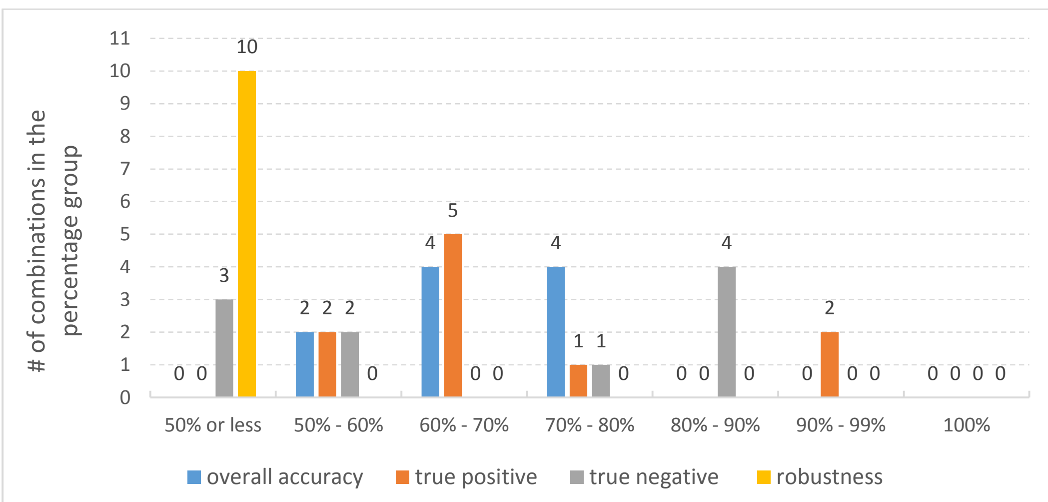


Figure 4.4. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (a) at the beginning of section 4.2.1.

Table 4.4. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*Robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_0, PSD_4
	64%	94%	25%	19%	PSD_0, PSD_3
	68%	75%	58%	33%	PSD_0, PSD_1
	57%	69%	42%	10%	PSD_3, PSD_4
	71%	63%	83%	46%	PSD_2, PSD_4
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_0, PSD_4
	71%	63%	83%	46%	PSD_2, PSD_4
	71%	63%	83%	46%	PSD_1, PSD_4
	71%	63%	83%	46%	PSD_1, PSD_2
	68%	75%	58%	33%	PSD_0, PSD_1

Again, the LDA classifier has performed poorly when combining two PSD bands except for few values in *true positive* and *true negative*. *overall accuracy* and *robustness* both achieved less than 50% and less than 75% respectively. The best result when looking into *true positive* followed by *robustness* sorting bucket was achieved by PSD_0+PSD_4 combination achieving a 75% *overall accuracy*, 94% *true positive*, 50% *true negative*, and 44% *robustness*. The only drawback is that half of the PNESs were classified as seizures. The same combination has also achieved the best *overall accuracy*. The LDA classification when combining two PSD bands achieved better results compared to choosing only one PSD band at a time.

- Equal test-train when choosing a combination of two bands at a time – QDA:

Figure 4.5 and table 4.5 highlight the results of applying QDA equal test-train classification when combining two PSD bands from the frequency range detailed in point (a) at the beginning of this section. In general, the performance of QDA two bands classification is better than the LDA two band classification and the QDA one band classification. One of the *robustness* index values exceeded 50% for the first time. The *overall accuracy* index is shifting more towards values higher than

60% but still below 75%. 30% of the combinations achieved a *true positive* of more than 90% and 40% of the combinations achieved a *true negative* of 80%-90%.

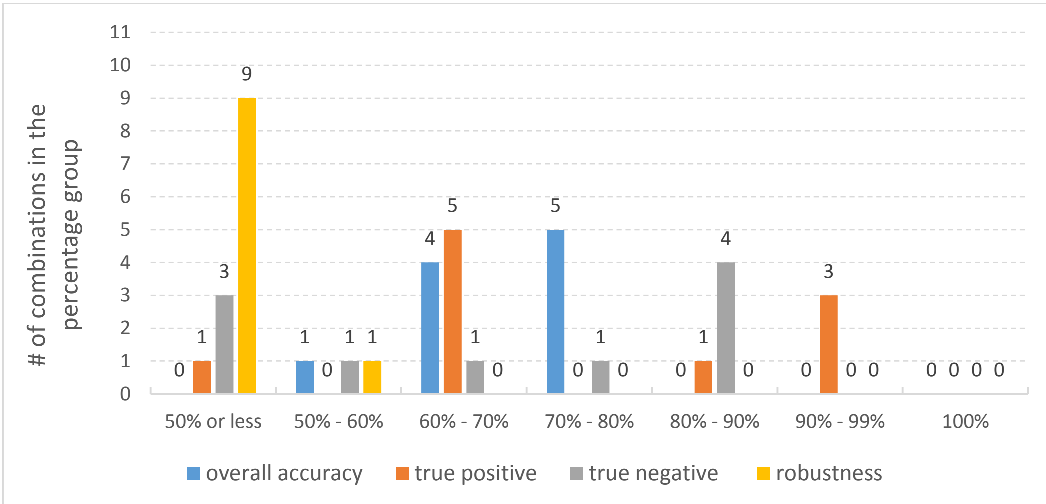


Figure 4.5. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (a) at the beginning of section 4.2.1.

Table 4.5. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	94%	42%	35%	PSD_0, PSD_2
	68%	94%	33%	27%	PSD_0, PSD_3
	68%	94%	33%	27%	PSD_0, PSD_1
	75%	88%	58%	46%	PSD_0, PSD_4
	75%	69%	83%	52%	PSD_1, PSD_4
In terms of *overall accuracy*	75%	88%	58%	46%	PSD_0, PSD_4
	75%	69%	83%	52%	PSD_1, PSD_4
	71%	94%	42%	35%	PSD_0, PSD_2
	71%	63%	83%	46%	PSD_2, PSD_4
	71%	63%	83%	46%	PSD_1, PSD_2

The combination PSD_0 and PSD_2 has achieved the best results when looking into *true positive* followed by *robustness* bucket, however, the *robustness* of this combination was still very low which means it still produces high false alarms. On the other hand, PSD_0 and PSD_4 combination achieved the best *overall accuracy* of 75%. It is also worth noting that PSD_0 and PSD_4 combination achieved relatively high results in the *true positive* followed by *robustness* bucket, ranked 3rd among the top 5 results.

- Equal test-train when choosing a combination of two bands at a time – SVM:

Figure 4.6 and table 4.6 highlights the results of classifying the combinations consisting of two PSD bands from point (a)'s frequency range using SVM classifier.

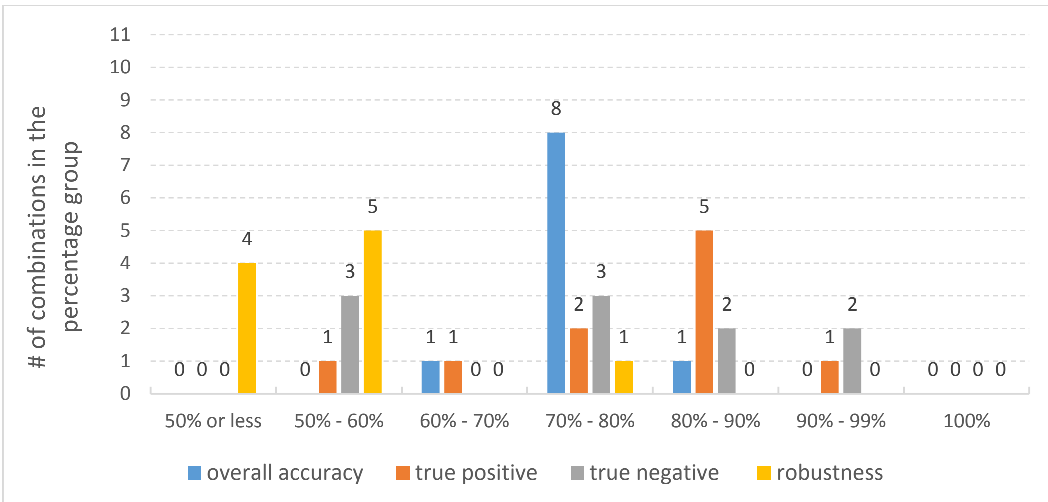


Figure 4.6. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (a) at the beginning of section 4.2.1.

Table 4.6. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	94%	58%	52%	PSD_0, PSD_3
	75%	88%	58%	46%	PSD_0, PSD_4
	86%	81%	92%	73%	PSD_2, PSD_4
	79%	81%	75%	56%	PSD_2, PSD_3
	79%	81%	75%	56%	PSD_1, PSD_3
In terms of *overall accuracy*	86%	81%	92%	73%	PSD_2, PSD_4
	79%	94%	58%	52%	PSD_0, PSD_3
	79%	81%	75%	56%	PSD_2, PSD_3
	79%	81%	75%	56%	PSD_1, PSD_3
	79%	75%	83%	58%	PSD_1, PSD_4

The SVM classification using two PSD bands has shown significant improvements compared to the previous classifications. The *robustness* index has shifted significantly towards the right with 50% of the combinations achieving 50%-60% *robustness* and 10% of the combinations achieving 70%-80%. On the accuracy side, 80% of the combinations achieved 70%-80% *overall accuracy* and 10% of the combinations achieved 80%-90%. Table 4.6 shows that PSD_0 and PSD_3 achieved the best results in the *true positive* followed by *robustness* bucket, albeit its *robustness* being unsatisfactory yet. However, PSD_2 and PSD_4 combination achieved a balanced result across the different categories with *overall accuracy* of 86%, 81% *true positive*, 92% *true negative*, and *robustness* of 73%. This is the first time to see balanced results. SVM two band classification highlighted a strong presence of PSD_3 in the top 5 results in the two buckets shown in table 4.6.

Again SVM was the best classifier when classifying samples based on two PSD bands. The top *overall accuracy* reached 86%, the first time to exceed 80% thus far, and also achieving balanced results across all available categories.

The aim of the next trials will be to achieve results of more than 90% in *true positive* and *robustness* indices simultaneously. Now, since the methodology of dealing with the results is clear, any results that do not satisfy the desired aim will not be shown. Appendix B will contain the histograms and tables of the top 5 results in each trial regardless of whether they achieve desired results or not.

- Equal test-train when choosing a combination of three bands at a time – LDA:

None of the combinations achieved the desired aim of 90% *true positive* and 90% *robustness*. It is worth noting that PSD_4 has achieved the best in both top results buckets, top 5 in terms of *true positive* followed by *robustness* and in terms of *overall accuracy*.

- Equal test-train when choosing a combination of three bands at a time – QDA:

None of the combinations achieved the desired aim using QDA classification with three PSD bands. However, PSD_4 has been present in all top 5 results in the two targeted buckets of focus in this study.

- Equal test-train when choosing a combination of three bands at a time – LDA:

None of the combinations achieved the desired aim albeit SVM classifier was able to achieve better results compared to LDA and QDA. The highest *overall accuracy* reached 89%. The same combination with highest *overall accuracy* achieved second highest *true positive* of 88% and the highest *robustness* of 79%. Please refer to appendix B for more details. PSD_2 and PSD_4 were present in 4 out of 5 top results in both targeted buckets.

SVM was again the best performing classifier when choosing three PSD bands at a time with PSD_4 being one of the most important feature present in most of the top results achieved.

In general, SVM classifier has been the dominant classifier for the frequency range 0 – 2.00kHz along 5 sub-frequencies described in point (a) at the beginning of this section. It achieved best results regardless of the number of features used, one, two, or three PSD bands at a time, with PSD_0 (0 – 250Hz) and PSD_4 (1.50kHz – 2.00kHz) being important classification features.

b. PSDs in the 0 – 2.00kHz frequency range along 6 sub-frequencies; 0 – 333Hz, 333Hz – 666Hz, 666Hz – 1.00kHz, 1.00kHz – 1.33kHz, 1.33kHz – 1.66kHz and 1.66kHz – 2.00kHz

- Equal test-train when choosing one band at a time – LDA:

None of the PSD bands achieved the desired aim.

- Equal test-train when choosing one band at a time – QDA:

None of the PSD bands achieved the desired aim.

- Equal test-train when choosing one band at a time – SVM:

  None of the PSD bands achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – SVM:

SVM classifier, when choosing a combination of four features at a time, has achieved the desired aim of at least 90% in both *true positive* and *robustness* for the first time. One combination only was able to achieve the aim, namely PSD_1 (0 – 333Hz), PSD_3 (666Hz – 1.00kHz), PSD_4 (1.00kHz – 1.33kHz), PSD_5 (1.33kHz – 1.66kHz). This combination not only achieved the desired aim but also achieved 100% across all categories. Figure 4.7 shows the histogram of SVM classifier with a combination of four features while table 4.7 shows the top 5 results. The overall results have also improved by more than 90% of the combinations achieving *overall accuracy*, *true positive*, and *true negative* of more than 70% while *robustness* is still lagging behind, 33% of combinations achieving less than 70%.

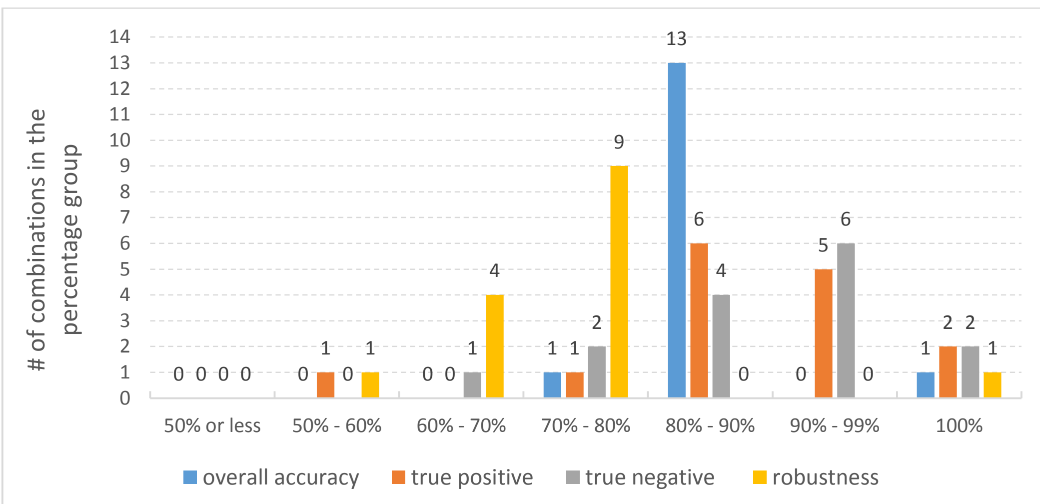


Figure 4.7. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (b) at the beginning of section 4.2.1.

In general, SVM classifier was again the best classifier for the frequency range described in point (b) at the beginning of this section. The most notable features across the different classification exercises were PSD_1 (0 – 333Hz) and PSD_6 (1.66kHz – 2.00kHz) which led to top results regardless of classification method and number of features chosen.

Table 4.7. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	86%	100%	67%	67%	PSD_2, PSD_3, PSD_4, PSD_6
	89%	94%	83%	77%	PSD_1, PSD_3, PSD_4, PSD_6
	89%	94%	83%	77%	PSD_1, PSD_2, PSD_4, PSD_6
	89%	94%	83%	77%	PSD_1, PSD_2, PSD_3, PSD_6
In terms of *overall accuracy*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	89%	94%	83%	77%	PSD_2, PSD_3, PSD_4, PSD_6
	89%	94%	83%	77%	PSD_1, PSD_3, PSD_4, PSD_6
	89%	94%	83%	77%	PSD_1, PSD_2, PSD_4, PSD_6
	89%	88%	92%	79%	PSD_1, PSD_2, PSD_3, PSD_6

c. <u>PSDs in the 0 – 2.00kHz frequency range along 8 sub-frequencies; 0 – 250Hz, 250Hz – 500Hz, 500Hz – 750Hz, 750Hz – 1.00kHz, 1.00kHz – 1.25kHz, 1.25kHz – 1.50kHz, 1.50kHz – 1.75kHz and 1.75kHz – 2.00kHz</u>

- Equal test-train when choosing one band at a time – LDA:

    None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – QDA:

    None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – SVM:

    None of the bands achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – LDA:

    None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – QDA:

    None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – SVM:

  None of the combinations achieved the desired aim.

In general, SVM was also the best performing classifier in this frequency range. The best achieved result was an SVM classifier when choosing a combination of either three or four bands. The *overall accuracy* reached 93%, *true positive* reached 100%, *true negative* reached 83%, and *robustness* reached 83%. PSD_1 (0 – 250Hz) was the most dominant feature which appeared in most of the top results throughout the frequency range described in point (c).

d. PSDs in the 0 – 3.00kHz frequency range along 7 sub-frequencies; 0 – 250Hz, 0 – 500Hz, 500Hz – 1.00kHz, 1.00kHz – 1.50kHz, 1.50kHz – 2.00kHz, 2.00kHz – 2.50kHz, and 2.50kHz – 3.00kHz

- Equal test-train when choosing one band at a time – LDA:

  None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – QDA:

  None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – SVM:

  None of the bands achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – SVM:

  None of the combinations achieved the desired aim.

SVM classifier was still the best performing among the three classification methods. The highest achieved result was by choosing a combination of three bands recording 93% *overall accuracy*, 100% *true positive*, 83% *true negative*, and 83% *robustness*. PSD_0 (0 – 250Hz), PSD_2 (500Hz – 1.00kHz), PSD_5 (2.00kHz – 2.50kHz), and PSD_6 (2.50kHz – 3.00kHz) were the features dominating best results achieved. The four features leading to top results indicate that it might be beneficial to expand the PSD frequency range to 3.00kHz. The remaining of this section will provide a better evaluation of whether expanding the frequency range adds value.

e. PSDs in the 0 – 3.00kHz frequency range along 9 sub-frequencies; 0 – 333Hz, 333Hz – 666Hz, 666Hz – 1.00kHz, 1.00kHz – 1.33kHz, 1.33kHz – 1.66kHz, 1.66kHz – 2.00kHz, 2.00kHz – 2.33kHz, 2.33kHz – 2.66kHz and 2.66kHz – 3.00kHz

- Equal test-train when choosing one band at a time – LDA:

  None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – QDA:

  None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – SVM:

  None of the bands achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – QDA:

    None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – SVM:

The SVM classifier this time was able to achieve the desired aim. Actually, four combinations were able to score the desired aim, as shown in table 4.8. Figure 4.8 below shows a high level view of the SVM classifier performance. 100% of the combinations achieved more than 70% in *overall accuracy* and *true negative* while ~85% of the combinations achieved more than 70% in *true positive* and ~68% achieve more than 70% in *robustness*. This is still in-line with the results achieved by the frequency range described in point (b). Similar to point (b), SVM top result was 100% across all four categories.

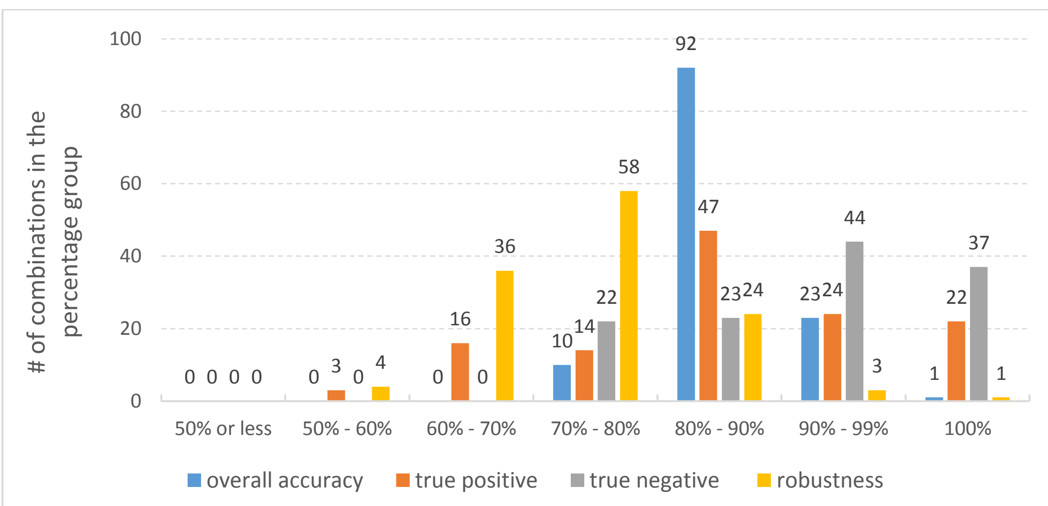


Figure 4.8. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (e) at the beginning of section 4.2.1.

The results in table 4.8 is quite promising since it indicates, to certain extent, that it is possible to separate the seizure samples from PNESs at high accuracy. Eleven combinations have achieved ultimately superior results.

Table 4.8. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy. (Seven combinations achieved the indicated results in the row. Check appendix B for details).*

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	96%	100%	92%	92%	PSD_1, PSD_4, PSD_7, PSD_8
	96%	100%	92%	92%	PSD_1, PSD_3, PSD_4, PSD_9
	96%	100%	92%	92%	PSD_1, PSD_2, PSD_3, PSD_4
	93%	100%	83%	83%	*Multiple combinations.**
In terms of *overall accuracy*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	96%	100%	92%	92%	PSD_1, PSD_4, PSD_7, PSD_8
	96%	100%	92%	92%	PSD_1, PSD_3, PSD_4, PSD_9
	96%	100%	92%	92%	PSD_1, PSD_2, PSD_3, PSD_4
	93%	100%	83%	83%	*Multiple combinations.**

In general, SVM classifier has been the best one so far being able to reach the desired aim set at the beginning of this chapter. PSD_1 (0 – 333Hz) was the feature presented in most of the top results related to the frequency range in part (e).

f. PSDs in the 0 – 3.00kHz frequency range along 12 sub-frequencies; 0 – 250Hz, 250Hz – 500Hz, 500Hz – 750Hz, 750Hz – 1.00kHz, 1.00kHz – 1.25kHz, 1.25kHz – 1.50kHz, 1.50kHz – 1.75kHz, 1.75kHz – 2.00kHz, 2.00kHz – 2.25kHz, 2.25kHz – 2.50kHz, 2.50kHz – 2.75kHz and 2.75kHz – 3.00kHz

- Equal test-train when choosing one band at a time – LDA:

  None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – QDA:

  None of the bands achieved the desired aim.

- Equal test-train when choosing one band at a time – SVM:

  None of the bands achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two bands at a time – SVM:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three bands at a time – SVM:

The SVM classifier choosing a combination of three bands was able to achieve the desired aim but with only one combination out of the 220 possible ones. This is the first time to achieve such results with three features. The *overall accuracy* recorded was 96% while *true positive*, *true negative*, and *robustness* were 100%, 92%, and 92% respectively. The combination comprised of PSD_3, PSD_5, and PSD_{10}. Figure 4.9 shows the histogram of the SVM choose three bands high level results while table 4.9 shed more details on the top recorded results.

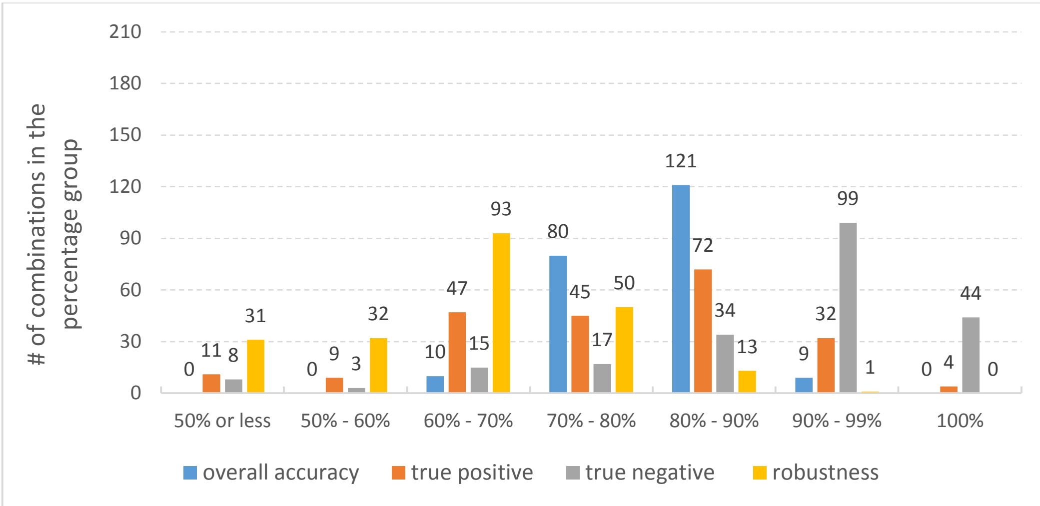


Figure 4.9. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (f) at the beginning of section 4.2.1.

Table 4.9. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy. (Multiple combinations achieved the indicated results in the row. Check appendix B for details).*

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	96%	100%	92%	92%	PSD_3, PSD_5, PSD_{10}
	86%	100%	67%	67%	PSD_1, PSD_5, PSD_8
	82%	100%	58%	58%	PSD_1, PSD_5, PSD_9
	75%	100%	42%	42%	PSD_6, PSD_7, PSD_8
	93%	94%	92%	85%	*Six combinations.**
In terms of *overall accuracy*	96%	100%	92%	92%	PSD_3, PSD_5, PSD_{10}
	93%	94%	92%	85%	*Six combinations.**
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – LDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – QDA:

  None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four bands at a time – SVM:

This time better results were achieved. The number of combinations achieving the desired aim reached 24. The top result achieved was 100% across the four categories monitored. The remaining results achieved 96% *overall accuracy* while *true positive* fluctuated between 100% and 94%, *true negative* between 100% and 92%, and *robustness* between 94% and 92%. Table 4.10 details out the top results. These results give hope that the percentage of energy stored in the sub-frequency bands can be a good feature to allow for proper separation of seizures and PNESs. Figure 4.10 shows the distribution of how the results look like across each monitored category. More than 85% of the combinations achieved an *overall accuracy* and *true negative* of more than 80%. ~67% of combinations achieved a *true positive* of more than 80% while ~28% of the combination achieved a *robustness* of 80% or more.

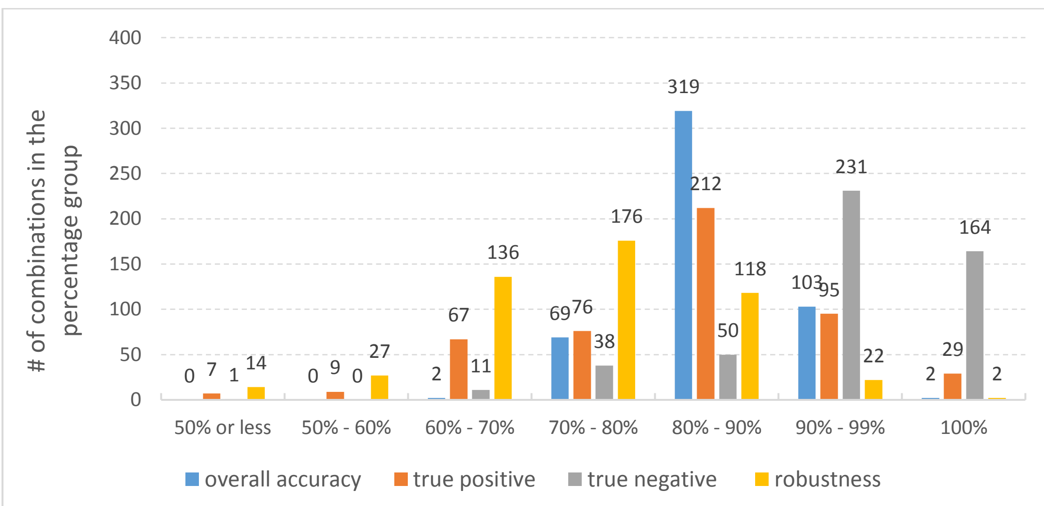


Figure 4.10. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (f) at the beginning of section 4.2.1.

To sum up part (f), SVM classifier has still shown the best classification results by achieving 100% across all categories. PSD_1 (0 – 250Hz), PSD_3 (500Hz – 750Hz), PSD_9 (2.00kHz – 2.25kHz), and PSD_{10} (2.25kHz – 2.50kHz) contributed to the top results across the different classification methods. The desired aim was possible to achieve by either choosing three or four PSD bands at a time as classification features.

Table 4.10. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy. (1) Order changed to focus on the most relevant results achieving high true positive and robustness simultaneously. (Multiple combinations achieved the indicated results in the row. Check appendix B for details).*

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*(1)	100%	100%	100%	100%	*Two combinations.**
	96%	100%	92%	92%	*16 combinations.**
	96%	94%	100%	94%	*Six combinations.*
	93%	94%	92%	85%	*49 combinations.*
	93%	88%	100%	88%	*28 combinations.*
In terms of *overall accuracy*	100%	100%	100%	100%	*Two combinations.**
	96%	100%	92%	92%	*16 combinations.**
	96%	94%	100%	94%	*Six combinations.*
	93%	100%	83%	83%	*Four combinations.*
	93%	94%	92%	85%	*49 combinations.*

Remarks

In summary, PSD bands are good features that can be used to separate seizures from PNESs. The results of parts (d) and (f) show that frequencies from 2.00kHz to 3.00kHz demonstrated a strong presence in the features contributing to the top results. While the results of parts (a) to (f) show that the lower frequencies are also vital to achieve good classification. Hence, the frequency range 0 – 3.00kHz dividing it into 12 bands, as detailed in part (f) at the beginning of this section, will be included in the cross-validation exercise. The remaining frequency ranges and their sub-frequencies will not be included.

4.2.2 Max of the Envelope and Mean Max of the Envelope Results

To understand the effectiveness of the max on the envelope feature, three trials have been done. First trial looked into max of the envelope itself. The second trial focused on the mean of the max of the envelopes while the third trial combined both. The three classification methods will be applied leading to 9 trials in total. Table 4.11 details the results of the 9 trials. The best result was achieved by the SVM classifier when combining both features, last row in the table below.

Table 4.11. Results of classifying the samples using max of the envelope and mean max of the envelope features.

Trial	Classification method	*overall accuracy*	*true positive*	*true negative*	*robustness*
a. Max of the envelope	LDA	57%	56%	58%	15%
	QDA	75%	81%	67%	48%
	SVM	75%	63%	92%	54%
b. Mean max of the envelope	LDA	57%	50%	67%	17%
	QDA	71%	75%	67%	42%
	SVM	79%	81%	75%	56%
Combining both (a) and (b)	LDA	54%	56%	50%	6%
	QDA	71%	75%	67%	42%
	SVM	86%	75%	100%	75%

Given the results in table 4.11, both features will be included in the cross-validation exercise although the desired aim is not reached. The reason to include these features is not only the acceptable results achieved but also to understand their impact when combined with other features.

4.2.3 Mel-Frequency Cepstral Coefficients Results

To test the separation capability of MFCCs, a total of 12 trials have been performed. Four for each classification method. The difference between these four trials was the number of coefficients chosen in each trial, 1, 2, 3, and 4 respectively. Due to the superior results achieved by some of the trials, the focus will be mainly on the histogram, standard deviation, and average of each category in the relevant trials. Overall remarks will be highlighted at the end of section 4.2.3 about MFCCs' classification results.

- Equal test-train when choosing one coefficient at a time – LDA:

  None of the coefficients achieved the desired aim.

- Equal test-train when choosing one coefficient at a time – QDA:

  Only MFCC coefficient 8 achieved the desired aim. 96% *overall accuracy*, 94% *true positive*, 100% *true negative*, and 94% *robustness* recorded. Table 4.12 shows the top result, mean, and standard deviation along the four monitored categories. The mean for *robustness* indicates that most of the results are dramatically below desired aim.

Table 4.12. Top result, mean, and standard deviation of QDA classifying the samples using MFCCs while choosing one coefficients at a time.

# combinations = 13	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	96%	94%	100%	94%
Mean	70%	64%	78%	42%
Standard deviation	10.05%	15.13%	16.85%	20.18%

- Equal test-train when choosing one coefficient at a time – SVM:

MFCC coefficient 8 was able again to achieve the desired aim of more than 90% in both *true positive* and *robustness*. The top result was the same as the one recorded by QDA. The remaining coefficients were far behind, however, performing slightly better than QDA. Table 4.13 shows top result, mean, and standard deviation of the results.

Table 4.13. Top result, mean, and standard deviation of SVM classifying the samples using MFCCs while choosing one coefficients at a time.

# combinations = 13	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	96%	94%	100%	94%
Mean	74%	66%	85%	52%
Standard deviation	8.97%	16.04%	10.29%	16.41%

- Equal test-train when choosing a combination of two coefficients at a time – LDA:

None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of two coefficients at a time – QDA:

Five combinations have achieved the desired aim with the best result being 100% across all categories. MFCC coefficient 8 was present in all five top results. Table 4.14 below shows the top result, mean, and standard deviation across the different four categories. Overall, the results are promising and indicates the importance of MFCCs in correctly classifying seizures and PNESs.

Table 4.14. Top result, mean, and standard deviation of QDA classifying the samples using MFCCs while choosing a combination of two coefficients at a time.

# combinations = 78	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	100%	100%	100%	100%
Mean	79%	73%	89%	61%
Standard deviation	9.09%	12.51%	9.94%	17.61%

- Equal test-train when choosing a combination of two coefficients at a time – SVM:

The SVM classification produced even better results compared to QDA. 18 combinations achieved the desired aim out of which 5 achieved 100% across all categories. MFCC coefficient 8 was the dominant one being present in 11 out of the 18 top results. Table 4.15 highlights the top result, mean, and standard deviation of SVM classification. The mean shows that the results are improving, however, identifying the classification dimensional space is still to be determined, i.e. how many features to be combined at a time.

Table 4.15. Top result, mean, and standard deviation of SVM classifying the samples using MFCCs while choosing a combination of two coefficients at a time.

# combinations = 78	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	100%	100%	100%	100%
Mean	90%	87%	94%	80%
Standard deviation	5.82%	8.93%	8.38%	11.38%

- Equal test-train when choosing a combination of three coefficients at a time – LDA:

None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of three coefficients at a time – QDA:

46 out of 286 possible combinations achieved the desired aim with the top result being 100% across all categories. MFCC coefficient 8 is still the most dominant one in the top results being present in 37 out of 46 combinations. Table 4.16 shows top result, mean, and standard deviation of QDA classification exercise when choosing three coefficients at a time.

Table 4.16. Top result, mean, and standard deviation of QDA classifying the samples using MFCCs while choosing a combination of three coefficients at a time.

# combinations = 286	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	100%	100%	100%	100%
Mean	87%	82%	94%	75%
Standard deviation	7.42%	10.00%	7.03%	14.27%

- Equal test-train when choosing a combination of three coefficients at a time – SVM:

The results of the SVM classification while choosing three coefficients is tremendous. 255 out of 286 possible combinations achieved the desired aim with 136 achieving 100% in all categories of interest, ~50% of total combinations. MFCC coefficient 8 was the only coefficient that would always produce desired aim result whenever it is part of a combination while MFCC coefficients 2, 9, and 12 were the ones contributing the least to desired aim. Since the results achieved are tremendous, it would make sense to show the histogram of the four monitored categories as shown in figure 4.11 below. ~97% of combinations exceeded 90% in *overall accuracy*, ~92% exceeded 90% in *true positive*, and ~99% had a *true negative* of more than 90% while ~91% of combinations scored more than 90% in *robustness*. Table 4.17 highlights top result, mean and standard deviation of the SVM classifier when choosing three coefficients at a time.

Table 4.17. Top result, mean, and standard deviation of SVM classifying the samples using MFCCs while choosing a combination of three coefficients at a time.

# combinations = 286	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	100%	100%	100%	100%
Mean	98%	97%	99%	96%
Standard deviation	2.72%	4.42%	2.93%	5.09%

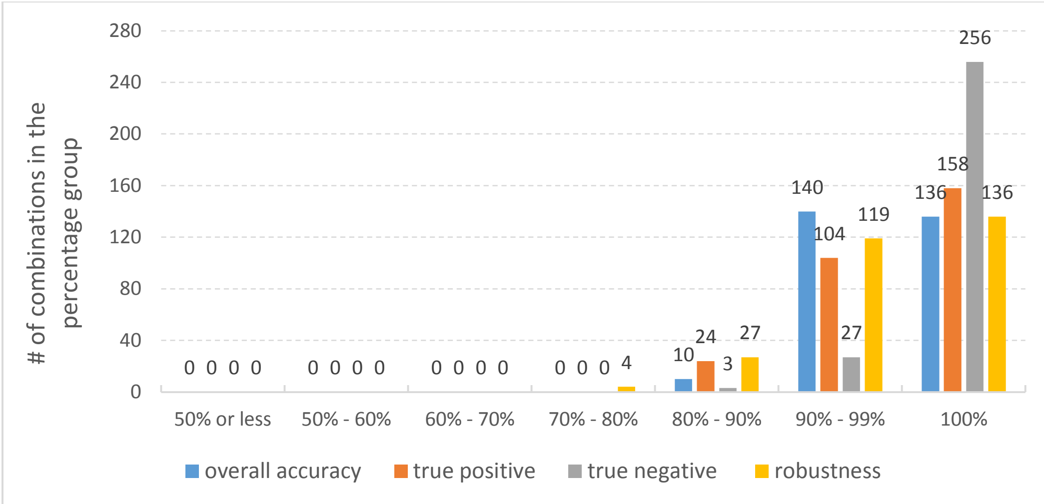


Figure 4.11. Equal test-train classification results using a SVM classifier while choosing a combination of three MFCC coefficients at a time.

- Equal test-train when choosing a combination of four coefficients at a time – LDA:

None of the combinations achieved the desired aim.

- Equal test-train when choosing a combination of four coefficients at a time – QDA:

The QDA classifier with four MFCC coefficients performed better than the previous QDA trial, i.e. with three MFCC coefficients. ~40% of all possible combinations achieved desired aim results; a total of 282 out of 715 possible. 80 combinations achieved 100% across all four categories. MFCC coefficient 8 was again the most contributing to desired aim results being present in 182 out of the 282 acceptable ones. Tables 4.18 provides a snapshot of the results limited to top result, mean, and standard deviation.

Table 4.18. Top result, mean, and standard deviation of QDA classifying the samples using MFCCs while choosing a combination of four coefficients at a time.

# combinations = 715	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	100%	100%	100%	100%
Mean	92%	88%	97%	86%
Standard deviation	5.44%	7.60%	5.26%	10.41%

- Equal test-train when choosing a combination of four coefficients at a time – SVM:

The SVM classifier when choosing four MFCC coefficients as classification dimension performed extraordinarily. All combinations except for three achieved desired aim results! The remaining three were not dramatically off. They achieved 93% *overall accuracy*, 88% *true positive*, 100% *true negative*, and 88% *robustness*. 645 combinations, ~90% of total combinations, achieved 100% across all four categories. The histogram of how the results are distributed across the four monitored categories is shown in figure 4.12 while table 4.19 shows top result, mean, and standard deviation of the results.

Table 4.19. Top result, mean, and standard deviation of SVM classifying the samples using MFCCs while choosing a combination of four coefficients at a time.

# combinations = 715	*overall accuracy*	*true positive*	*true negative*	*robustness*
Top result	100%	100%	100%	100%
Mean	100%	99%	100%	99%
Standard deviation	1.13%	1.96%	0.44%	2.00%

Figure 4.12. Equal test-train classification results using a SVM classifier while choosing a combination of four MFCC coefficients at a time.

4.2.4 Remarks

The trials of the PSD bands have shown that a frequency range of 0 – 3.00kHz divided into 12 equal sub-frequencies separated by 250Hz produces the best classification results but only by using an SVM classifier. The main PSD bands contributing to top results were the ones included in lower frequencies, namely 0 – 250Hz, and the ones included at the end of the frequency range, 2.00kHz – 3.00kHz. Hence, the frequency range 0 – 3.00kHz including all its 12 energy bands will be included in the cross-validation exercise. It is still possible to focus on the ones that contribute most to top results, i.e. 0 – 250Hz and 2.25kHz – 2.50kHz, but including all bands could reveal more correlation between certain PSD bands and other elements, i.e. MFCCs and maximum of the envelope, which will be included in cross-validation.

The maximum and mean maximum of the envelope will both be included in the cross-validation exercise. The combination of both produced good results using QDA and SVM classifiers. Likewise the bands that didn't perform well in PSD bands equal test-train, maximum and mean maximum of the envelope could reveal interesting results when coupled with other features. The cross-validation will be performed with and without maximum and mean maximum of the envelope to determine their impact in the classification of the samples.

The trials of MFCC coefficients show the importance of MFCCs in classifying the samples. It has been clear that by increasing the number of coefficients from one to four, the results have improved regardless of the classification method. The last trial for example, SVM classifying the samples when choosing a 4-dimensional MFCC coefficient space, achieved superior results. Since MFCCs mimic how human ears interpret voice, the results suggest that a person can determine whether a person undergoing a seizure or PNES by mainly listening to the patient. To move forward, MFCCs will be included in the cross-validation exercise. Although coefficient 8, for example, always contributed to top results and desired aim results while others were not so effective, all coefficients will be included when conducting cross-validation. The reason is that each coefficient by itself does not have a clear meaning but it is the group of the 13 coefficients that mimic how human ears work.

For the choice of which classifier to focus on during cross-validation, the decision is to test all three methods, LDA, QDA, and SVM, although equal test-train suggested that SVM is always best performing. Future research on the same topic would, for example, benefit from understanding how LDA classifier performs in the different feature spaces.

4.3 Cross-Validation Results and Remarks

To recap, the purpose of the cross-validation exercise is to understand how effective is the classification of samples when conducting supervised learning, i.e. training the classifier on certain set of data and testing it against others that are unknown to the classifier. Based on the results of equal test-train trials, cross-validation will be done for four different set of features:

a. 13 MFCCs only – *Four and five-dimensional feature spaces will be tested.*
b. Combining top performing PSD bands of part (f) (namely PSD_1, PSD_3, PSD_5, PSD_9, and PSD_{10}) and 13 MFCCs – *Four-dimensional feature space will be tested.*
c. Combining 12 PSD bands detailed in part (f) of 4.2.1 and 13 MFCCs – *Four-dimensional feature space will be tested.*
d. Combining all available features, 12 PSD bands detailed in part (f) of 4.2.1, maximum of the envelope, mean maximum of the envelope, and 13 MFCCs – *Four-dimensional feature space will be tested.*

The section will show first the results of the cross-validation, section 4.3.1. The goal will be to highlight top and lowest 15-25 results based on *robustness*, mean, standard deviation, and a histogram of *overall accuracy*, *true positive*, *true negative*, and *robustness*. Remarks highlighting how the results can be interpreted will be included in the following section, section 4.3.2.

4.3.1 Cross-Validation Results

a. 13 MFCCs only

In this part of the section, the goal is to confirm the findings of equal test-train which indicated that MFCCs can classify the samples into seizures and PNESs with a high level accuracy. The results of the cross-validation have, to some extent, confirmed equal test-train's findings, as shown in the discussion below. Also, the impact of feature space dimensionality is tested to determine whether four- or five-dimensional MFCCs feature space work better. It turns out that four-dimensional MFCCs feature space is better.

- Cross-validation when choosing a combination of four coefficients at a time – LDA:

The total number of combinations that compromise four coefficients at a time is 13 choose 4 which equals 715 possible combinations. None of the results has achieved the desired aim set for equal test-train, 90% in both *true positive* and *robustness*. This is normal since in equal test-train, the classifier is expected to score highly because the testing data set is exactly the same as the training data set. In cross-validation, training and testing datasets are different. 30% of the samples are isolated as testing data set while the remaining 70% are used to train the classifier on the two available classes, seizures and PNESs. The top result was achieved by the combination containing coefficients 4, 5, 8, and 13; 89% *overall accuracy*, 82% *true positive*, 97% *true negative*, and 79% *robustness*. The *robustness* mean was only 37% with a standard deviation of 16.82% which indicates that the results are widely scattered and not centered around the mean value. The highest *robustness* reached

Table 4.20. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using LDA classifier while choosing four MFCC coefficients at a time.

# combinations = 715	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	89%	82%	97%	79%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	88%	80%	98%	77%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	82%	94%	76%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	82%	93%	75%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	86%	78%	97%	75%	$MFCC_2$, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	86%	78%	95%	74%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	86%	82%	92%	74%	$MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	86%	84%	89%	72%	$MFCC_2$, $MFCC_3$, $MFCC_9$, $MFCC_{13}$
	85%	78%	94%	72%	$MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	85%	81%	91%	72%	$MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	85%	80%	91%	71%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	85%	80%	91%	71%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	84%	74%	97%	70%	$MFCC_3$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	84%	75%	94%	69%	$MFCC_3$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	84%	75%	94%	69%	$MFCC_3$, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	84%	77%	93%	69%	$MFCC_3$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
Mean	68%	62%	74%	37%	n/a
Standard dev.	8.28%	8.03%	10.27%	16.82%	n/a
Lowest results	48%	50%	46%	-4%	$MFCC_2$, $MFCC_4$, $MFCC_{11}$, $MFCC_{13}$
	48%	49%	47%	-4%	$MFCC_2$, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	48%	46%	50%	-4%	$MFCC_4$, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	49%	48%	49%	-3%	$MFCC_2$, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	49%	46%	54%	-1%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_{12}$
	50%	45%	56%	0%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_{12}$
	50%	46%	54%	1%	$MFCC_2$, $MFCC_4$, $MFCC_{12}$, $MFCC_{13}$
	50%	45%	58%	2%	$MFCC_1$, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	51%	51%	51%	3%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_6$
	52%	53%	50%	3%	$MFCC_1$, $MFCC_4$, $MFCC_{10}$, $MFCC_{11}$
	51%	45%	59%	4%	$MFCC_1$, $MFCC_6$, $MFCC_{10}$, $MFCC_{12}$
	52%	48%	56%	4%	$MFCC_1$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	52%	47%	58%	5%	$MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{12}$
	52%	53%	52%	5%	$MFCC_1$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$
	52%	48%	57%	5%	$MFCC_1$, $MFCC_4$, $MFCC_{10}$, $MFCC_{12}$
	53%	53%	52%	5%	$MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	53%	57%	49%	6%	$MFCC_2$, $MFCC_4$, $MFCC_{10}$, $MFCC_{11}$
	53%	54%	52%	6%	$MFCC_1$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	53%	53%	54%	6%	$MFCC_1$, $MFCC_4$, $MFCC_9$, $MFCC_{11}$
	53%	48%	58%	6%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	52%	42%	64%	6%	$MFCC_4$, $MFCC_6$, $MFCC_{10}$, $MFCC_{12}$

79% while the lowest was -4%. Negative *robustness* value indicates that false alarms related to misclassifying PNESs were higher than real alarms related to classifying seizures correctly; a status that is highly unfavorable. Table 4.20 highlights top and lowest results based on *robustness*, mean, and standard deviation of results. The individual features which contributed most to top results are MFCC coefficients 5, 8, and 13 while the ones that contributed to lowest results are coefficients 1, 4, and 12. Figure 4.13 uncovers how the combinations performed across the individual monitored categories. LDA classifier in four-dimensional feature space recorded good results in *true negative* (~67% of combinations above 70%), adequate results in *overall accuracy* (~42% of combinations above 70%, ~22% below 60%) and *true positive* (~19% of combinations above 70%, ~41% below 60%), and poor results in *robustness* (~98% of combinations below 70%).

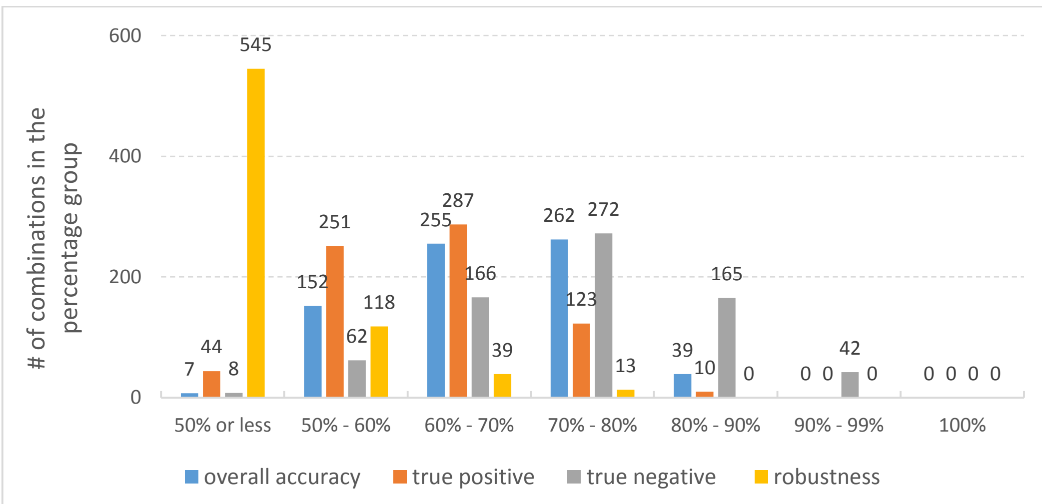


Figure 4.13. Cross-validation results using a LDA classifier while choosing four MFCC coefficients at a time. 70% of samples are used as training data set while the remaining 30% served as testing data set.

- Cross-validation when choosing a combination of four coefficients at a time – QDA:

Although none of the 715 combinations achieved equal test-train desired aim, the QDA classifier performed better than the LDA. Figure 4.14 shows a high level view of how each category performed. ~77% of combinations achieved an *overall accuracy* of more than 70% with five records exceeding 90%. QDA's *overall accuracy* results are interesting since ~85% of combinations scored less than 70% in *true negative*! The reason behind high *overall accuracy* with low *true negative* relies in the fact that QDA achieved superior results in correctly classifying seizure samples. ~77% of combinations recorded *true positive* of more than 80%, of which 18 combinations achieved 100% *true positive*. Only 12 combinations (~2%) achieved *true positive* of less than 70%. It is unexpected for QDA to achieve poor *true negative* results given the fact that *true negative* average of QDA's four-dimensional equal test-train was 97% with a standard deviation of 5%! *robustness*, which includes false alarm - a factor related to *true negative*, achieved poor results as well. Only 34 combinations of 715 exceeded 70%. Table 4.21 shows top and lowest results, mean, and standard deviation of QDA four-dimensional MFCC space. *overall accuracy* mean was 75% with 6.69% standard deviation. *ture positive* mean was highest, 86%, with 7.39% standard deviation. The mean for *true negative* was 62% with a standard deviation of 7.13% indicating that most of *true negative* values are relatively close to 62%. *robustness* mean was lowest reaching 48% with a standard deviation of 13.33%. The combination consisting of MFCC coefficients 3, 5, 8, and 13 recorded the top result; 94% *overall accuracy*, 100% *true positive*, 87% *true negative*, and 86% *robustness*. MFCC coefficients 5, 8, 13 contributed the most to top results while coefficients 3, 6, and 11 contributed the most to lowest results.

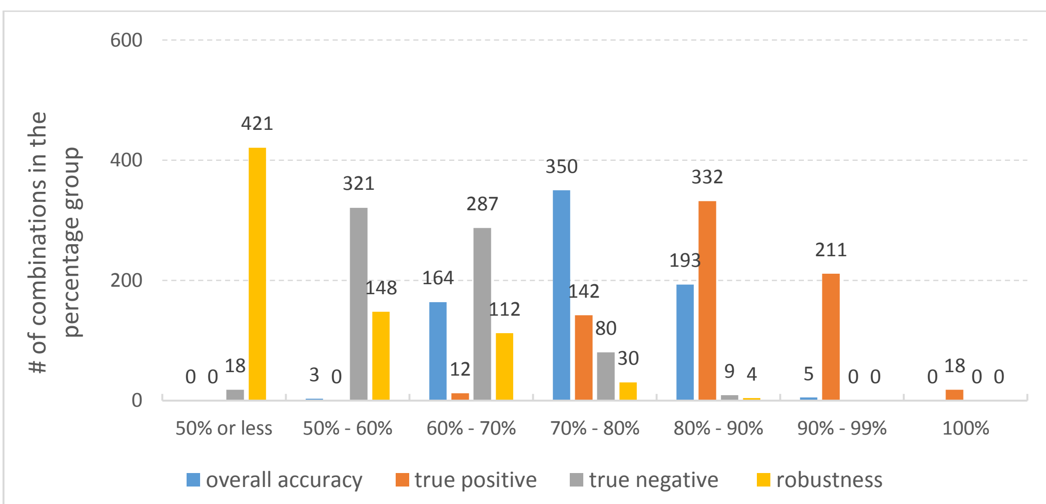


Figure 4.14. Cross-validation results using a QDA classifier while choosing four MFCC coefficients at a time. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.21. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using QDA classifier while choosing four MFCC coefficients at a time.

# combinations = 715	*overall accuracy*	*true positive*	*True negative*	*robustness*	Combination details
Top results	94%	100%	87%	86%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	93%	100%	85%	85%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	99%	84%	83%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	99%	81%	80%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	99%	80%	80%	$MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	93%	84%	77%	$MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	89%	95%	81%	76%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	95%	81%	76%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	89%	100%	76%	76%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	89%	99%	76%	75%	$MFCC_2$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	98%	77%	75%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	88%	93%	81%	75%	$MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	88%	95%	79%	74%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	88%	95%	78%	73%	$MFCC_2$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	88%	99%	74%	73%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{11}$
	88%	100%	73%	73%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$
	88%	100%	73%	73%	$MFCC_1$, $MFCC_4$, $MFCC_5$, $MFCC_8$
	87%	95%	78%	73%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{12}$
Mean	**75%**	**86%**	**62%**	**48%**	**n/a**
Standard dev.	**6.69%**	**7.39%**	**7.13%**	**13.33%**	**n/a**
Lowest results	58%	67%	48%	14%	$MFCC_2$, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	58%	69%	46%	14%	$MFCC_3$, $MFCC_6$, $MFCC_{10}$, $MFCC_{11}$
	59%	66%	50%	16%	$MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$
	61%	67%	52%	20%	$MFCC_3$, $MFCC_6$, $MFCC_{11}$, $MFCC_{13}$
	62%	72%	48%	20%	$MFCC_2$, $MFCC_4$, $MFCC_9$, $MFCC_{11}$
	61%	64%	56%	21%	$MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$
	62%	74%	47%	21%	$MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	62%	71%	50%	21%	$MFCC_3$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$
	62%	71%	50%	21%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_{11}$
	62%	68%	53%	22%	$MFCC_1$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$
	62%	73%	49%	22%	$MFCC_3$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	62%	67%	55%	22%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{11}$
	62%	69%	54%	23%	$MFCC_1$, $MFCC_3$, $MFCC_9$, $MFCC_{11}$
	62%	66%	57%	23%	$MFCC_3$, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	64%	80%	43%	23%	$MFCC_2$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	63%	71%	53%	23%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	62%	68%	55%	23%	$MFCC_3$, $MFCC_4$, $MFCC_9$, $MFCC_{11}$
	63%	73%	50%	23%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_{11}$
	63%	71%	53%	23%	$MFCC_3$, $MFCC_4$, $MFCC_{10}$, $MFCC_{11}$
	63%	69%	55%	23%	$MFCC_3$, $MFCC_6$, $MFCC_{10}$, $MFCC_{13}$

- Cross-validation when choosing a combination of four coefficients at a time – SVM:

SVM four-dimensional MFCC classifier followed the same trajectory of QDA albeit at a better rate. Figure 4.15 shows that ~81% of 715 possible combinations achieved *overall accuracy* of more than 70%; 14 combinations scored more than 90%. *true positive* was again the main factor leading to good *overall accuracy* results. Almost all combination achieved *true positive* of more than 80% except for two combinations! *true negative* records were again disappointing. Only 10% of combinations exceeded 70% of which none reached 90% or more. *robustness* was also disappointing. Only 7% of possible combinations achieved more than 70%; none in more than 90% bucket. Looking into individual records reveals that the combination MFCC coefficients 8, 9, 12, and 13 achieved top result of 95% *overall accuracy*, 100% *true positive*, 88% *true negative*, and 88% *robustness*. The lowest result was achieved by the combination consisting of coefficients 2, 3, 4, 6 – 55% *overall accuracy*, 77% *true positive*, 28% *true negative*, and 5% *robustness*. Table 4.22 details top and lowest results, mean, and standard deviation of SVM classifying the samples in four-dimensional MFCCs space. The coefficients 8 and 13 contributed the most to top results while coefficients 2, 4, and 6 contributed the most to lowest results. Mean values for *overall accuracy* and *robustness* were similar to

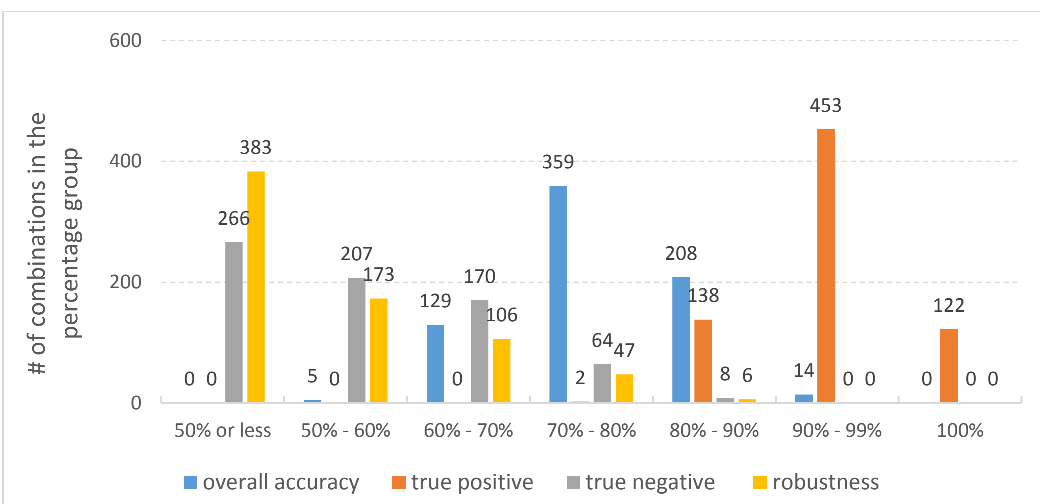


Figure 4.15. Cross-validation results using a SVM classifier while choosing four MFCC coefficients at a time. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.22. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using SVM classifier while choosing four MFCC coefficients at a time.

# combinations = 715	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	95%	100%	88%	88%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	93%	100%	84%	84%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	100%	84%	84%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	92%	100%	83%	82%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	92%	100%	82%	82%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{10}$
	92%	100%	81%	81%	$MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	91%	100%	79%	79%	$MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{12}$
	91%	100%	79%	79%	$MFCC_4$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	100%	79%	79%	$MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{13}$
	90%	99%	79%	79%	$MFCC_6$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_5$, $MFCC_6$, $MFCC_7$, $MFCC_{10}$
	90%	95%	83%	78%	$MFCC_4$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	89%	94%	83%	77%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{12}$
	90%	100%	77%	77%	$MFCC_3$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	98%	78%	76%	$MFCC_4$, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	89%	100%	76%	76%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{10}$
Mean	**76%**	**94%**	**55%**	**48%**	**n/a**
Standard dev.	**6.85%**	**4.61%**	**11.63%**	**14.56%**	**n/a**
Lowest results	55%	77%	28%	5%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_6$
	57%	81%	26%	8%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	57%	75%	36%	11%	$MFCC_2$, $MFCC_3$, $MFCC_6$, $MFCC_{12}$
	59%	89%	23%	12%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_7$
	60%	84%	30%	13%	$MFCC_2$, $MFCC_4$, $MFCC_7$, $MFCC_{12}$
	60%	83%	33%	15%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_7$
	61%	87%	28%	16%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_9$
	61%	86%	30%	16%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	61%	85%	32%	17%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_9$
	61%	82%	36%	17%	$MFCC_1$, $MFCC_2$, $MFCC_{11}$, $MFCC_{12}$
	62%	91%	26%	17%	$MFCC_1$, $MFCC_2$, $MFCC_4$, $MFCC_7$
	62%	85%	33%	18%	$MFCC_1$, $MFCC_2$, $MFCC_3$, $MFCC_6$
	61%	80%	38%	18%	$MFCC_2$, $MFCC_6$, $MFCC_9$, $MFCC_{12}$
	63%	91%	27%	18%	$MFCC_2$, $MFCC_4$, $MFCC_7$, $MFCC_9$
	63%	90%	29%	19%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_{11}$
	63%	86%	33%	19%	$MFCC_2$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$
	63%	84%	35%	20%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_7$
	63%	84%	36%	20%	$MFCC_1$, $MFCC_6$, $MFCC_{11}$, $MFCC_{13}$
	63%	83%	37%	20%	$MFCC_3$, $MFCC_4$, $MFCC_7$, $MFCC_{12}$

that of QDA's. *true positive* mean was 94% and its standard deviation was 4.61% indicating the values are higher than QDA and more concentrated around the mean. *true negative* on the hand had a lower mean, 55%, and a higher standard deviation, 11.63%, compared to QDA.

- Cross-validation when choosing a combination of five coefficients at a time – LDA:

Classification results of MFCCs four-dimensional space sparked the question of whether increasing the dimensionality of the feature space to five would produce better results or not. Figure 4.16 below shows a high level results of LDA five-dimensional MFCCs classifier. LDA five-dimensional space classification produced slightly better results compared to four-dimensional space, figures 4.13 and 4.16. Top and lowest results, means, and standard deviations were slightly better as well compared to four-dimensional space, tables 4.20 and 4.23. Likewise four-dimensional space, MFCC coefficients 5, 8, and 13 contributed to the most to top results. Coefficients 1, 4, and 10 contributed the most to lowest results, almost similar to four-dimensional except for coefficient 10 replacing 12. Moving forward in parts (b) to (d) of cross-validation, the focus will be only on four-dimensional spaces due to the marginal gain achieved by five-dimensional feature space.

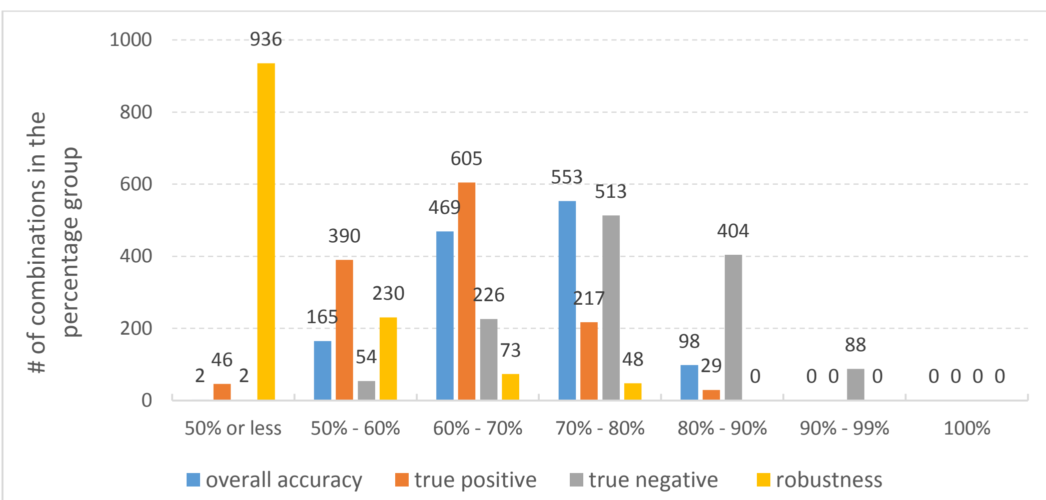


Figure 4.16. Cross-validation results using a LDA classifier while choosing five MFCC coefficients at a time. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.23. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using LDA classifier while choosing five MFCC coefficients at a time.

# combinations = 1,288	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	88%	80%	99%	79%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	89%	83%	95%	79%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	88%	81%	97%	78%	$MFCC_3$, $MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	88%	80%	98%	78%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	88%	79%	98%	77%	$MFCC_2$, $MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	88%	79%	98%	77%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	82%	94%	76%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{11}$, $MFCC_{13}$
	87%	80%	96%	76%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	77%	98%	76%	$MFCC_3$, $MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	87%	81%	95%	76%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	87%	82%	94%	76%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	87%	85%	90%	75%	$MFCC_2$, $MFCC_3$, $MFCC_5$, $MFCC_9$, $MFCC_{13}$
	87%	86%	89%	75%	$MFCC_2$, $MFCC_3$, $MFCC_5$, $MFCC_{10}$, $MFCC_{13}$
	86%	77%	98%	75%	$MFCC_4$, $MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	87%	79%	96%	75%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	86%	80%	94%	74%	$MFCC_2$, $MFCC_3$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	86%	81%	94%	74%	$MFCC_2$, $MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	86%	80%	95%	74%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
Mean	**69%**	**63%**	**77%**	**40%**	**n/a**
Standard dev.	**7.79%**	**7.76%**	**9.19%**	**15.74%**	**n/a**
Lowest results	46%	45%	47%	-8%	$MFCC_2$, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	49%	44%	55%	-1%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	50%	45%	57%	2%	$MFCC_1$, $MFCC_4$, $MFCC_6$, $MFCC_{10}$, $MFCC_{12}$
	51%	49%	54%	2%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$
	51%	50%	53%	2%	$MFCC_1$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	50%	44%	59%	3%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{10}$, $MFCC_{12}$
	51%	50%	53%	3%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{10}$
	51%	44%	59%	3%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_{10}$, $MFCC_{12}$
	52%	57%	47%	4%	$MFCC_2$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	52%	53%	51%	4%	$MFCC_2$, $MFCC_4$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{12}$
	51%	47%	57%	4%	$MFCC_1$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{12}$
	52%	47%	58%	5%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_{10}$, $MFCC_{12}$
	52%	50%	55%	5%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$
	53%	54%	52%	5%	$MFCC_2$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{12}$
	53%	53%	54%	6%	$MFCC_1$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	53%	53%	54%	6%	$MFCC_1$, $MFCC_4$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$
	53%	51%	56%	6%	$MFCC_1$, $MFCC_4$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{12}$

- Cross-validation when choosing a combination of five coefficients at a time – QDA:

Five-dimensional QDA classification using MFCCs achieved worse results compared to four-dimensional QDA classification. Except for *true positive* which achieved better results, the

Table 4.24. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using QDA classifier while choosing five MFCC coefficients at a time.

# combinations = 1,288	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	90%	99%	77%	77%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	89%	99%	77%	76%	$MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	89%	100%	76%	76%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	89%	99%	76%	75%	$MFCC_3$, $MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	100%	75%	75%	$MFCC_1$, $MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	88%	99%	75%	74%	$MFCC_2$, $MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	88%	99%	73%	72%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	87%	99%	73%	72%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	88%	100%	72%	72%	$MFCC_1$, $MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	100%	72%	72%	$MFCC_1$, $MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	99%	73%	72%	$MFCC_2$, $MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	100%	72%	72%	$MFCC_3$, $MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	87%	100%	72%	71%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	99%	71%	70%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	100%	71%	70%	$MFCC_1$, $MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	99%	71%	70%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	99%	71%	70%	$MFCC_2$, $MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	87%	100%	70%	70%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
Mean	**74%**	**91%**	**52%**	**43%**	**n/a**
Standard dev.	**5.51%**	**5.24%**	**7.17%**	**11.24%**	**n/a**
Lowest results	56%	73%	35%	8%	$MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	60%	74%	41%	16%	$MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{13}$
	61%	81%	35%	16%	$MFCC_2$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	60%	78%	38%	16%	$MFCC_3$, $MFCC_6$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{13}$
	60%	73%	43%	16%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$
	61%	77%	41%	18%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{13}$
	61%	74%	44%	18%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$
	61%	76%	43%	18%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$
	62%	82%	37%	19%	$MFCC_2$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	62%	77%	42%	20%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{11}$
	62%	77%	43%	20%	$MFCC_3$, $MFCC_4$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	62%	75%	45%	21%	$MFCC_2$, $MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$
	62%	75%	46%	21%	$MFCC_2$, $MFCC_3$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$
	63%	81%	41%	21%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$
	63%	80%	41%	22%	$MFCC_3$, $MFCC_5$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	63%	82%	40%	22%	$MFCC_1$, $MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	63%	79%	43%	22%	$MFCC_1$, $MFCC_3$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$
	63%	79%	43%	22%	$MFCC_3$, $MFCC_6$, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	63%	77%	45%	22%	$MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$, $MFCC_{13}$
	63%	77%	45%	22%	$MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$, $MFCC_{12}$
	64%	84%	38%	22%	$MFCC_6$, $MFCC_9$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{13}$
	64%	84%	38%	22%	$MFCC_1$, $MFCC_3$, $MFCC_6$, $MFCC_7$, $MFCC_{13}$
	63%	76%	46%	22%	$MFCC_1$, $MFCC_3$, $MFCC_4$, $MFCC_9$, $MFCC_{11}$

remaining three categories were worse off, compare figures 4.14 and 4.17 as well as tables 4.21 and 4.24. This applies to mean and standard deviation values as well. This observation supports the decision to limit future cross-validation trials to four-dimensional feature spaces only. MFCC coefficients contributing to top and lowest results were the same as observed in four-dimensional QDA classification.

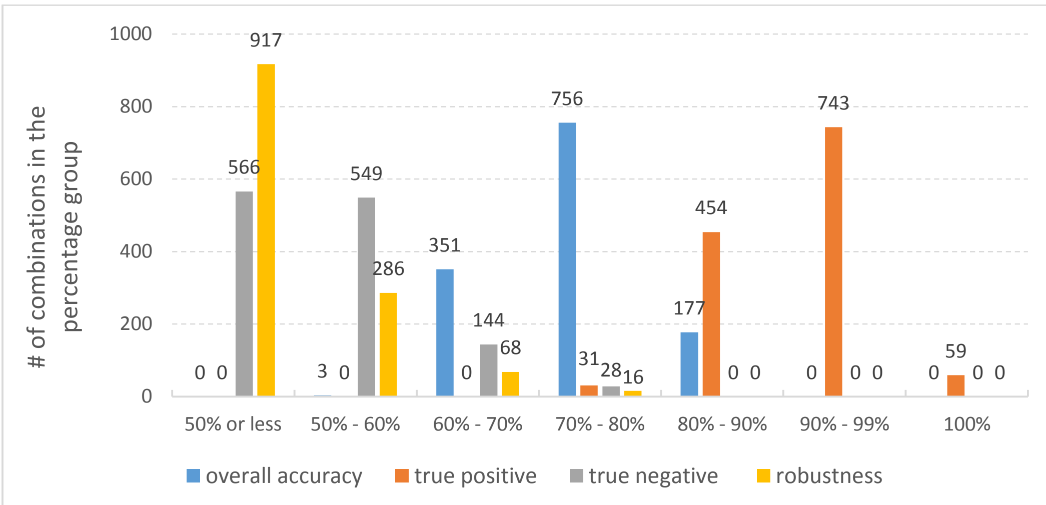


Figure 4.17. Cross-validation results using a QDA classifier while choosing five MFCC coefficients at a time. 70% of samples are used as training data set while the remaining 30% served as testing data set.

- Cross-validation when choosing a combination of five coefficients at a time – SVM:

SVM five-dimensional coefficient space experienced similar observations as QDA classification. The only category achieving better results was *true positive* while the remaining three were worse off. This observation applies to mean and standard deviation values as well. Figures 4.15 and 4.18 as well as tables 4.22 and 4.25 provide more comparison details. Likewise four-dimensional space, coefficients 8 and 13 contributed the most to top results while coefficients 2, 4, and 6 contributed the most to lowest results. Classification in five-dimensional space has also shown that it is difficult to achieve proper results when exceeding four-dimensional space. Figure 4.18 highlights that almost all combinations achieve more than 90% *true positive* but at the same time achieve less than 70% *true negative*; eliminating any balance in the results across the four monitored categories.

Table 4.25. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using SVM classifier while choosing five MFCC coefficients at a time.

# combinations = 1,288	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	91%	100%	79%	79%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	90%	100%	77%	77%	$MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	89%	100%	75%	75%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	89%	100%	75%	75%	$MFCC_4$, $MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	88%	99%	75%	74%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	88%	100%	73%	73%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	88%	100%	73%	73%	$MFCC_8$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	88%	100%	72%	72%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	100%	71%	71%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	87%	100%	70%	70%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{10}$, $MFCC_{12}$
	87%	100%	70%	70%	$MFCC_4$, $MFCC_8$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{13}$
	87%	100%	70%	70%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{11}$
	87%	100%	70%	70%	$MFCC_3$, $MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	86%	100%	69%	69%	$MFCC_4$, $MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	86%	100%	69%	69%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{11}$, $MFCC_{12}$
	86%	100%	69%	69%	$MFCC_7$, $MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{13}$
Mean	**74%**	**98%**	**43%**	**41%**	**n/a**
Standard dev.	**5.83%**	**2.65%**	**11.61%**	**12.77%**	**n/a**
Lowest results	57%	90%	16%	6%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_9$
	57%	86%	20%	6%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$
	57%	89%	17%	6%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_9$, $MFCC_{12}$
	58%	90%	18%	8%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_9$, $MFCC_{12}$
	59%	93%	16%	9%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_7$, $MFCC_9$
	59%	96%	13%	9%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_7$, $MFCC_{12}$
	59%	93%	16%	9%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_7$
	60%	99%	11%	10%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_7$, $MFCC_9$
	60%	100%	10%	10%	$MFCC_1$, $MFCC_2$, $MFCC_4$, $MFCC_7$, $MFCC_9$
	59%	91%	20%	11%	$MFCC_2$, $MFCC_4$, $MFCC_7$, $MFCC_9$, $MFCC_{12}$
	59%	88%	24%	12%	$MFCC_3$, $MFCC_4$, $MFCC_7$, $MFCC_9$, $MFCC_{12}$
	59%	86%	27%	12%	$MFCC_2$, $MFCC_3$, $MFCC_6$, $MFCC_9$, $MFCC_{12}$
	61%	96%	17%	12%	$MFCC_1$, $MFCC_2$, $MFCC_3$, $MFCC_7$, $MFCC_9$
	60%	92%	20%	12%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_9$, $MFCC_{11}$
	61%	94%	20%	13%	$MFCC_2$, $MFCC_4$, $MFCC_6$, $MFCC_9$, $MFCC_{13}$
	61%	95%	19%	13%	$MFCC_1$, $MFCC_2$, $MFCC_3$, $MFCC_6$, $MFCC_7$
	60%	89%	25%	14%	$MFCC_2$, $MFCC_3$, $MFCC_4$, $MFCC_7$, $MFCC_{12}$
	61%	91%	23%	14%	$MFCC_3$, $MFCC_4$, $MFCC_6$, $MFCC_{12}$, $MFCC_{13}$
	61%	94%	20%	14%	$MFCC_2$, $MFCC_4$, $MFCC_5$, $MFCC_6$, $MFCC_7$
	61%	95%	20%	14%	$MFCC_2$, $MFCC_4$, $MFCC_5$, $MFCC_7$, $MFCC_9$

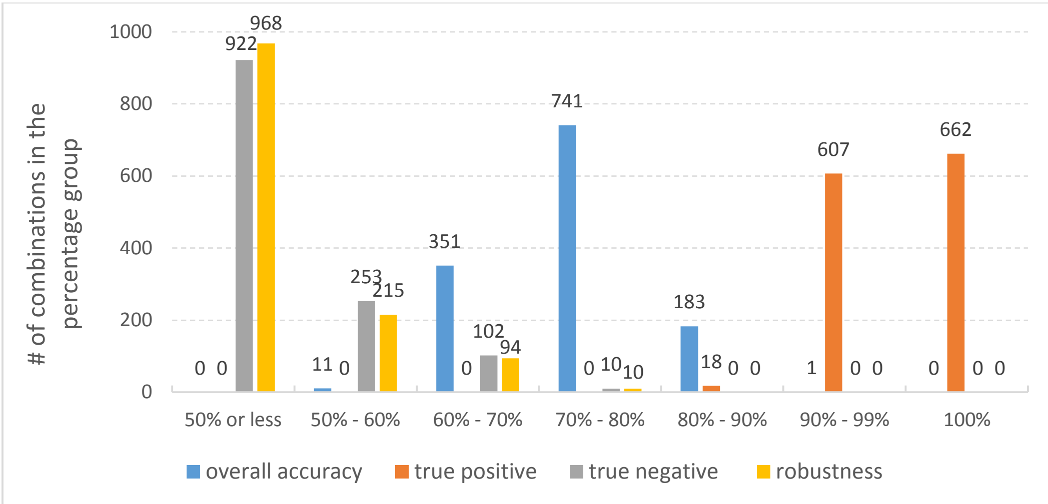


Figure 4.18. Cross-validation results using a SVM classifier while choosing five MFCC coefficients at a time. 70% of samples are used as training data set while the remaining 30% served as testing data set.

b. <u>Top performing PSDs in the 0 – 3.00kHz frequency range [PSD_1 (0 – 250Hz), PSD_3 (500Hz – 750Hz), PSD_5 (1.00kHz – 1.25kHz), PSD_9 (2.00kHz – 2.25kHz), PSD_{10} (2.25kHz – 2.50kHz)] and 13 MFCCs</u>

So far, the impact of classification space dimensionality using only MFCCs has been studied and outlined in part (a) above. Four-dimensional space classification produced better results. Moving forward, the focus will be on four-dimensional spaces only. The aim of this part of the section, part (b), is to understand how top PSD bands in the frequency range 0 – 3.00kHz will impact the results when coupled with MFCCs. The total number of possible combinations was 3,060. The discussion below shows there is no improvement and MFCCs still play the main role in achieving top results.

- Cross-validation when choosing a combination of four coefficients at a time – LDA:

Adding the top PSD bands as additional features to the MFCCs didn't show significant improvement in the overall results. PSD_1 and PSD_3, however, played marginal role in top results while PSD_9 and PSD_{10} contributed moderately in lowest results as indicated in table 4.26. Figure 4.19 shows that ~42% out of total 3,060 possible combinations achieved *overall accuracy* of more than 70%. *overall accuracy*'s good results were highly driven by classifying PNESs correctly. ~57% of combinations achieved *true negative* of more than 70%. The results of *true positive* were rather disappointing, ~31% of combinations achieved more than 70%. *robustness* index was again the least performing index. Only 40 combinations exceeded 70% *robustness* which indicates that a combination would either classify seizures or PNESs correctly but not both, most of the times. The top result was achieved by the combination consisting of MFCC coefficients 4, 5, 8, and 13; 89% *overall accuracy*, 83% *true positive*, 97% *true negative*, and 80% *robustness*. On the other hand, the combination consisting of MFCC coefficients 4, 12, 13, and PSD_{10} was lowest performing; 42% *overall accuracy*, 45% *true positive*, 39% *true negative*, and -17% *robustness*. Table 4.26 shows top and lowest results, mean, and standard deviation of the results along monitored categories. The mean of *overall accuracy* was 68% and the standard deviation reached 8.41%. *true positive*'s mean was 66% and standard deviation was 8.84%. *true negative* achieved highest mean of 71% but more scattered as indicated by a 12.10% standard deviation. *robustness* index had the lowest mean of 36% and most scattered records indicated by a 17.22% standard deviation. MFCC coefficients 5, 8, and 13 were the features contributing most to top results, similar to previous trials, while MFCC coefficients 4, 11, and PSD_{10} are the ones contributing most to lowest results.

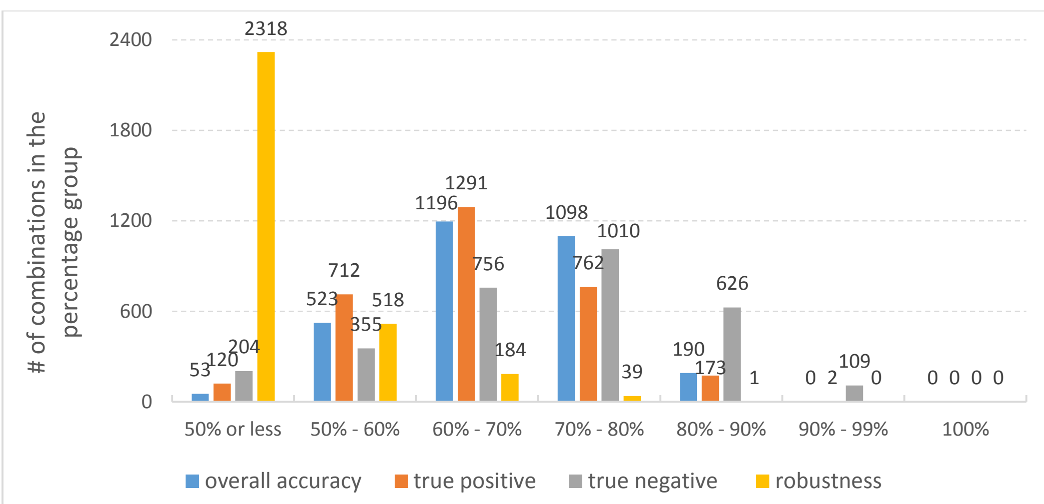


Figure 4.19. Cross-validation results using a LDA classifier while choosing four features at a time from point (b) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.26. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using LDA classifier while choosing four features at a time from point (b) above.

# combinations = 3,060	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	89%	83%	97%	80%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	95%	83%	79%	PSD_1, $MFCC_1$, $MFCC_2$, $MFCC_{13}$
	88%	82%	95%	77%	PSD_3, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	88%	83%	93%	77%	PSD_1, $MFCC_2$, $MFCC_3$, $MFCC_{13}$
	87%	80%	97%	77%	$MFCC_2$, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	87%	81%	95%	76%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	82%	95%	76%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	87%	79%	97%	76%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	88%	83%	93%	76%	PSD_1, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	81%	95%	76%	PSD_3, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	81%	94%	75%	PSD_9, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	86%	81%	93%	74%	PSD_3, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	86%	80%	94%	74%	PSD_3, PSD_{10}, $MFCC_8$, $MFCC_{13}$
	86%	84%	90%	74%	$MFCC_2$, $MFCC_3$, $MFCC_9$, $MFCC_{13}$
	86%	82%	92%	74%	$MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	86%	82%	91%	74%	PSD_3, $MFCC_3$, $MFCC_5$, $MFCC_{13}$
	86%	79%	95%	74%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
Mean	**68%**	**66%**	**71%**	**36%**	**n/a**
Standard dev.	**8.41%**	**8.84%**	**12.10%**	**17.22%**	**n/a**
Lowest results	42%	45%	39%	-17%	PSD_{10}, $MFCC_4$, $MFCC_{12}$, $MFCC_{13}$
	42%	40%	43%	-17%	PSD_5, PSD_{10}, $MFCC_4$, $MFCC_{12}$
	43%	47%	38%	-15%	PSD_{10}, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	43%	46%	40%	-14%	PSD_5, PSD_{10}, $MFCC_{11}$, $MFCC_{12}$
	44%	48%	39%	-14%	PSD_{10}, $MFCC_2$, $MFCC_4$, $MFCC_{12}$
	44%	48%	40%	-12%	PSD_{10}, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	44%	46%	42%	-12%	PSD_5, PSD_{10}, $MFCC_4$, $MFCC_{11}$
	45%	48%	40%	-11%	PSD_{10}, $MFCC_4$, $MFCC_{11}$, $MFCC_{13}$
	46%	53%	37%	-10%	PSD_9, $MFCC_4$, $MFCC_{11}$, $MFCC_{13}$
	46%	49%	41%	-10%	PSD_9, $MFCC_4$, $MFCC_{12}$, $MFCC_{13}$
	46%	53%	37%	-10%	PSD_9, $MFCC_2$, $MFCC_{11}$, $MFCC_{13}$
	46%	53%	38%	-9%	PSD_9, $MFCC_2$, $MFCC_4$, $MFCC_{13}$
	46%	52%	38%	-9%	PSD_9, $MFCC_2$, $MFCC_{11}$, $MFCC_{12}$
	46%	51%	40%	-9%	PSD_9, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	46%	50%	40%	-9%	PSD_9, $MFCC_{11}$, $MFCC_{12}$, $MFCC_{13}$
	46%	55%	36%	-9%	PSD_9, $MFCC_2$, $MFCC_4$, $MFCC_{11}$
	47%	54%	38%	-8%	PSD_{10}, $MFCC_2$, $MFCC_4$, $MFCC_{11}$
	47%	53%	39%	-7%	PSD_9, $MFCC_2$, $MFCC_4$, $MFCC_{12}$
	46%	42%	52%	-7%	PSD_5, $MFCC_4$, $MFCC_{11}$, $MFCC_{12}$
	47%	52%	41%	-6%	PSD_{10}, $MFCC_2$, $MFCC_{11}$, $MFCC_{12}$

- Cross-validation when choosing a combination of four coefficients at a time – QDA:

Adding top performing PSD bands to MFCCs didn't change QDA classification results when only using MFCCs. Coefficients 5, 8, and 13 were still the features that contributed most to top results. PSD_9 and PSD_{10} were among the features that contributed most to lowest results besides MFCC coefficient 2. The top result achieved was 94% *overall accuracy*, 100% *true positive*, 87% *true negative*, and 87% *robustness* by the combination consisting of MFCC coefficients 3, 5, 8, and 13. This top result was similar to the top ones achieved by QDA and SVM classifier in a four-dimensional MFCCs spaces. Table 4.27, which contains top and lowest results, mean, and standard deviation, highlights that there are three additional results close to the top one. The lowest result was 53% *overall accuracy*, 71% *true positive*, 29% *true negative*, and 0% *robustness*. The mean value for *overall accuracy* was 73% with a standard deviation of 6.68%. *true positive*'s mean value was 85% and its standard deviation was 7.09% indicating high scores for *true positive* by all combinations. *true negative*, however, achieved a lower mean of 58% and a standard deviation of 8.81% which led to low *robustness* mean of 43% and widely scattered *robustness* results as indicated by its 13.45% standard deviation. Figure 4.20 shows how the results are distributed across the four monitored categories. ~77% of combinations classified true seizures correctly as indicated by *true positive* results. Poor classification

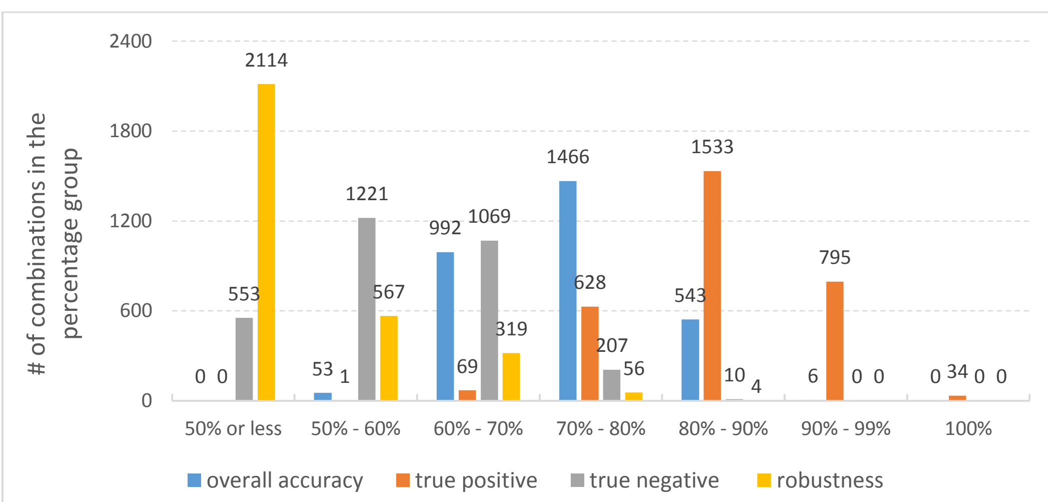


Figure 4.20. Cross-validation results using a QDA classifier while choosing four features at a time from point (b) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.27. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using QDA classifier while choosing four features at a time from point (b) above.

# combinations = 3,060	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	94%	100%	87%	87%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	94%	100%	87%	86%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	99%	83%	82%	$MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	99%	83%	82%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	90%	98%	81%	78%	PSD_9, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	100%	79%	78%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	90%	99%	79%	78%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	95%	82%	78%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	89%	92%	85%	77%	PSD_1, $MFCC_1$, $MFCC_2$, $MFCC_{13}$
	89%	93%	84%	77%	$MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	90%	99%	78%	77%	PSD_{10}, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	94%	82%	76%	$MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	89%	95%	80%	76%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	98%	77%	75%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	89%	100%	76%	75%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{11}$
	89%	100%	75%	75%	PSD_5, $MFCC_1$, $MFCC_5$, $MFCC_8$
	88%	97%	78%	75%	PSD_1, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
Mean	**73%**	**85%**	**58%**	**43%**	**n/a**
Standard dev.	**6.68%**	**7.09%**	**8.81%**	**13.54%**	**n/a**
Lowest results	53%	71%	29%	0%	PSD_9, PSD_{10}, $MFCC_2$, $MFCC_{11}$
	55%	76%	29%	6%	PSD_9, PSD_{10}, $MFCC_{11}$, $MFCC_{12}$
	56%	80%	26%	6%	PSD_9, PSD_{10}, $MFCC_2$, $MFCC_{10}$
	56%	82%	25%	7%	PSD_9, PSD_{10}, $MFCC_9$, $MFCC_{11}$
	57%	83%	24%	7%	PSD_9, PSD_{10}, $MFCC_9$, $MFCC_{10}$
	55%	63%	44%	7%	PSD_5, PSD_{10}, $MFCC_3$, $MFCC_6$
	56%	73%	35%	8%	PSD_{10}, $MFCC_2$, $MFCC_6$, $MFCC_{11}$
	55%	62%	47%	9%	PSD_5, PSD_{10}, $MFCC_2$, $MFCC_6$
	57%	75%	34%	9%	PSD_{10}, $MFCC_2$, $MFCC_9$, $MFCC_{10}$
	57%	75%	34%	9%	PSD_{10}, $MFCC_2$, $MFCC_6$, $MFCC_9$
	57%	78%	31%	9%	PSD_9, PSD_{10}, $MFCC_2$, $MFCC_9$
	56%	63%	46%	9%	PSD_5, PSD_{10}, $MFCC_2$, $MFCC_{10}$
	56%	67%	43%	9%	PSD_5, PSD_9, $MFCC_2$, $MFCC_{10}$
	56%	62%	48%	10%	PSD_3, PSD_{10}, $MFCC_3$, $MFCC_6$
	58%	80%	30%	10%	PSD_9, PSD_{10}, $MFCC_4$, $MFCC_{11}$
	59%	85%	25%	11%	PSD_9, PSD_{10}, $MFCC_{10}$, $MFCC_{11}$
	58%	78%	33%	11%	PSD_{10}, $MFCC_2$, $MFCC_9$, $MFCC_{11}$
	57%	73%	38%	11%	PSD_3, PSD_9, PSD_{10}, $MFCC_{11}$
	58%	75%	36%	11%	PSD_{10}, $MFCC_2$, $MFCC_6$, $MFCC_{10}$

of PNESs noticed since only 10 combinations achieved *true negative* of more than 80%, however, none exceeding 90%. A majority of the remaining combinations, approximately 93%, couldn't exceed *true negative* of 70%. *overall accuracy* of classifying samples correctly was somewhere between *true positive* and *true negative* values; ~66% of combinations achieving *overall accuracy* between 70% and 90%. *robustness* followed *true negative*; only 60 combinations were able to exceed 70%.

- Cross-validation when choosing a combination of four coefficients at a time – SVM:

Adding the top PSD bands to the MFCCs didn't improve the overall results of SVM cross-validation classification. Although the top result was identical to the one observed in SVM four-dimensional MFCCs classification (check part (a) of this section), the mean and standard deviation of the four monitored categories were lower. Table 4.28 highlights top and lowest results, mean, and standard deviation of SVM four-dimensional space classification using features detailed in part (b) above. The mean of *overall accuracy* was 72% with a standard deviation of 8.34%. *true positive*'s mean was 88% and its standard deviation was 8.45%. *true negative*'s was far lower reaching 52% coupled by a standard deviation of 10.76%; slightly scattered results. As usual, the lowest mean was recorded by *robustness*, reaching 40%, but highly scattered values demonstrated by a standard deviation of 16.94%. The range of *robustness* values extended from 89% to -13%. Figure 4.21 shows that SVM cross-validation four-dimensional space classification, using features detailed in part (b), was very effective in correctly classifying seizures, however, very inefficient in PNESs' classification.

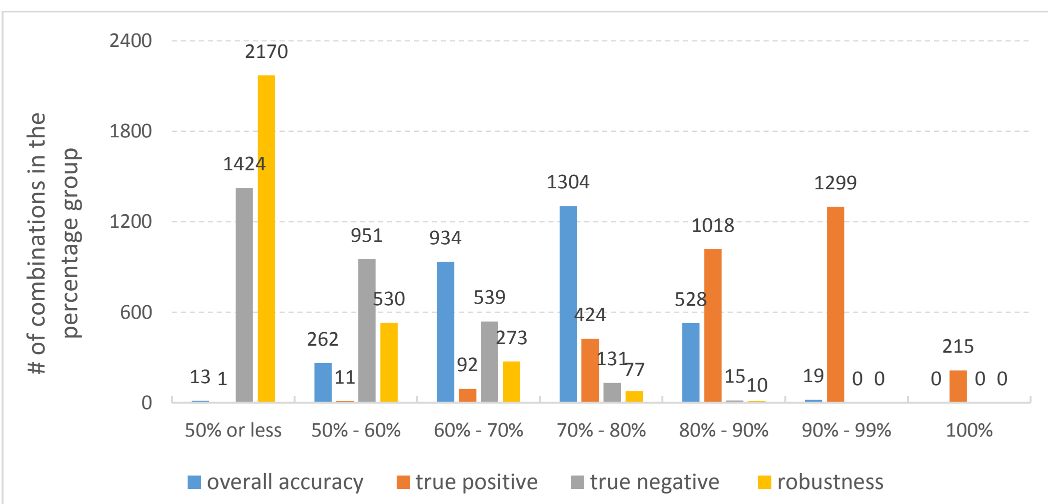


Figure 4.21. Cross-validation results using a SVM classifier while choosing four features at a time from point (b) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.28. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using SVM classifier while choosing four features at a time from point (b) above.

# combinations = 3,060	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	95%	100%	89%	89%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	93%	100%	85%	85%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	99%	85%	84%	PSD_3, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	93%	100%	84%	84%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	92%	98%	85%	83%	PSD_3, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	92%	100%	82%	82%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{10}$
	92%	100%	82%	82%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	100%	82%	82%	PSD_3, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	100%	81%	81%	$MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	91%	100%	80%	80%	$MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{13}$
	91%	100%	80%	80%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	99%	80%	79%	$MFCC_6$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	91%	100%	79%	79%	$MFCC_4$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	90%	99%	79%	79%	PSD_5, $MFCC_4$, $MFCC_8$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_2$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	90%	100%	78%	78%	$MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{12}$
	90%	100%	78%	78%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	90%	100%	78%	78%	PSD_5, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
Mean	**72%**	**88%**	**52%**	**40%**	**n/a**
Standard dev.	**8.34%**	**8.45%**	**10.76%**	**16.94%**	**n/a**
Lowest results	45%	60%	26%	-13%	PSD_5, PSD_9, $MFCC_2$, $MFCC_{12}$
	46%	61%	28%	-11%	PSD_9, PSD_{10}, $MFCC_2$, $MFCC_6$
	46%	58%	32%	-10%	PSD_9, PSD_{10}, $MFCC_2$, $MFCC_{11}$
	47%	62%	28%	-10%	PSD_5, PSD_{10}, $MFCC_2$, $MFCC_6$
	48%	67%	25%	-8%	PSD_1, PSD_5, PSD_9, $MFCC_{12}$
	47%	50%	43%	-8%	PSD_1, PSD_{10}, $MFCC_3$, $MFCC_6$
	48%	60%	33%	-7%	PSD_1, PSD_3, PSD_5, $MFCC_3$
	49%	72%	21%	-7%	PSD_1, PSD_{10}, $MFCC_{11}$, $MFCC_{12}$
	49%	68%	26%	-6%	PSD_1, PSD_3, PSD_5, $MFCC_2$
	49%	66%	29%	-5%	PSD_1, PSD_9, $MFCC_4$, $MFCC_{12}$
	50%	66%	30%	-4%	PSD_1, PSD_3, $MFCC_3$, $MFCC_4$
	50%	65%	31%	-4%	PSD_1, PSD_3, PSD_5, PSD_9
	50%	64%	32%	-4%	PSD_5, PSD_9, PSD_{10}, $MFCC_2$
	50%	66%	31%	-3%	PSD_5, PSD_9, $MFCC_2$, $MFCC_6$
	51%	74%	23%	-3%	PSD_1, PSD_3, $MFCC_2$, $MFCC_{11}$
	51%	65%	33%	-2%	PSD_5, PSD_9, $MFCC_2$, $MFCC_9$
	50%	60%	38%	-2%	PSD_1, PSD_{10}, $MFCC_1$, $MFCC_{11}$

Only 146 combination our of 3,060 possible ones exceeded 70% *true negative* yet below 90%. MFCCs coefficients 8 and 13 contributed the most to the top results while PSD bands 1, 5, and 9 contributed most to the lowest results; in-line with the observation of part (b)'s overall results being lower than those of part (a).

c. <u>12 PSDs in the 0 – 3.00kHz frequency range and 13 MFCCs</u>

In this part of the section, the results of including the remaining of the 12 PSD bands in the frequency range 0 – 3.00kHz, the ones excluded from part (b) above, are discussed. The total number of possible combinations was 12,650. In general, no improvements have been noticed as revealed by the discussion below.

- Cross-validation when choosing a combination of four coefficients at a time – LDA:

Likewise adding the top PSD bands to MFCCs, the addition of more PSD bands, i.e. to include all 12 PSD bands in the frequency range 0 – 3.00kHz, to MFCCs produced even worse overall results. However, the top result observed was still similar to LDA's part (b) top result; 89% *overall accuracy*, 83% *true positive*, 97% *true negative*, and 80% *robustness* achieved by the combination containing MFCCs coefficients 4, 5, 8, and 13. A majority of the 12,650 possible combinations achieved less than 80% across all monitored categories. *true negative* results were slightly better than

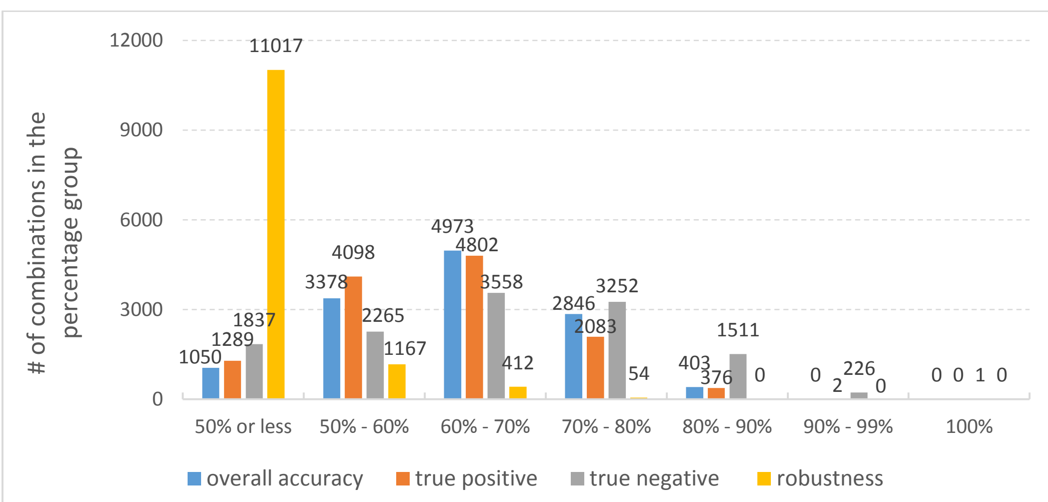


Figure 4.22. Cross-validation results using a LDA classifier while choosing four features at a time from point (c) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.29. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using LDA classifier while choosing four features at a time from point (c) above.

# combinations = 12,650	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	89%	83%	97%	80%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	86%	92%	79%	PSD_4, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	88%	83%	94%	77%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	95%	82%	77%	PSD_1, $MFCC_1$, $MFCC_2$, $MFCC_{13}$
	88%	83%	94%	77%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	87%	81%	96%	77%	PSD_3, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	88%	84%	92%	76%	PSD_1, $MFCC_2$, $MFCC_3$, $MFCC_{13}$
	87%	81%	95%	76%	PSD_3, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	83%	93%	76%	PSD_1, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	81%	95%	75%	PSD_{10}, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	79%	96%	75%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	86%	78%	97%	75%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	81%	94%	75%	PSD_4, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	79%	96%	75%	$MFCC_2$, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	86%	80%	94%	74%	PSD_{12}, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	86%	79%	95%	74%	PSD_9, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	86%	82%	92%	74%	PSD_7, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
Mean	64%	62%	66%	27%	n/a
Standard dev.	9.31%	9.40%	13.23%	19.08%	n/a
Lowest results	35%	38%	31%	-30%	PSD_7, PSD_{10}, $MFCC_4$, $MFCC_{12}$
	35%	38%	32%	-30%	PSD_6, PSD_7, PSD_{10}, $MFCC_{12}$
	37%	43%	30%	-28%	PSD_7, PSD_{10}, PSD_{11}, $MFCC_{12}$
	37%	42%	30%	-27%	PSD_7, PSD_{10}, PSD_{12}, $MFCC_4$
	36%	35%	37%	-27%	PSD_4, PSD_7, PSD_{10}, $MFCC_{12}$
	37%	41%	31%	-27%	PSD_{10}, PSD_{11}, $MFCC_4$, $MFCC_{12}$
	36%	33%	40%	-27%	PSD_5, PSD_7, PSD_{12}, $MFCC_{12}$
	37%	40%	33%	-27%	PSD_6, PSD_{10}, $MFCC_4$, $MFCC_{12}$
	37%	36%	38%	-26%	PSD_5, PSD_6, PSD_{12}, $MFCC_{12}$
	36%	31%	43%	-26%	PSD_5, PSD_6, PSD_{11}, $MFCC_{12}$
	38%	46%	28%	-26%	PSD_6, PSD_{10}, PSD_{12}, $MFCC_4$
	36%	31%	43%	-26%	PSD_5, PSD_7, PSD_{11}, $MFCC_{12}$
	38%	42%	32%	-26%	PSD_6, PSD_{10}, PSD_{11}, $MFCC_{12}$
	38%	46%	29%	-26%	PSD_7, PSD_{10}, PSD_{12}, $MFCC_{12}$
	37%	40%	35%	-26%	PSD_6, PSD_7, PSD_{10}, $MFCC_4$
	38%	42%	32%	-26%	PSD_6, PSD_{10}, PSD_{11}, $MFCC_4$
	37%	36%	38%	-26%	PSD_5, PSD_6, PSD_{11}, PSD_{12}

the remaining three categories, however, not as good as part (b) above. Figure 4.22 highlights the performance of *overall accuracy*, *true positive*, *true negative*, and *robustness* independent of each other. More detailed results including top and lowest results, means, and standard deviations are included in table 4.29. MFCCs coefficients 8 and 13, again, contributed the most to top results while PSD_{10} and

MFCCs coefficient 12 contributed the most to lowest results. The lowest observed *robustness* was -30% which is much lower than any *robustness* result achieved so far.

- Cross-validation when choosing a combination of four coefficients at a time – QDA:

QDA classification of samples using a four-dimensional space of features detailed in part (c) was still worse than part (b), similar observation as LDA. Figure 4.23 shows that QDA still does a good job in correctly classifying seizures, as indicated by *true positive* overall results, but demonstrating moderate accuracy in classifying PNESs correctly, as indicated by *true negative* overall results. *overall accuracy* lies in between *true positive* and *true negative* while *robustness* has been the most suffering, in comparison to all previous trials. Table 4.30 details top and lowest results, means, and standard deviations of QDA's part (c) classification. The top result was still achieved by the combination consisting of MFCCs only, coefficients 3, 5, 8, and 13; as experienced in parts (a) and (b). MFCCs coefficients 5, 8, and 13 are still the features contributing the most to top results. PSD bands 6 and 8 as well as MFCCs coefficient 2 are the features contributing the most to lowest results.

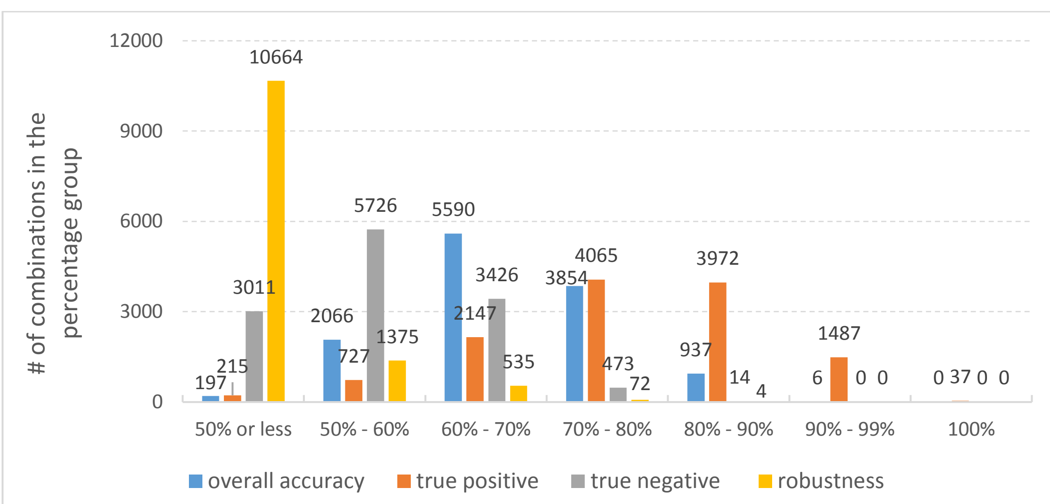


Figure 4.23. Cross-validation results using a QDA classifier while choosing four features at a time from point (c) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

Table 4.30. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using QDA classifier while choosing four features at a time from point (c) above.

# combinations = 12,650	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	94%	100%	88%	87%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	94%	100%	86%	86%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	93%	98%	87%	84%	PSD_7, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	99%	82%	82%	$MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	91%	98%	82%	80%	PSD_9, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	99%	80%	78%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	93%	85%	78%	PSD_1, $MFCC_1$, $MFCC_2$, $MFCC_{13}$
	90%	100%	78%	77%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	89%	95%	83%	77%	PSD_6, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	99%	78%	77%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	95%	82%	77%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	90%	100%	77%	77%	PSD_{10}, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	99%	78%	77%	PSD_5, $MFCC_2$, $MFCC_5$, $MFCC_8$
	89%	93%	83%	76%	$MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	89%	98%	78%	76%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
Mean	**68%**	**77%**	**56%**	**33%**	**n/a**
Standard dev.	**8.21%**	**11.13%**	**8.55%**	**16.02%**	**n/a**
Lowest results	38%	23%	56%	-21%	PSD_4, PSD_6, PSD_8, $MFCC_2$
	40%	41%	39%	-20%	PSD_6, PSD_8, PSD_{12}, $MFCC_{11}$
	39%	30%	51%	-19%	PSD_6, PSD_8, PSD_{11}, $MFCC_2$
	41%	36%	47%	-17%	PSD_6, PSD_{11}, $MFCC_2$, $MFCC_{11}$
	43%	51%	33%	-16%	PSD_6, PSD_8, PSD_9, PSD_{12}
	41%	28%	56%	-16%	PSD_6, PSD_7, PSD_8, $MFCC_2$
	42%	39%	45%	-15%	PSD_6, PSD_8, PSD_{11}, $MFCC_{11}$
	43%	47%	38%	-15%	PSD_8, PSD_{11}, $MFCC_2$, $MFCC_{11}$
	43%	43%	43%	-14%	PSD_6, PSD_8, PSD_{10}, PSD_{11}
	44%	49%	37%	-14%	PSD_6, PSD_8, PSD_{10}, PSD_{12}
	42%	35%	51%	-14%	PSD_4, PSD_6, PSD_8, PSD_{11}
	42%	37%	49%	-14%	PSD_6, PSD_8, PSD_9, $MFCC_2$
	42%	34%	52%	-14%	PSD_6, PSD_8, $MFCC_2$, $MFCC_{11}$
	42%	37%	50%	-14%	PSD_4, PSD_8, PSD_{11}, $MFCC_2$
	43%	38%	49%	-14%	PSD_6, PSD_7, PSD_9, $MFCC_2$

- Cross-validation when choosing a combination of four coefficients at a time – SVM:

The SVM classifier in part (c) has shown similar behavior to QDA and LDA. The overall results are lower compared to SVM results of parts (a) and (b) mainly due to adding all 12 PSD bands in the frequency range 0 – 3.00kHz. Top result is still achieved by the same combination as

SVM results in parts (a) and (b); MFCCs coefficients 8, 9, 12, and 13. Mean and standard deviation values are lower than those of parts (a) and (b), however, following a similar pattern.

Table 4.31. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using SVM classifier while choosing four features at a time from point (c) above.

# combinations = 12,650	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	94%	100%	87%	87%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	94%	100%	86%	86%	PSD_2, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	100%	85%	85%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	93%	100%	85%	84%	PSD_3, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	92%	98%	86%	83%	PSD_3, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	93%	100%	83%	83%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	92%	100%	83%	83%	PSD_6, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	92%	100%	83%	82%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	92%	100%	81%	81%	$MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	92%	100%	81%	81%	PSD_3, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	100%	81%	81%	$MFCC_8$, $MFCC_9$, $MFCC_{10}$, $MFCC_{13}$
	91%	99%	81%	80%	$MFCC_6$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
	91%	100%	80%	80%	PSD_2, $MFCC_8$, $MFCC_9$, $MFCC_{10}$
	91%	97%	83%	80%	PSD_2, PSD_3, $MFCC_8$, $MFCC_{13}$
Mean	**69%**	**82%**	**52%**	**34%**	**n/a**
Standard dev.	**9.09%**	**10.90%**	**10.18%**	**18.04%**	**n/a**
Lowest results	39%	54%	21%	-26%	PSD_6, PSD_7, PSD_9, $MFCC_{12}$
	40%	55%	21%	-24%	PSD_7, PSD_8, PSD_{12}, $MFCC_2$
	39%	51%	25%	-24%	PSD_7, PSD_9, PSD_{12}, $MFCC_{12}$
	40%	56%	20%	-23%	PSD_8, PSD_9, $MFCC_2$, $MFCC_{12}$
	40%	56%	21%	-23%	PSD_6, PSD_7, PSD_8, $MFCC_2$
	41%	59%	19%	-22%	PSD_7, PSD_8, PSD_{11}, $MFCC_2$
	40%	50%	27%	-22%	PSD_6, PSD_9, PSD_{11}, PSD_{12}
	40%	53%	25%	-22%	PSD_6, PSD_8, PSD_9, PSD_{11}
	41%	54%	25%	-22%	PSD_6, PSD_7, PSD_8, PSD_{12}
	41%	52%	26%	-22%	PSD_5, PSD_6, PSD_8, PSD_9
	41%	52%	26%	-22%	PSD_6, PSD_7, PSD_8, PSD_{11}
	42%	61%	18%	-21%	PSD_7, PSD_8, $MFCC_2$, $MFCC_{12}$
	41%	54%	25%	-21%	PSD_4, PSD_6, PSD_7, PSD_8
	41%	52%	28%	-20%	PSD_5, PSD_8, PSD_9, $MFCC_2$
	41%	54%	25%	-20%	PSD_6, PSD_7, PSD_8, PSD_9
	42%	55%	25%	-20%	PSD_6, PSD_9, PSD_{12}, $MFCC_{12}$
	41%	51%	29%	-20%	PSD_7, PSD_8, PSD_9, PSD_{12}
	41%	51%	29%	-20%	PSD_6, PSD_9, PSD_{11}, $MFCC_{12}$

Figure 4.24 highlights overall performance of SVM classifier of part (c) while table 4.31 provides more details on top and lowest results, means, and standard deviation values. MFCCs

coefficients 8 and 13 are still the features contributing most to top results while PSD bands 6, 7, 8, and 9 are the features contributing most to lowest results.

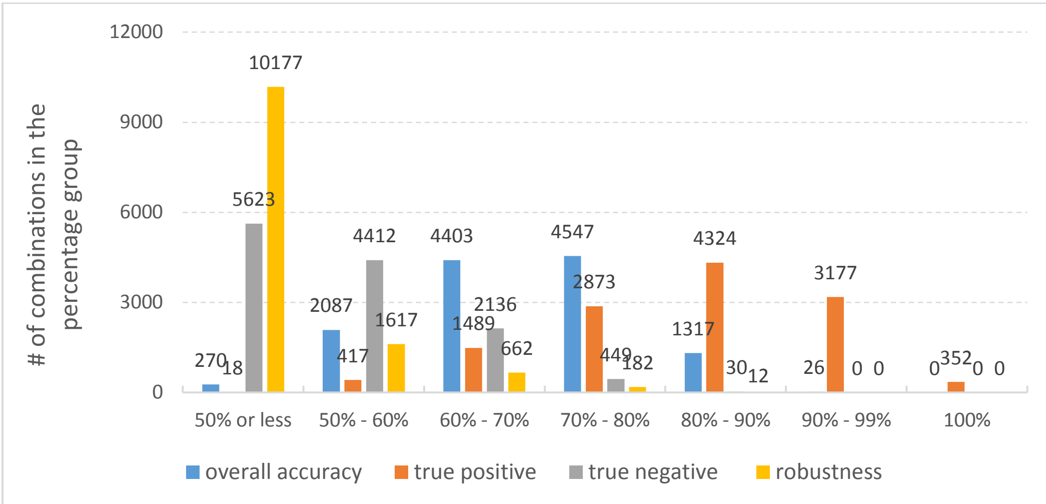


Figure 4.24. Cross-validation results using a SVM classifier while choosing four features at a time from point (c) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

d. <u>12 PSDs in the 0 – 3.00kHz frequency range, max and mean max of the envelope, and 13 MFCCs</u>

The last part of this section was to understand the impact of including maximum and mean maximum of the envelope to the set of features tested above in parts (a), (b), and (c). The total number of possible combinations was 17,550. Again, no improvements are noticed in the overall results due to the addition of the maximum and mean maximum of the envelope.

- Cross-validation when choosing a combination of four coefficients at a time – LDA:

The top results of LDA's four-dimensional feature space cross-validation using all available features were in-line with previous LDA trials, although the top two results included PSD_1, PSD_4, and mean maximum of the envelope. The distribution of the results across the monitored categories, *overall accuracy*, *true positive*, *true negative*, and *robustness*, was not any better compared to parts (a), (b), and (c) above. Actually, the mean and standard deviation values were the worst. Figure 4.25 highlights the performance of the different categories independent of each other while

Table 4.32. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using LDA classifier while choosing four features at a time from point (d) above.

# combinations = 17,550	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	90%	91%	89%	80%	PSD_1, MeanMaxEnv, $MFCC_2$, $MFCC_{13}$
	90%	87%	93%	80%	PSD_4, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	89%	82%	96%	79%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	79%	98%	77%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	94%	82%	76%	PSD_1, $MFCC_1$, $MFCC_2$, $MFCC_{13}$
	88%	83%	93%	76%	PSD_1, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	88%	84%	92%	76%	PSD_1, $MFCC_2$, $MFCC_3$, $MFCC_{13}$
	87%	81%	95%	76%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	87%	80%	96%	76%	PSD_3, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	87%	81%	95%	76%	PSD_9, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	80%	95%	76%	PSD_3, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	81%	94%	75%	PSD_3, PSD_9, $MFCC_8$, $MFCC_{13}$
	87%	81%	94%	75%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	87%	81%	94%	75%	PSD_4, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	87%	83%	92%	75%	PSD_7, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
	87%	83%	92%	75%	$MFCC_5$, $MFCC_8$, $MFCC_{11}$, $MFCC_{13}$
	86%	79%	95%	75%	$MFCC_5$, $MFCC_8$, $MFCC_{10}$, $MFCC_{13}$
Mean	**63%**	**61%**	**64%**	**26%**	**n/a**
Standard dev.	**9.51%**	**9.56%**	**13.23%**	**19.45%**	**n/a**
Lowest results	33%	31%	35%	-34%	PSD_7, PSD_{11}, maxEnv, $MFCC_{12}$
	34%	36%	31%	-33%	PSD_7, PSD_{12}, maxEnv, $MFCC_4$
	33%	33%	33%	-33%	PSD_5, PSD_7, PSD_{12}, maxEnv
	33%	31%	36%	-33%	PSD_5, PSD_7, maxEnv, $MFCC_{12}$
	33%	31%	37%	-33%	PSD_6, PSD_{11}, maxEnv, $MFCC_{12}$
	34%	32%	35%	-33%	PSD_7, maxEnv, $MFCC_4$, $MFCC_{12}$
	35%	38%	30%	-32%	PSD_7, PSD_{10}, $MFCC_4$, $MFCC_{12}$
	34%	35%	33%	-32%	PSD_7, PSD_{11}, PSD_{12}, maxEnv
	34%	34%	34%	-32%	PSD_7, PSD_{12}, maxEnv, $MFCC_{12}$
	34%	31%	38%	-31%	PSD_4, PSD_5, PSD_7, maxEnv
	35%	36%	33%	-31%	PSD_5, PSD_7, PSD_{11}, maxEnv
	35%	32%	37%	-30%	PSD_5, PSD_6, PSD_{11}, maxEnv
	35%	34%	36%	-30%	PSD_5, PSD_{11}, maxEnv, $MFCC_{12}$
	35%	40%	30%	-30%	PSD_7, PSD_{10}, maxEnv, $MFCC_{12}$
	35%	36%	34%	-30%	PSD_6, PSD_7, PSD_{12}, maxEnv
	35%	35%	35%	-30%	PSD_5, PSD_{11}, PSD_{12}, maxEnv
	34%	28%	42%	-30%	PSD_5, PSD_6, maxEnv, $MFCC_{12}$
	35%	34%	36%	-30%	PSD_4, PSD_7, PSD_{11}, maxEnv
	34%	28%	42%	-30%	PSD_4, PSD_5, maxEnv, $MFCC_{12}$
	35%	35%	35%	-30%	PSD_5, PSD_{12}, maxEnv, $MFCC_{12}$
	36%	39%	31%	-30%	PSD_7, PSD_{10}, maxEnv, $MFCC_4$
	35%	35%	35%	-30%	PSD_4, PSD_7, PSD_{10}, $MFCC_{12}$
	35%	33%	38%	-30%	PSD_6, PSD_7, PSD_{11}, maxEnv

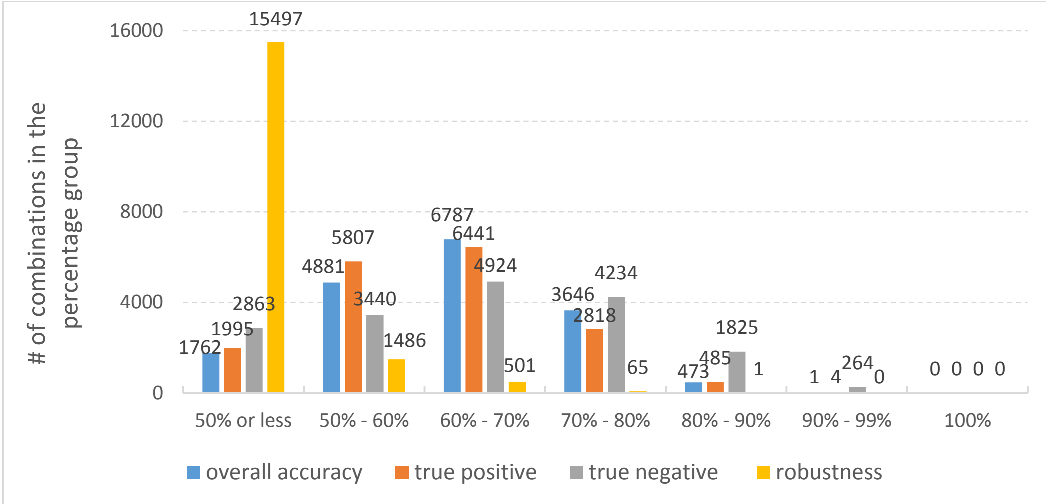


Figure 4.25. Cross-validation results using a LDA classifier while choosing four features at a time from point (d) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

table 4.32 details top and lowest results as well as mean and standard deviation values. As noticed previously, MFCCs coefficients 5, 8, and 13 were the features contributing the most to top results. Surprisingly, PSD_7 and the maximum of the envelope contributed the most to lowest ones.

- Cross-validation when choosing a combination of four coefficients at a time – QDA:

QDA's cross-validation results using features detailed in part (d) were almost identical to those observed in part (c). The first few top results are identical! Also, mean and standard deviation values revealed slight unnoticeable change. Additionally, the pattern of how the four monitored categories are distributed was similar to that of part (c), figures 4.23 and 4.26. Table 4.33 below highlights top and lowest results as well as mean and standard deviation values.

MFCCs coefficients 8 and 13 are still the features contributing most to top results. On the other hand, PSD bands 6 and 8 contributed the most to lowest results for the first time.

Table 4.33. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using QDA classifier while choosing four features at a time from point (d) above.

# combinations = 17,550	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	95%	100%	88%	88%	$MFCC_3$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	95%	100%	88%	88%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	97%	86%	84%	PSD_7, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	99%	82%	82%	$MFCC_2$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	91%	100%	80%	80%	MeanMaxEnv, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	91%	99%	81%	80%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	91%	99%	82%	80%	PSD_9, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	99%	79%	78%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	90%	96%	82%	78%	$MFCC_4$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	97%	80%	77%	maxEnv, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	93%	85%	77%	PSD_1, $MFCC_1$, $MFCC_2$, $MFCC_{13}$
	89%	96%	81%	77%	PSD_4, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	90%	100%	77%	77%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	89%	99%	77%	76%	PSD_{10}, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	89%	94%	82%	76%	$MFCC_5$, $MFCC_7$, $MFCC_8$, $MFCC_{13}$
	89%	100%	76%	76%	MeanMaxEnv, $MFCC_5$, $MFCC_8$, $MFCC_{12}$
	88%	92%	83%	76%	PSD_1, MeanMaxEnv, $MFCC_2$, $MFCC_{13}$
	89%	96%	79%	76%	PSD_3, $MFCC_3$, $MFCC_8$, $MFCC_{13}$
Mean	**67%**	**77%**	**56%**	**33%**	**n/a**
Standard dev.	**8.19%**	**11.11%**	**8.45%**	**15.97%**	**n/a**
Lowest results	39%	22%	60%	-19%	PSD_4, PSD_6, PSD_8, $MFCC_2$
	41%	43%	38%	-19%	PSD_6, PSD_8, PSD_{12}, $MFCC_{11}$
	40%	29%	53%	-18%	PSD_6, PSD_8, PSD_{11}, $MFCC_2$
	42%	39%	45%	-16%	PSD_6, PSD_8, PSD_{11}, $MFCC_{11}$
	42%	43%	41%	-16%	PSD_7, PSD_8, PSD_{12}, maxEnv
	43%	47%	38%	-16%	PSD_6, PSD_8, PSD_{10}, PSD_{12}
	41%	34%	51%	-16%	PSD_6, PSD_8, $MFCC_2$, $MFCC_{11}$
	42%	42%	43%	-15%	PSD_6, PSD_8, PSD_{10}, PSD_{11}
	43%	50%	36%	-15%	PSD_6, PSD_8, PSD_9, PSD_{12}
	41%	29%	56%	-15%	PSD_4, PSD_6, PSD_{11}, $MFCC_2$
	42%	33%	53%	-14%	PSD_2, PSD_4, PSD_6, PSD_8
	43%	41%	45%	-14%	PSD_6, PSD_9, PSD_{11}, $MFCC_2$
	42%	38%	48%	-14%	PSD_6, PSD_{11}, $MFCC_2$, $MFCC_{11}$
	42%	35%	50%	-14%	PSD_4, PSD_8, PSD_{11}, $MFCC_2$
	41%	27%	59%	-14%	PSD_6, PSD_7, PSD_8, $MFCC_2$
	42%	37%	49%	-14%	PSD_6, PSD_8, PSD_9, $MFCC_2$
	44%	49%	37%	-14%	PSD_7, PSD_8, PSD_{10}, $MFCC_2$
	43%	45%	42%	-14%	PSD_2, PSD_4, PSD_8, PSD_{12}
	42%	37%	50%	-14%	PSD_6, PSD_7, PSD_9, $MFCC_2$
	43%	38%	49%	-14%	PSD_6, PSD_8, PSD_{10}, maxEnv
	42%	34%	52%	-14%	PSD_4, PSD_6, PSD_8, PSD_{11}

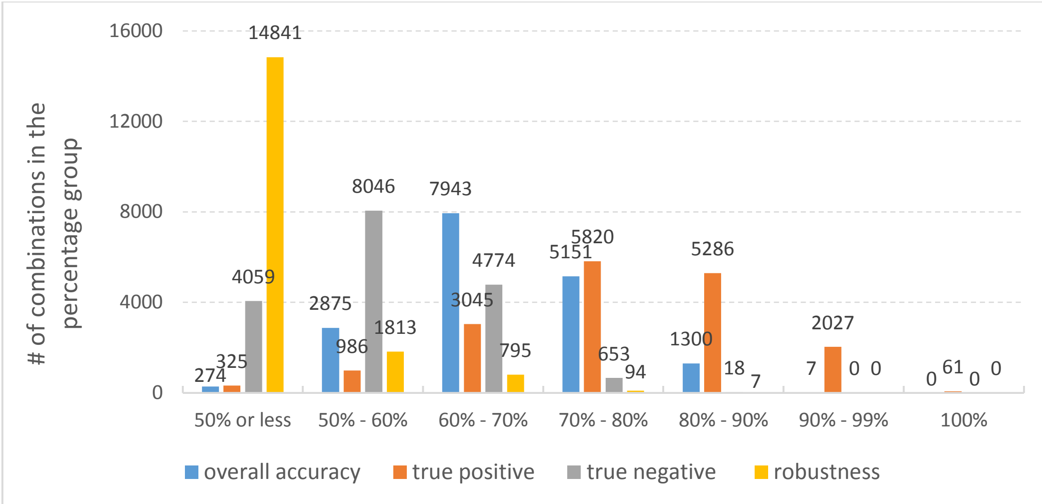


Figure 4.26. Cross-validation results using a QDA classifier while choosing four features at a time from point (d) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

- Cross-validation when choosing a combination of four coefficients at a time – SVM:

Similar to QDA's observation, SVM's cross-validation results of part (d) were almost identical to those observed in part (c); whether it is top result, lowest result, mean, or standard deviation values, tables 4.31 and 4.34. The distribution of *overall accuracy*, *true positive*, *true negative*, and *robustness* was also similar, figures 4.24 and 4.27. The feature contributing the most to top results were MFCCs coefficients 8 and 13 while PSD bands 7 and 8 were the ones contributing most to lowest results. Maximum of the envelope and mean maximum of the envelope had no visible impact on SVM's cross-validation results albeit adding ~5,000 more combinations.

Table 4.34. Top and lowest 15-25 results, mean, and standard deviation of cross-validation using SVM classifier while choosing four features at a time from point (d) above.

# combinations = 17,550	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
Top results	94%	100%	86%	86%	$MFCC_8$, $MFCC_9$, $MFCC_{12}$, $MFCC_{13}$
	94%	100%	86%	86%	PSD_2, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	100%	85%	85%	MeanMaxEnv, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	93%	99%	85%	85%	PSD_3, $MFCC_6$, $MFCC_8$, $MFCC_{13}$
	93%	100%	84%	84%	maxEnv, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	100%	84%	84%	PSD_6, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	92%	97%	86%	84%	PSD_3, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	93%	100%	84%	84%	$MFCC_5$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	100%	84%	84%	MeanMaxEnv, $MFCC_1$, $MFCC_5$, $MFCC_8$
	93%	100%	84%	83%	$MFCC_6$, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	93%	100%	83%	83%	$MFCC_8$, $MFCC_{10}$, $MFCC_{12}$, $MFCC_{13}$
	92%	100%	83%	83%	$MFCC_5$, $MFCC_6$, $MFCC_8$, $MFCC_{10}$
	92%	100%	83%	83%	$MFCC_5$, $MFCC_8$, $MFCC_{12}$, $MFCC_{13}$
	92%	100%	82%	82%	PSD_3, $MFCC_8$, $MFCC_9$, $MFCC_{13}$
	92%	100%	81%	81%	$MFCC_1$, $MFCC_5$, $MFCC_8$, $MFCC_{13}$
	92%	99%	82%	81%	PSD_3, maxEnv, $MFCC_8$, $MFCC_{13}$
Mean	**69%**	**83%**	**52%**	**35%**	**n/a**
Standard dev.	**8.83%**	**10.42%**	**10.11%**	**17.58%**	**n/a**
Lowest results	39%	52%	23%	-25%	PSD_6, PSD_7, PSD_9, $MFCC_{12}$
	40%	55%	20%	-25%	PSD_6, PSD_7, PSD_8, $MFCC_2$
	40%	55%	21%	-24%	PSD_7, PSD_8, PSD_{12}, $MFCC_2$
	41%	58%	20%	-22%	PSD_7, PSD_8, PSD_{11}, $MFCC_2$
	40%	52%	26%	-22%	PSD_6, PSD_7, PSD_8, PSD_{12}
	40%	52%	26%	-22%	PSD_6, PSD_7, PSD_8, PSD_{11}
	40%	51%	27%	-22%	PSD_6, PSD_7, PSD_8, PSD_9
	41%	54%	24%	-22%	PSD_7, PSD_9, PSD_{12}, $MFCC_{12}$
	42%	61%	17%	-22%	PSD_7, PSD_8, $MFCC_2$, $MFCC_{12}$
	41%	52%	27%	-21%	PSD_7, PSD_8, PSD_9, PSD_{12}
	41%	58%	21%	-21%	PSD_8, PSD_9, $MFCC_2$, $MFCC_{12}$
	41%	53%	26%	-21%	PSD_6, PSD_8, PSD_{11}, $MFCC_2$
	41%	53%	27%	-21%	PSD_4, PSD_6, PSD_7, PSD_8
	41%	54%	25%	-21%	PSD_6, PSD_8, PSD_9, PSD_{11}
	41%	56%	24%	-21%	PSD_5, PSD_8, PSD_9, $MFCC_2$
	41%	55%	24%	-21%	PSD_8, PSD_9, PSD_{11}, PSD_{12}

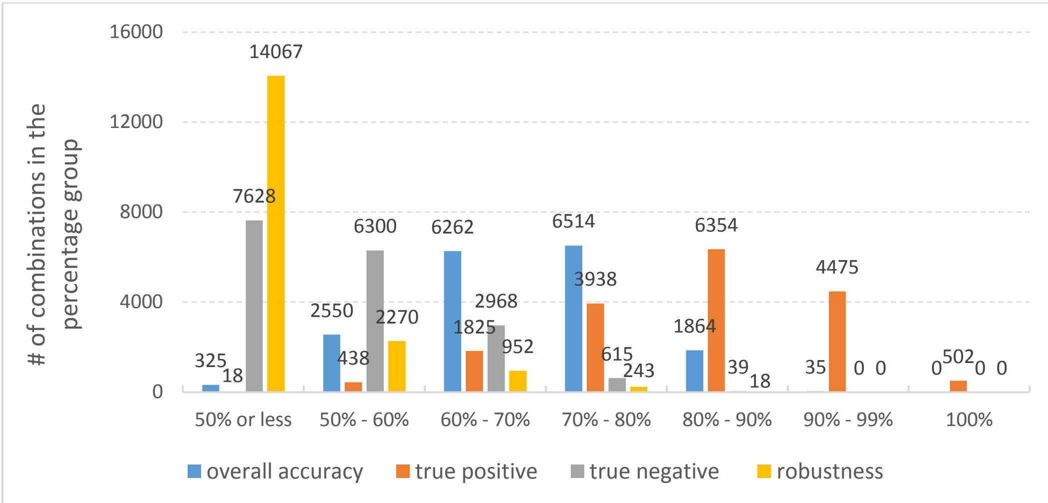


Figure 4.27. Cross-validation results using a SVM classifier while choosing four features at a time from point (d) above. 70% of samples are used as training data set while the remaining 30% served as testing data set.

4.3.2 Remarks

Cross-validation trials, parts (a) to (d), have revealed few interesting remarks. They indicate that the separation between the samples into seizures and PNESs is actually possible. The remarks will be discussed in four aspects: 1) Reliability of classification features, 2) Feature space dimensionality, 3) Categories' performance, and 4) Preferred classification method.

1) Reliability of features

The order followed in conducting the trials allowed for clear understanding of which features contribute the most to best results. MFCCs were the features contributing the most to top results. This conclusion was of no surprise since equal test-train has shown significant results when testing MFCCs for separation reliability. Cross-validation not only confirmed MFCCs clustering possibility but also demonstrated high efficiency in classifying samples correctly into seizures and PNESs. Parts (a) to (d) trials have shown that adding more features at each step didn't improve the results. Actually, the overall results were worse off! Hence, other features but MFCCs can be eliminated when conducting such a classification of seizures and PNESs.

Among the MFCCs, not all coefficients are powerful in correctly classifying samples into their respective groups. MFCCs coefficients 5, 8, and 13 have always been presented in top results regardless of features mix, number of features, and/or classification method.

Looking into lowest results revealed no clear blame to any specific feature for those lowest results. Sometimes it is a MFCC which is to blame while other times it is a PSD band or maximum of the envelope.

2) Feature space dimensionality

The impact of number of features on the results was tested exclusively using MFCCs, mainly due to equal test-train results which suggested MFCCs would perform best among available set of features. Two feature-space dimensions have been tested, four- and five-dimensional spaces. The results were unexpected since four-dimensional feature space produced better results by far. This finding is also helpful since it allows for more efficient computational time.

3) Categories' performance

Looking into each category (*overall accuracy*, *true positive*, *true negative*, and *robustness*) separately has revealed interesting findings. QDA and SVM classifiers were always consistent in classifying seizures correctly with a high accuracy. Using SVM classifier, mean values for *true positive* have consistently always exceeded 83% with low standard deviation; the best *true positive* mean value was 94%. QDA classifier also followed SVM in correctly classifying seizures; *true positive* has always exceeded 77% with relatively low standard deviation. This indicates that both SVM and QDA can accurately tell a seizure sound sample is actually a seizure by looking into a database of seizure samples. The issue with SVM and QDA is their inability to classify PNESs correctly; vast majority of combinations would not exceed *true negative* of 70%.

On the other hand, *true negative* never demonstrated a clear pattern. LDA was best classifier in determining that a PNES sound sample is actually a PNES. The maximum mean value for *true* *negative* did not exceeding 77% in best case scenario; the lowest was 64%. There is still more room to look into additional sound features that can produce both superior *true positive* and *true negative* at the same time.

4) Preferred classification method

The results of cross-validation indicates that both QDA and SVM classifiers can effective classification results in four-dimensional feature space. The difference between the two lies in the fact that SVM demonstrated very high accuracy in classifying seizures, however, it demonstrated moderate accuracy in classifying PNESs. QDA, on the other hand, demonstrated lower accuracy in classifying seizures, compared to SVM, but at the same classified PNESs more accurately providing a more balanced option. However, the main factor will be patients' safety. Hence, lower level of mistakes in classifying seizures is favorable which leads to SVM being the best classifier. To better understand the issue with SVM's low *true negative* accuracy, let's imagine the classification algorithm in this study is utilized in a product similar to a baby monitor which beeps if a patient is undergoing a seizure. SVM classifier would make the monitor beeps incorrectly when classifying PNESs incorrectly as seizures. This will create unrealistic panic and waste of efforts, for example, to care takers. However, the issue of patient safety is more important thus the SVM is recommended.

CHAPTER V CONCLUSION AND FUTURE RESEARCH

The efforts to determine whether it is possible to use computer aid in identifying seizures shows great success. The conducted research has shown that it is possible to identify seizures and PNESs correctly by the means of signal processing and pattern recognition. However, due to the small sample size, 28 patients, cautious must be examined in generalizing the findings. Although certain classifiers are able to identify seizures correctly, they detected PNESs less accurately. No classifier was able to detect both, seizures and PNESs, highly accurate. There is still more room for improvement. Additionally, the relatively simple algorithm used makes its applicability more favorable which adds another layer of success. Researchers always try to implement the simplest solution to the difficult problems so that these solutions can become easily available for future consumption.

For the good of patients and care givers, the aim is to always identify seizures with a very high accuracy, 100% if possible, while at the same time not neglecting PNESs' detection accuracy. Cross-validation classification is used as a basis since it consists of training the classifier on predetermined samples followed by testing it against unknown ones. Comparing the different classifiers shows that SVM classifier produced best results. The top result achieved was 95% *overall accuracy* (100% accuracy in classifying seizures and 89% accuracy in classifying PNESs) coupled with a very high *robustness* of 89%. This top result was present in all trials except for five-dimensional MFCCs feature space which detected PNESs less accurately at 79%. QDA has also demonstrated strong top result, similar to that of SVM. However, SVM has shown a higher mean in detecting seizures accurately, the best achieved was 98% for five-dimensional MFCCs feature space, compared to QDA, 91% for the same feature space dimensionality. The mean of detecting seizures accurately was always higher than that of PNESs for both SVM and QDA. LDA, on the other hand, was a more balanced classifier compared to SVM and QDA. For example, the accuracy of detecting seizures and PNESs were closer. However, the accuracy of detecting PNESs was higher than those of seizures. The best LDA result was 89% *overall accuracy* (82% accuracy in detecting seizures and 97% in detecting PNESs). LDA's mean related to the accuracy of detecting PNESs was higher than that of seizure samples in the different trials.

For the sake of being comprehensive, multiple sets of features have been examined in this research; among which are the amount of energy in low frequencies (PSD bands), loudness of recorded samples (maximum/mean maximum of the envelope), and MFCCs. Equal test-train has shown early in the process that MFCCs tend to produce excellent results alone, even if not coupled with other features. Almost all four-feature MFCC combinations would achieve 100% *overall accuracy*. Cross-validation has confirmed that equal test-train's observation is, indeed, true. MFCCs are the features that led to best results regardless of the set of features or classifier used. In cross-validation classification, MFCCs coefficients 5, 8, and 13 were the ones contributing to top results most of the time. It was rare for other features to surpass. The other set of features, namely PSDs and maximum/mean maximum of the envelope, didn't perform as great as MFCCs, however, they produced results rather in mid-ranges between best and lowest results.

Feature-space dimensionality was another aspect that was touched upon in this study. Equal test-train has shown that increasing the dimensionality of the feature space would produce better results. Four-feature dimensional space produced results better than three-feature space and so on. The ultimate choice of feature space dimensionality should not exceed the number of samples divided by 5, five in equal test-train vs four for cross-validation in our case. The results have confirmed the ultimate number of features choice. Cross-validation using four-dimensional feature space produced best results compared to five.

This piece of work can still be further studied and enhanced. There are multiple elements that can be considered in the future. The number of seizures and PNESs can be increased to several hundreds to ensure the results can be generalized. Also, the demographics of the samples can be further stretched to allow for better analysis by multiple sub-groups, i.e. gender and age group, and examine how the results might vary. Additional voice signal features can also be studied to knock out features which can produce high accuracy in detecting both, seizures and PNESs, at the same time. Epileptic seizures are clinically classified into multiple types, the study can be extended to test whether it is possible to classify not only seizures and PNESs but also the different seizure types correctly, i.e., focal, generalized, and unknown. Additionally, future research can investigate how real-time streaming of sound can be recorded and utilized to identify seizure cries among other sounds (i.e., corridor footsteps, door opening and closing, people talk in and outside patient's room, objects moving in patient's room, etc.) and classify them correctly. The last point that can enhance this research further touches on technical aspects related to programming platform. For certain trials, the processing time exceeded multiple hours. SVM cross-validation, for example, costs ~3 seconds per combination. In the case of choosing a combination of four features out of all available features, PSDs, maximum/mean maximum of the envelope, and MFCCs, the number of possible combinations reached 17,550. Hence, the total processing time of cross-validation is close to 14 hours! Using other operating systems, i.e. Linux, combined with other programming language, i.e. C++, could reduce processing time significantly which allows for easy inclusion of more samples.

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APPENDIX A MATLAB CODE

maxEnv.m

```
% This function takes a signal "s" and its sampling frequency "fs" as input
% and returns two features a) Max of the Envelope, and b) Mean Max of the
% Envelope

function [max_Env_S, mean_Max_Env_S] = maxEnv(s,fs)

%%%% Passing The Envelope of The Signal "S" Through A Low-Pass Filter %%%%
[b, a] = butter(2,0.1);
y = filter(b,a,abs(s));

%%%% Calculate Maximum Of The Envelope %%%%
max_Env_S = max(y);

%%%% Define A Window Frame Of 15ms %%%%
Nframe = round(fs*0.015);
NumFrames = floor(length(s)/Nframe);

%%%% Calculate The Mean Maximum Of The Envelope For Each Window Frame %%%%
meanMaxEnv_S = [];

for k = 0:NumFrames-1
   tmp = max(y(k*Nframe+1:(k+1)*Nframe));
   meanMaxEnv_S = [meanMaxEnv_S tmp];
end

mean_Max_Env_S = mean(meanMaxEnv_S);
end
```

pdgm_sum_2k.m

```
% This function takes the signal "s" and its sampling frequency "fs" as an
% input and calculates PSD using the method of periodogram. Same approach
% was used for 0 - 3.0kHz

% to collect 4 bands - uncomment (a), (d) and up to (g)
% to collect 6 bands - uncomment (b), (e) and up to (h)
% to collect 8 bands - uncomment (c), (f) and up to (i)

function [mean_energy] = pdgm_sum_2k(s,fs)

Twin = 0.015; % window size = 15ms
Nwin = round(Twin*fs);

% Compute the number of non-overlapping windows
Nlen = length(s);
Nwins = floor(Nlen/Nwin);

% Force the signal, x, to have exactly Nwins frames
x = s(1:(Nwins*Nwin));
Nlen = length(x);

% Each column c of X is a non-overlapping frames of size Nwin
X = reshape(x, Nwin, Nwins);

[Xr,Xc] = size(X);

% Calculate the periodogram for each frame
psd = [];

for i = 1:Xc
    Xmag = (abs(fft(X(:,i),fs)).^2)/Nwin;
    psd = [psd Xmag];
end

% % 4 BANDS ------------------------------ (a)
%  % assigning variables for 4 bands and full range
%  total_band0=[];
%  total_band1=[];
%  total_band2=[];
%  total_band3=[];
%  total_band4=[];
%
%  total_area=[];
%
%  total_ratio0=[];
%  total_ratio1=[];
%  total_ratio2=[];
%  total_ratio3=[];
%  total_ratio4=[];
%
%  fr0 = 1:251;
%  fr1 = 1:501;
```

```
%  fr2 = 502:1001;
%  fr3 = 1002:1501;
%  fr4 = 1502:2001;
%  ftotal = 1:2001;
%
%  bandarea0 = [];
%  bandarea1 = [];
%  bandarea2 = [];
%  bandarea3 = [];
%  bandarea4 = [];
%
%  allarea = [];

% % 6 BANDS----------------------- (b)
% total_band1 = [];
% total_band2 = [];
% total_band3 = [];
% total_band4 = [];
% total_band5 = [];
% total_band6 = [];
%
% total_area = [];
%
% total_ratio1 = [];
% total_ratio2 = [];
% total_ratio3 = [];
% total_ratio4 = [];
% total_ratio5 = [];
% total_ratio6 = [];
%
% fr1 = 1:333;
% fr2 = 334:667;
% fr3 = 668:1001;
% fr4 = 1002:1335;
% fr5 = 1336:1669;
% fr6 = 1670:2001;
% ftotal = 1:2001;
%
% bandarea1 = [];
% bandarea2 = [];
% bandarea3 = [];
% bandarea4 = [];
% bandarea5 = [];
% bandarea6 = [];
%
% allarea = [];

% 8 BANDS----------------------- (c)
total_band1 = [];
total_band2 = [];
total_band3 = [];
total_band4 = [];
total_band5 = [];
total_band6 = [];
total_band7 = [];
total_band8 = [];
```

```
total_area = [];

total_ratio1 = [];
total_ratio2 = [];
total_ratio3 = [];
total_ratio4 = [];
total_ratio5 = [];
total_ratio6 = [];
total_ratio7 = [];
total_ratio8 = [];

fr1 = 1:251;
fr2 = 252:501;
fr3 = 502:751;
fr4 = 752:1001;
fr5 = 1002:1251;
fr6 = 1252:1501;
fr7 = 1502:1751;
fr8 = 1752:2001;
ftotal = 1:2001;

bandarea1 = [];
bandarea2 = [];
bandarea3 = [];
bandarea4 = [];
bandarea5 = [];
bandarea6 = [];
bandarea7 = [];
bandarea8 = [];

allarea = [];

for j=1:Xc;

    psdtotal = psd(1:2001,j);

% % 4 BANDS ---------------------------------------- (d)
%     psdr0=psd(1:251,j);
%     psdr1=psd(1:501,j);
%     psdr2=psd(502:1001,j);
%     psdr3=psd(1002:1501,j);
%     psdr4=psd(1502:2001,j);
%
%     %Area calculation
%     totalarea=trapz(ftotal,psdtotal);
%     band0area=trapz(fr0,psdr0);
%     band1area=trapz(fr1,psdr1);
%     band2area=trapz(fr2,psdr2);
%     band3area=trapz(fr3,psdr3);
%     band4area=trapz(fr4,psdr4);
%
%     bandarea0 = [bandarea0 band0area];
%     bandarea1 = [bandarea1 band1area];
%     bandarea2 = [bandarea2 band2area];
```

```
%     bandarea3 = [bandarea3 band3area];
%     bandarea4 = [bandarea4 band4area];
%
%     allarea = [allarea totalarea];

% % 6 BANDS ---------------------------------------- (e)
%     psdr1 = psd(1:333,j);
%     psdr2 = psd(334:667,j);
%     psdr3 = psd(668:1001,j);
%     psdr4 = psd(1002:1335,j);
%     psdr5 = psd(1336:1669,j);
%     psdr6 = psd(1670:2001,j);
%
%     % Area calculation
%     totalarea = trapz(ftotal,psdtotal);
%     area1 = trapz(fr1,psdr1);
%     area2 = trapz(fr2,psdr2);
%     area3 = trapz(fr3,psdr3);
%     area4 = trapz(fr4,psdr4);
%     area5 = trapz(fr5,psdr5);
%     area6 = trapz(fr6,psdr6);
%
%     bandarea1 = [bandarea1 area1];
%     bandarea2 = [bandarea2 area2];
%     bandarea3 = [bandarea3 area3];
%     bandarea4 = [bandarea4 area4];
%     bandarea5 = [bandarea5 area5];
%     bandarea6 = [bandarea6 area6];
%
%     allarea = [allarea totalarea];

% 8 BANDS ---------------------------------------- (f)
    psdr1 = psd(1:251,j);
    psdr2 = psd(252:501,j);
    psdr3 = psd(502:751,j);
    psdr4 = psd(752:1001,j);
    psdr5 = psd(1002:1251,j);
    psdr6 = psd(1252:1501,j);
    psdr7 = psd(1502:1751,j);
    psdr8 = psd(1752:2001,j);

    % Area calculation
    totalarea = trapz(ftotal,psdtotal);
    area1 = trapz(fr1,psdr1);
    area2 = trapz(fr2,psdr2);
    area3 = trapz(fr3,psdr3);
    area4 = trapz(fr4,psdr4);
    area5 = trapz(fr5,psdr5);
    area6 = trapz(fr6,psdr6);
    area7 = trapz(fr7,psdr7);
    area8 = trapz(fr8,psdr8);

    bandarea1 = [bandarea1 area1];
    bandarea2 = [bandarea2 area2];
    bandarea3 = [bandarea3 area3];
    bandarea4 = [bandarea4 area4];
```

```
    bandarea5 = [bandarea5 area5];
    bandarea6 = [bandarea6 area6];
    bandarea7 = [bandarea7 area7];
    bandarea8 = [bandarea8 area8];

    allarea = [allarea totalarea];
end

%ratio0 = sum(bandarea0)/sum(allarea); % 0 - 250Hz in 4 bands
ratio1 = sum(bandarea1)/sum(allarea);
ratio2 = sum(bandarea2)/sum(allarea);
ratio3 = sum(bandarea3)/sum(allarea);
ratio4 = sum(bandarea4)/sum(allarea); %--- (g) 4bands
ratio5 = sum(bandarea5)/sum(allarea);
ratio6 = sum(bandarea6)/sum(allarea); %--- (h) 6bands
ratio7 = sum(bandarea7)/sum(allarea);
ratio8 = sum(bandarea8)/sum(allarea); %--- (i) 8bands

% last ratio can be discarded because it is redundant - add ratio0 for 4
bands
mean_energy = [ratio1 ratio2 ratio3 ratio4 ratio5 ratio6 ratio7 ratio8];
end
```

mfcc.m

```
%  mfcc - Mel frequency cepstrum coefficient analysis.
%   [ceps,freqresp,fb,fbrecon,freqrecon] = ...
%           mfcc(input, samplingRate, [frameRate])
% Find the cepstral coefficients (ceps) corresponding to the
% input.  Four other quantities are optionally returned that
% represent:
%   the detailed fft magnitude (freqresp) used in MFCC calculation,
%   the mel-scale filter bank output (fb)
%   the filter bank output by inverting the cepstrals with a cosine
%       transform (fbrecon),
%   the smooth frequency response by interpolating the fb reconstruction
%       (freqrecon)
%  -- Malcolm Slaney, August 1993
% Modified a bit to make testing an algorithm easier... 4/15/94
% Fixed Cosine Transform (indices of cos() were swapped) - 5/26/95
% Added optional frameRate argument - 6/8/95
% Added proper filterbank reconstruction using inverse DCT - 10/27/95
% Added filterbank inversion to reconstruct spectrum - 11/1/95

% (c) 1998 Interval Research Corporation

function ceps = mfcc(input, samplingRate, frameRate)
global mfccDCTMatrix mfccFilterWeights

[r c] = size(input);
if (r > c)
    input=input';
end

% Filter bank parameters
lowestFrequency = 30;
linearFilters = 13;
linearSpacing = 88;
logFilters = 27;
logSpacing = 1.05512;
fftSize = 2048;
cepstralCoefficients = 13;

% Set window (frame) size
windowSize = samplingRate/frameRate;
if (nargin < 2) samplingRate = 16000; end;
if (nargin < 3) frameRate = 100; end;

% Keep this around for later....
totalFilters = linearFilters + logFilters;

% Now figure the band edges.  Interesting frequencies are spaced
% by linearSpacing for a while, then go logarithmic.  First figure
% all the interesting frequencies.  Lower, center, and upper band
% edges are all consequtive interesting frequencies.
freqs = lowestFrequency + (0:linearFilters-1)*linearSpacing;
freqs(linearFilters+1:totalFilters+2) = ...
              freqs(linearFilters) * logSpacing.^(1:logFilters+2);
```

```
lower = freqs(1:totalFilters);
center = freqs(2:totalFilters+1);
upper = freqs(3:totalFilters+2);

% We now want to combine FFT bins so that each filter has unit
% weight, assuming a triangular weighting function.  First figure
% out the height of the triangle, then we can figure out each
% frequencies contribution
mfccFilterWeights = zeros(totalFilters,fftSize);
triangleHeight = 2./(upper-lower);
fftFreqs = (0:fftSize-1)/fftSize*samplingRate;

for chan=1:totalFilters
    mfccFilterWeights(chan,:) = ...
  (fftFreqs > lower(chan) & fftFreqs <= center(chan)).* ...
   triangleHeight(chan).*(fftFreqs-lower(chan))/(center(chan)-lower(chan)) +
...
  (fftFreqs > center(chan) & fftFreqs < upper(chan)).* ...
   triangleHeight(chan).*(upper(chan)-fftFreqs)/(upper(chan)-center(chan));
end


hamWindow = 0.54 - 0.46*cos(2*pi*(0:windowSize-1)/windowSize);

% Window it like ComplexSpectrum
if 0
    windowStep = samplingRate/frameRate;
    a = .54;
    b = -.46;
    wr = sqrt(windowStep/windowSize);
    phi = pi/windowSize;
    hamWindow = 2*wr/sqrt(4*a*a+2*b*b)* ...
        (a + b*cos(2*pi*(0:windowSize-1)/windowSize + phi));
end

% Figure out Discrete Cosine Transform.  We want a matrix
% dct(i,j) which is totalFilters x cepstralCoefficients in size.
% The i,j component is given by cos( i * (j+0.5)/totalFilters pi )
% where we have assumed that i and j start at 0.
mfccDCTMatrix = 1/sqrt(totalFilters/2)*cos((0:(cepstralCoefficients-1))' *
...
                (2*(0:(totalFilters-1))+1) * pi/2/totalFilters);
mfccDCTMatrix(1,:) = mfccDCTMatrix(1,:) * sqrt(2)/2;

% Filter the input with the preemphasis filter.  Also figure how
% many columns of data we will end up with.
if 1
    preEmphasized = filter([1 -.97], 1, input);
else
    preEmphasized = input;
end
windowStep = samplingRate/frameRate;
cols = fix((length(input))/windowStep);
```

```
% Allocate all the space we need for the output arrays.
ceps = zeros(cepstralCoefficients, cols);
if (nargout > 1) freqresp = zeros(fftSize/2, cols); end;
if (nargout > 2) fb = zeros(totalFilters, cols); end;

% Invert the filter bank center frequencies.  For each FFT bin
% we want to know the exact position in the filter bank to find
% the original frequency response.  The next block of code finds the
% integer and fractional sampling positions.
if (nargout > 4)
    fr = (0:(fftSize/2-1))'/(fftSize/2)*samplingRate/2;
    j = 1;
    for i=1:(fftSize/2)
        if fr(i) > center(j+1)
            j = j + 1;
        end
        if j > totalFilters-1
            j = totalFilters-1;
        end
        fr(i) = min(totalFilters-.0001, ...
            max(1,j + (fr(i)-center(j))/(center(j+1)-center(j))));
    end
    fri = fix(fr);
    frac = fr - fri;

    freqrecon = zeros(fftSize/2, cols);
end

% Ok, now let's do the processing.  For each chunk of data:
%     * Window the data with a hamming window,
%     * Shift it into FFT order,
%     * Find the magnitude of the fft,
%     * Convert the fft data into filter bank outputs,
%     * Find the log base 10,
%     * Find the cosine transform to reduce dimensionality.

for start=0:cols-1
    first = start*windowStep + 1;
    last = first + windowSize-1;
    fftData = zeros(1,fftSize);
    fftData(1:windowSize) = preEmphasized(first:last).*hamWindow;
    fftMag = abs(fft(fftData));
    earMag = log10(mfccFilterWeights * fftMag');

    ceps(:,start+1) = mfccDCTMatrix * earMag;
    if (nargout > 1) freqresp(:,start+1) = fftMag(1:fftSize/2)'; end;
    if (nargout > 2) fb(:,start+1) = earMag; end
    if (nargout > 3)
        fbrecon(:,start+1) = ...
            mfccDCTMatrix(1:cepstralCoefficients,:)' * ...
            ceps(:,start+1);
    end
    if (nargout > 4)
        f10 = 10.^fbrecon(:,start+1);
        freqrecon(:,start+1) = samplingRate/fftSize * ...
            (f10(fri).*(1-frac) + f10(fri+1).*frac);
```

```
    end
end

% OK, just to check things, let's also reconstruct the original FB
% output.  We do this by multiplying the cepstral data by the transpose
% of the original DCT matrix.  This all works because we were careful to
% scale the DCT matrix so it was orthonormal.
if 1 & (nargout > 3)
    fbrecon = mfccDCTMatrix(1:cepstralCoefficients,:)' * ceps;
end;
end
```

equalTest.m

```
% This function takes samples labels (labels) vector, samples features
% (originalData) matrix, and feature space dimension (NFeatures) value as
% input and returns equal test-train results for LDA, QDA, and SVM

function [results_ETT_L, results_ETT_Q, results_ETT_SVM] = equalTest(labels,
originalData, NFeatures)

results_ETT_L = [];
results_ETT_Q = [];
results_ETT_SVM = [];

r1 = find(labels == 1);
r2 = find(labels == 2);

[r, c] = size(originalData);

%%%% Determine All Possible Combincations of NFeatures %%%%
C = combnk(1:c, NFeatures);
[ncomb, tmp] = size(C);

for icomb=1:ncomb
    [icomb    ncomb]

    %%%% Extract The Data That Corresponds To Desired Features Combination
%%%%
    data = originalData(: , C(icomb , :));

    %%%% LDA Equal Test-Train Classification And Results %%%%
    [decisionL,errl,Pl,logpl,coeffl] = classify(data,data,labels,'linear');
    percentageaccuracyL = sum(decisionL==labels)/length(labels);
    truepositiveL = sum(decisionL(r1)==labels(r1))/length(r1);
    missL = 1 - truepositiveL;
    truenegativeL = sum(decisionL(r2)==labels(r2))/length(r2);
    falsealarmL = 1 - truenegativeL;
    results_ETT_L = [results_ETT_L; percentageaccuracyL truepositiveL
truenegativeL (truepositiveL-falsealarmL)];

    %%%% QDA Equal Test-Train Classification And Results %%%%
    [decisionQ,errq,Pq,logpq,coeffq] =
classify(data,data,labels,'quadratic');
    percentageaccuracyQ = sum(decisionQ==labels)/length(labels);
    truepositiveQ = sum(decisionQ(r1)==labels(r1))/length(r1);
    missQ = 1 - truepositiveQ;
    truenegativeQ = sum(decisionQ(r2)==labels(r2))/length(r2);
    falsealarmQ = 1 - truenegativeQ;
    results_ETT_Q = [results_ETT_Q; percentageaccuracyQ truepositiveQ
truenegativeQ (truepositiveQ-falsealarmQ)];

    %%%% SVM Equal Test-Train Classification And Results %%%%
    sigma = 0.5; % SVM Kernel Function Specifics
    svm = svmtrain(data, labels,
'kernel_function','rbf','rbf_sigma',sigma,'autoscale',true);
```

```
    decisionSVM = svmclassify( svm , data);
    percentageaccuracySVM = sum(decisionSVM==labels)/length(labels);
    truepositiveSVM = sum(decisionSVM(r1)==labels(r1))/length(r1);
    missSVM = 1 - truepositiveSVM;
    truenegativeSVM = sum(decisionSVM(r2)==labels(r2))/length(r2);
    falsealarmSVM = 1 - truenegativeSVM;
    results_ETT_SVM = [results_ETT_SVM; percentageaccuracySVM truepositiveSVM
truenegativeSVM (truepositiveSVM-falsealarmSVM)];
end
end
```

crossValidation.m

```
% This function takes samples labels vector (labels), samples features
% (originalData), and feature space dimension value (NFeatures) as an input
% and calculates cross-validation results for LDA, QDA, and SVM. Training
% dataset size is set to 70% of the total number of samples while the
% remaining 30% are used as testing samples

function [results_CV_L, results_CV_Q, results_CV_SVM] =
crossValidation(labels, originalData, NFeatures)

results_CV_L = [];
results_CV_Q = [];
results_CV_SVM = [];

r1 = find(labels == 1);
r2 = find(labels == 2);

%%%%%%%%%%%%%% Calculating Number of Possible Combinations %%%%%%%%%%%%%
[r, c] = size(originalData);
C = combnk(1:c,NFeatures);
[ncombs, ntmp]=size(C);

for icomb = 1:ncombs
    [icomb ncombs]

    decisionsL = [];
    decisionsQ = [];
    decisionsSVM = [];
    groundtruth = [];

    %%%%%%%%%%%%%% Extracting Relevant Features As Per Desired Features
Combination %%%%%%%%%%%%%
    data = originalData(: , C(icomb , :));

    D1 = data(r1,:);
    D2 = data(r2,:);
    [nrows1,ncols1]=size(D1);
    [nrows2,ncols2]=size(D2);

    %%%%%%%%%%%%%% Setting Test/Train Data Ratio %%%%%%%%%%%%%
    crossvalpercentage = 0.3;
    Ncrossval1 = round(nrows1 * crossvalpercentage);
    Ncrossval2 = round(nrows2 * crossvalpercentage);

    Numtrials = 500;    % Number Of Trials Is Set To Ensure Sufficient
Test/Train Combinations Are Tested

    sigma = 0.5;     % SVM Kernel Function Specific

    for i=1:Numtrials
        %%%%%%%%%%%%%% Training and Test Data Preparation %%%%%%%%%%%%%
        tmp1 = randn(nrows1,1);
        [svals,I1]= sort(tmp1);
```

```
        tmp2 = randn(nrows2,1);
        [svals,I2]= sort(tmp2);

        D1test = D1( I1(1:Ncrossval1) , :);
        D2test = D2( I2(1:Ncrossval2) , :);
        D1train = D1( I1( (Ncrossval1 + 1):nrows1 ) , :);
        D2train = D2( I2( (Ncrossval2 + 1):nrows2 ) , :);

        groundtruth1 = ones(Ncrossval1, 1);
        groundtruth2 = 2*ones(Ncrossval2, 1);
        traininglabels1 = ones( nrows1 - Ncrossval1 , 1);
        traininglabels2 = 2*ones( nrows2 - Ncrossval2 , 1);
        Dtraining = [D1train ; D2train];
        Dtest = [D1test ; D2test];
        traininglabels = [traininglabels1 ; traininglabels2];

        %%%%%%%%%%%%%% Linear Classification %%%%%%%%%%%%%%
        decL = classify(Dtest, Dtraining, traininglabels);
        decisionsL = [decisionsL ; decL];

        %%%%%%%%%%%%%% Quadratic Classification %%%%%%%%%%%%%%
        decQ = classify(Dtest, Dtraining, traininglabels, 'quadratic');
        decisionsQ = [decisionsQ ; decQ];

        %%%%%%%%%%%%%% SVM Classification %%%%%%%%%%%%%%
        svm = svmtrain( Dtraining, traininglabels,
'kernel_function','rbf','rbf_sigma',sigma,'autoscale',true);
        decSVM = svmclassify( svm , Dtest);
        decisionsSVM = [decisionsSVM ; decSVM];

        %%%%%%%%%%%%%% Actual Clinical Classification %%%%%%%%%%%%%%
        groundtruth = [ groundtruth ; [groundtruth1 ; groundtruth2] ];
    end

    Iw1 = find( groundtruth == 1);
    Iw2 = find( groundtruth == 2);

    %%%%%%%%%%%%%%% Linear Cross Validation Results %%%%%%%%%%%%%%%
    percentaccuracyL = sum( decisionsL == groundtruth ) / length(decisionsL);

    truepositiveL = sum( decisionsL(Iw1) == groundtruth(Iw1) )/ length(Iw1);
    missL = 1 - truepositiveL;

    truenegativeL = sum( decisionsL(Iw2) == groundtruth(Iw2) )/ length(Iw2);
    falsealarmL = 1 - truenegativeL;

    results_CV_L = [results_CV_L ; percentaccuracyL truepositiveL
truenegativeL (truepositiveL-falsealarmL)];

    %%%%%%%%%%%%%%% Quadratic Cross Validation Results %%%%%%%%%%%%%%%
    percentaccuracyQ = sum( decisionsQ == groundtruth ) / length(decisionsQ);

    truepositiveQ = sum( decisionsQ(Iw1) == groundtruth(Iw1) )/ length(Iw1);
    missQ = 1 - truepositiveQ;
```

```
    truenegativeQ = sum( decisionsQ(Iw2) == groundtruth(Iw2) )/ length(Iw2);
    falsealarmQ = 1 - truenegativeQ;

    results_CV_Q = [results_CV_Q ; percentaccuracyQ truepositiveQ
truenegativeQ (truepositiveQ-falsealarmQ)];

    %%%%%%%%%%%%%%% SVM Cross Validation Results %%%%%%%%%%%%%%%
    percentaccuracySVM = sum( decisionsSVM == groundtruth ) /
length(decisionsSVM);

    truepositiveSVM = sum( decisionsSVM(Iw1) == groundtruth(Iw1) )/
length(Iw1);
    missSVM = 1 - truepositiveSVM;

    truenegativeSVM = sum( decisionsSVM(Iw2) == groundtruth(Iw2) )/
length(Iw2);
    falsealarmSVM = 1 - truenegativeSVM;

    results_CV_SVM = [results_CV_SVM ; percentaccuracySVM truepositiveSVM
truenegativeSVM (truepositiveSVM-falsealarmSVM)];
end
end
```

APPENDIX B HISTOGRAMS AND TOP 5 RESULTS OF PSD EQUAL TEST-TRAIN TRIALS

a. *PSDs in the 0 – 2.00kHz frequency range along 5 sub-frequencies; 0 – 250Hz, 0 – 500Hz, 500Hz – 1.00kHz, 1.00kHz – 1.50kHz, and 1.50kHz – 2.00kHz*

- Equal test-train when choosing one band at a time – LDA:

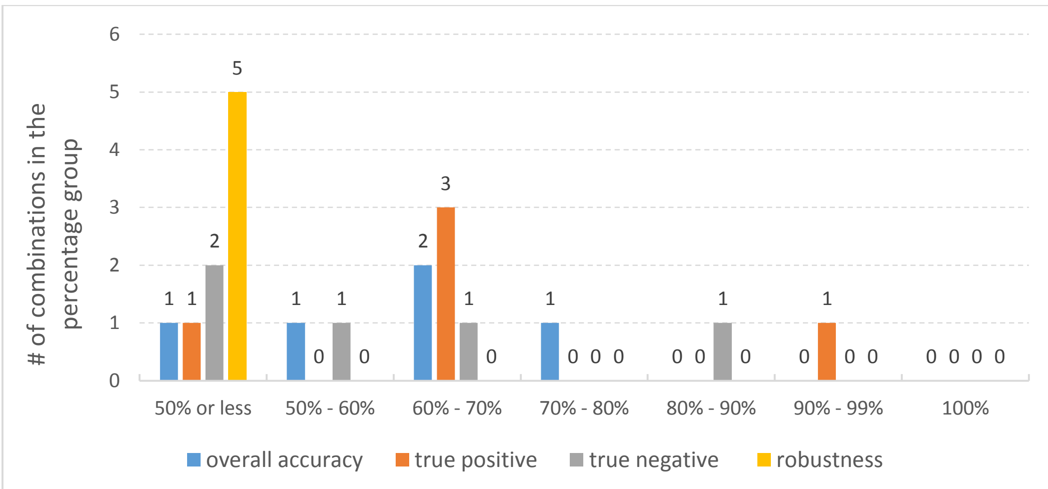

Figure C.1. Equal test-train classification results using a LDA classifier while choosing one PSD band at a time for the frequency range detailed in point (a).

Table C.1. Top 5 results of equal test-train LDA classification while choosing one PSD band at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_0
	57%	69%	42%	10%	PSD_4
	71%	63%	83%	46%	PSD_2
	61%	63%	58%	21%	PSD_1
	43%	25%	67%	-8%	PSD_3
In terms of *overall accuracy*	71%	63%	83%	46%	PSD_2
	68%	94%	33%	27%	PSD_0
	61%	63%	58%	21%	PSD_1
	57%	69%	42%	10%	PSD_4
	43%	25%	67%	-8%	PSD_3

- Equal test-train when choosing one band at a time – QDA:

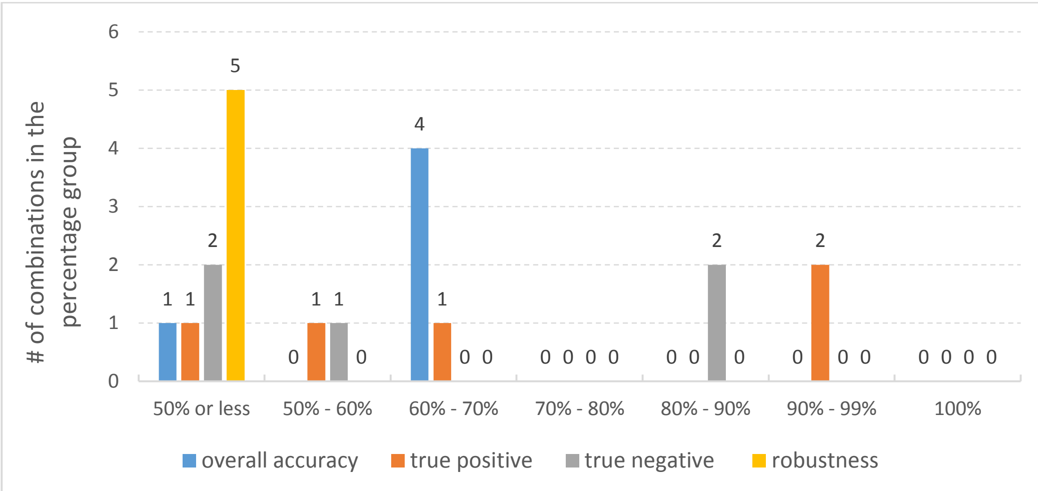

Figure C.2. Equal test-train classification results using a QDA classifier while choosing one PSD band at a time for the frequency range detailed in point (a).

Table C.2. Top 5 results of equal test-train QDA classification while choosing one PSD band at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_0
	64%	94%	25%	19%	PSD_4
	64%	69%	58%	27%	PSD_1
	68%	56%	83%	40%	PSD_2
	39%	6%	83%	-10%	PSD_3
In terms of *overall accuracy*	68%	94%	33%	27%	PSD_0
	68%	56%	83%	40%	PSD_2
	64%	94%	25%	19%	PSD_4
	64%	69%	58%	27%	PSD_1
	39%	6%	83%	-10%	PSD_3

- Equal test-train when choosing one band at a time – SVM:

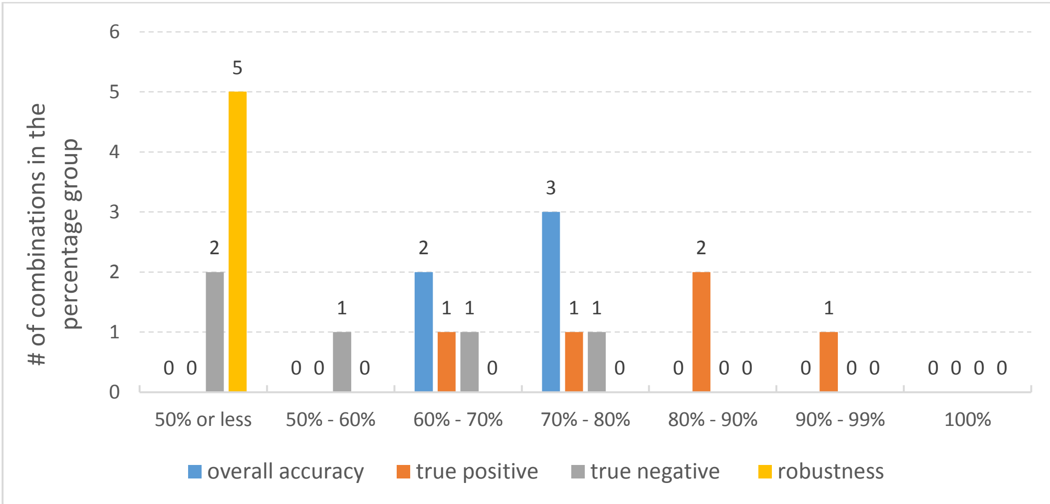

Figure C.3. Equal test-train classification results using a SVM classifier while choosing one PSD band at a time for the frequency range detailed in point (a).

Table C.3. Top 5 results of equal test-train SVM classification while choosing one PSD band at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	64%	94%	25%	19%	PSD_4
	71%	88%	50%	38%	PSD_0
	71%	81%	58%	40%	PSD_1
	75%	75%	75%	50%	PSD_2
	64%	63%	67%	29%	PSD_3
In terms of *overall accuracy*	75%	75%	75%	50%	PSD_2
	71%	88%	50%	38%	PSD_0
	71%	81%	58%	40%	PSD_1
	64%	94%	25%	19%	PSD_4
	64%	63%	67%	29%	PSD_3

- Equal test-train when choosing a combination of two bands at a time – LDA:

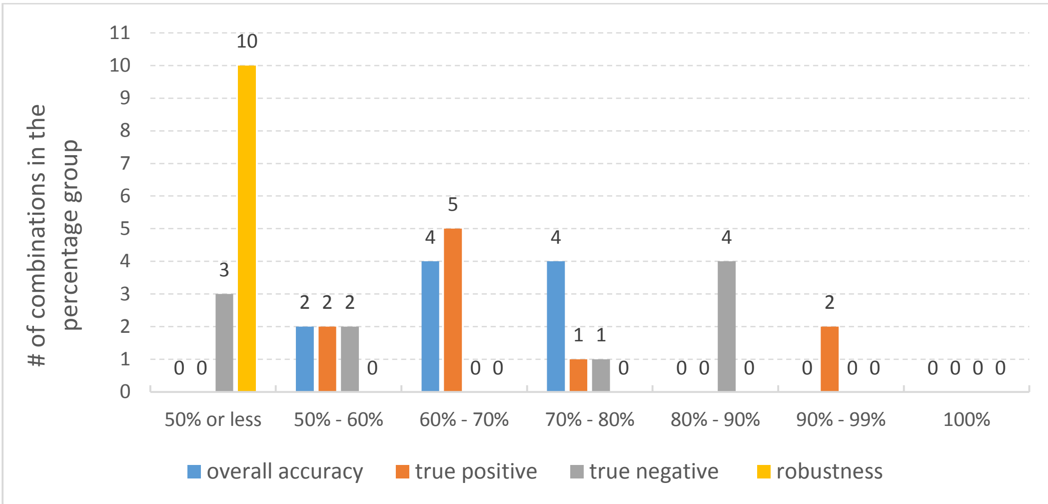

Figure C.4. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (a).

Table C.4. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*Robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_0, PSD_4
	64%	94%	25%	19%	PSD_0, PSD_3
	68%	75%	58%	33%	PSD_0, PSD_1
	57%	69%	42%	10%	PSD_3, PSD_4
	71%	63%	83%	46%	PSD_2, PSD_4
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_0, PSD_4
	71%	63%	83%	46%	PSD_2, PSD_4
	71%	63%	83%	46%	PSD_1, PSD_4
	71%	63%	83%	46%	PSD_1, PSD_2
	68%	75%	58%	33%	PSD_0, PSD_1

- Equal test-train when choosing a combination of two bands at a time – QDA:

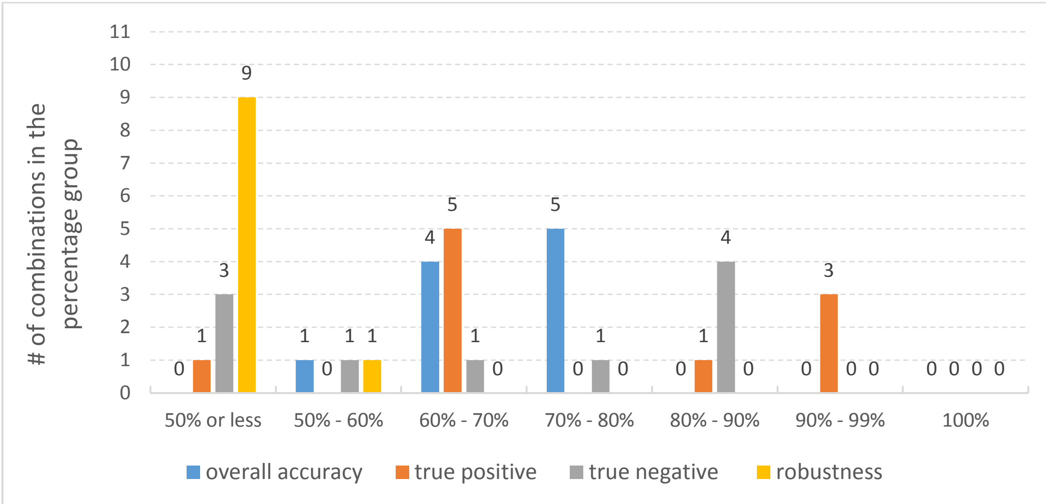

Figure C.5. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (a).

Table C.5. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	94%	42%	35%	PSD_0, PSD_2
	68%	94%	33%	27%	PSD_0, PSD_3
	68%	94%	33%	27%	PSD_0, PSD_1
	75%	88%	58%	46%	PSD_0, PSD_4
	75%	69%	83%	52%	PSD_1, PSD_4
In terms of *overall accuracy*	75%	88%	58%	46%	PSD_0, PSD_4
	75%	69%	83%	52%	PSD_1, PSD_4
	71%	94%	42%	35%	PSD_0, PSD_2
	71%	63%	83%	46%	PSD_2, PSD_4
	71%	63%	83%	46%	PSD_1, PSD_2

- Equal test-train when choosing a combination of two bands at a time – SVM:

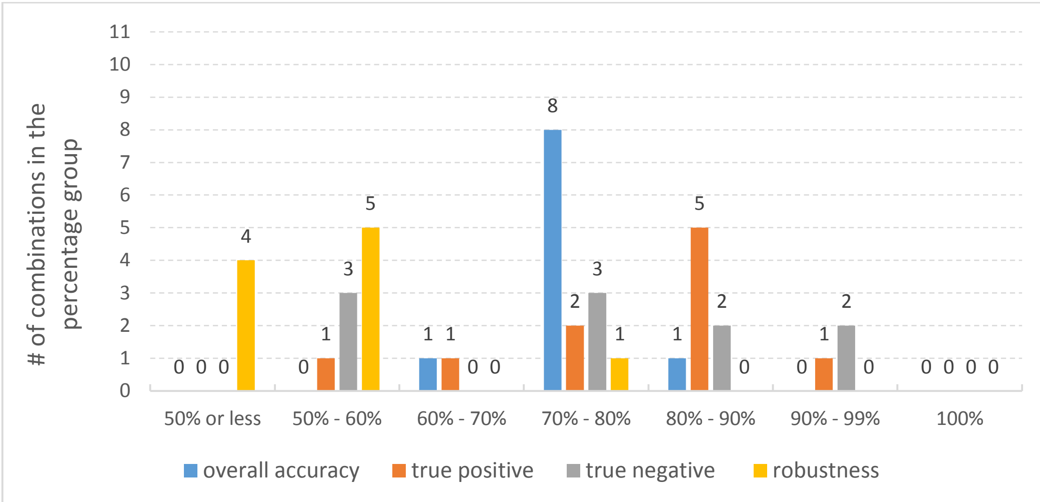

Figure C.6. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (a).

Table C.6. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	94%	58%	52%	PSD_0, PSD_3
	75%	88%	58%	46%	PSD_0, PSD_4
	86%	81%	92%	73%	PSD_2, PSD_4
	79%	81%	75%	56%	PSD_2, PSD_3
	79%	81%	75%	56%	PSD_1, PSD_3
In terms of *overall accuracy*	86%	81%	92%	73%	PSD_2, PSD_4
	79%	94%	58%	52%	PSD_0, PSD_3
	79%	81%	75%	56%	PSD_2, PSD_3
	79%	81%	75%	56%	PSD_1, PSD_3
	79%	75%	83%	58%	PSD_1, PSD_4

- Equal test-train when choosing a combination of three bands at a time – LDA:

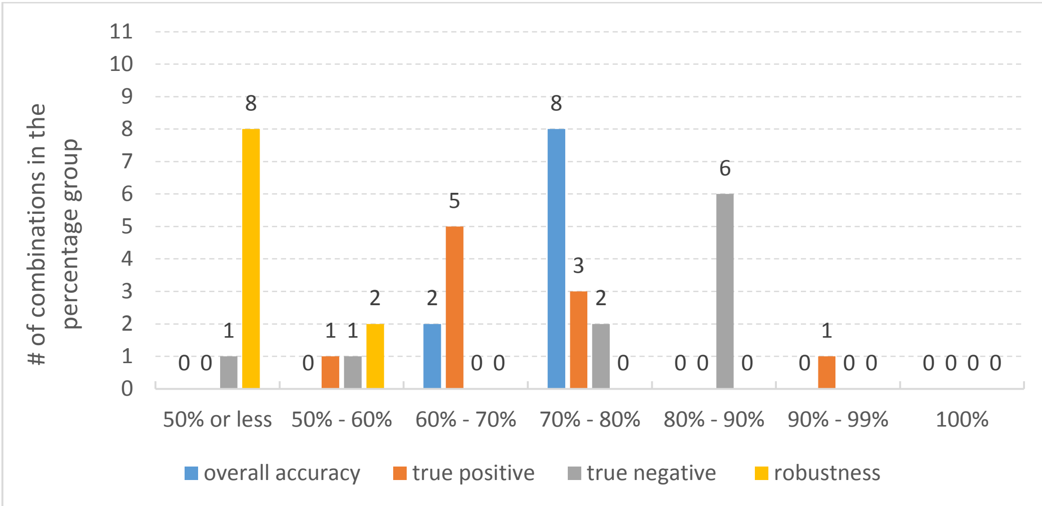

Figure C.7. Equal test-train classification results using a LDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (a).

Table C.7. Top 5 results of equal test-train LDA classification while choosing three PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_0 ,PSD_3 ,PSD_4
	79%	75%	83%	58%	PSD_0 ,PSD_1 ,PSD_4
	79%	75%	83%	58%	PSD_0 ,PSD_1 ,PSD_2
	75%	75%	75%	50%	PSD_0 ,PSD_2 ,PSD_4
	64%	69%	58%	27%	PSD_0 ,PSD_1 ,PSD_3
In terms of *overall accuracy*	79%	75%	83%	58%	PSD_0 ,PSD_1 ,PSD_4
	79%	75%	83%	58%	PSD_0 ,PSD_1 ,PSD_2
	75%	94%	50%	44%	PSD_0 ,PSD_3 ,PSD_4
	75%	75%	75%	50%	PSD_0 ,PSD_2 ,PSD_4
	71%	63%	83%	46%	PSD_2 ,PSD_3 ,PSD_4
					PSD_1 ,PSD_3 ,PSD_4
					PSD_1 ,PSD_2 ,PSD_4
					PSD_1 ,PSD_2 ,PSD_3

- Equal test-train when choosing a combination of three bands at a time – QDA:

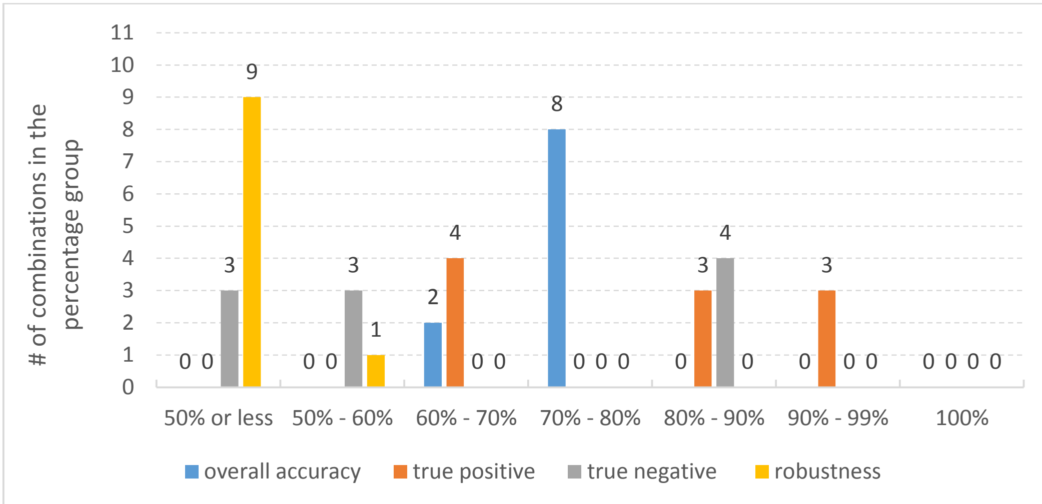

Figure C.8. Equal test-train classification results using a QDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (a).

Table C.8. Top 5 results of equal test-train QDA classification while choosing three PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	94%	58%	52%	PSD_0 ,PSD_3 ,PSD_4
	68%	94%	33%	27%	PSD_0 ,PSD_2 ,PSD_3
	68%	94%	33%	27%	PSD_0 ,PSD_1 ,PSD_3
	75%	88%	58%	46%	PSD_0 ,PSD_2 ,PSD_4
	75%	88%	58%	46%	PSD_0 ,PSD_1 ,PSD_4
In terms of *overall accuracy*	79%	94%	58%	52%	PSD_0 ,PSD_3 ,PSD_4
	75%	88%	58%	46%	PSD_0 ,PSD_2 ,PSD_4
	75%	88%	58%	46%	PSD_0 ,PSD_1 ,PSD_4
	71%	88%	50%	38%	PSD_0 ,PSD_1 ,PSD_2
	71%	63%	83%	46%	PSD_2 ,PSD_3 ,PSD_4 PSD_1 ,PSD_3 ,PSD_4 PSD_1 ,PSD_2 ,PSD_4 PSD_1 ,PSD_2 ,PSD_3

- Equal test-train when choosing a combination of three bands at a time – SVM:

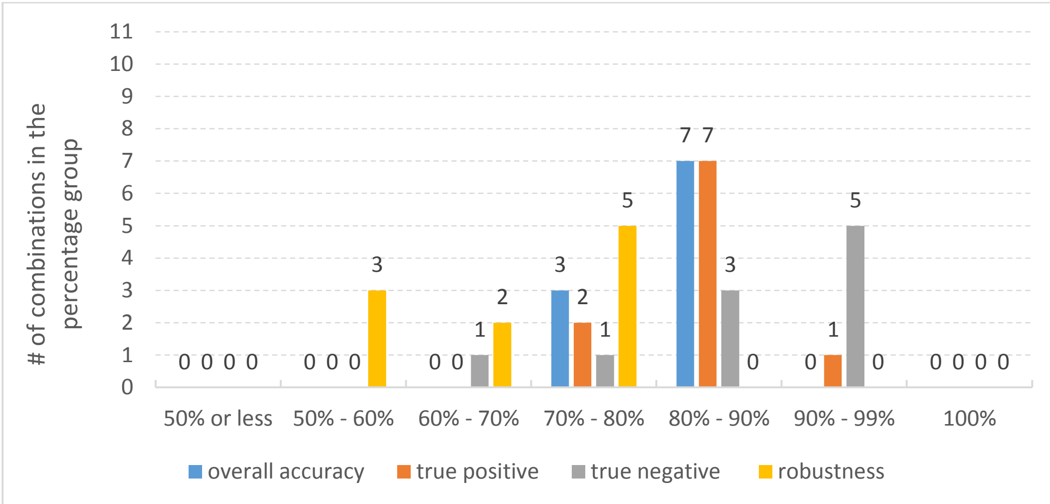

Figure C.9. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (a).

Table C.9. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (a) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	89%	94%	83%	77%	PSD_0 ,PSD_2 ,PSD_4
	89%	88%	92%	79%	PSD_2 ,PSD_3 ,PSD_4
	89%	88%	92%	79%	PSD_1 ,PSD_2 ,PSD_4
	89%	88%	92%	79%	PSD_1 ,PSD_2 ,PSD_3
	79%	88%	67%	54%	PSD_0 ,PSD_3 ,PSD_4
In terms of *overall accuracy*	89%	94%	83%	77%	PSD_0 ,PSD_2 ,PSD_4
	89%	88%	92%	79%	PSD_2 ,PSD_3 ,PSD_4
	89%	88%	92%	79%	PSD_1 ,PSD_2 ,PSD_4
	89%	88%	92%	79%	PSD_1 ,PSD_2 ,PSD_3
	86%	81%	92%	73%	PSD_1 ,PSD_3 ,PSD_4

b. <u>PSDs in the 0 – 2.00kHz frequency range along 6 sub-frequencies; 0 – 333Hz, 333Hz – 666Hz, 666Hz – 1.00kHz, 1.00kHz – 1.33kHz, 1.33kHz – 1.67kHz, and 1.67kHz – 2.00kHz</u>

- Equal test-train when choosing one band at a time – LDA:

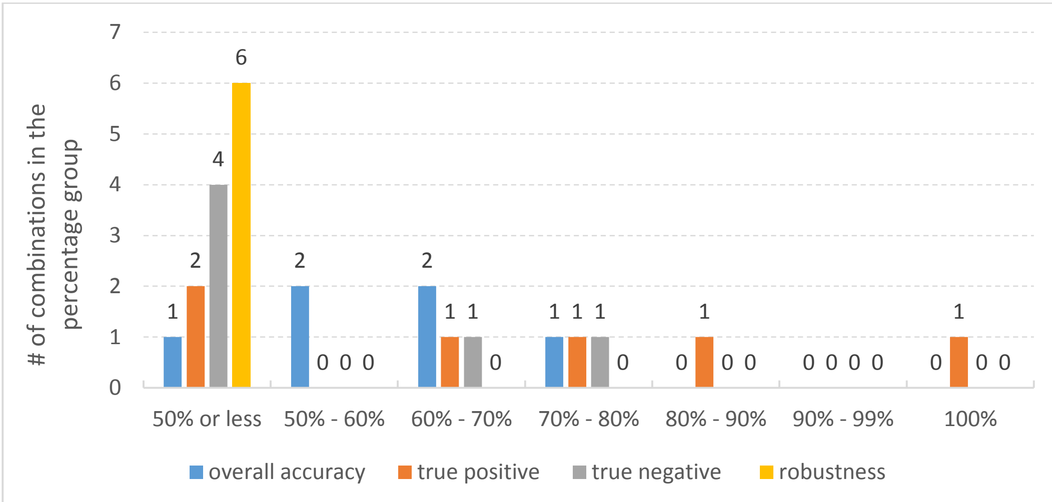

Figure C.10. Equal test-train classification results using a LDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (b).

Table C.10. Top 5 results of equal test-train LDA classification while choosing one PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_1
	68%	88%	42%	29%	PSD_6
	57%	75%	33%	8%	PSD_4
	61%	69%	50%	19%	PSD_2
	54%	38%	75%	13%	PSD_3
In terms of *overall accuracy*	71%	100%	33%	33%	PSD_1
	68%	88%	42%	29%	PSD_6
	61%	69%	50%	19%	PSD_2
	57%	75%	33%	8%	PSD_4
	54%	38%	75%	13%	PSD_3

- Equal test-train when choosing one band at a time – QDA:

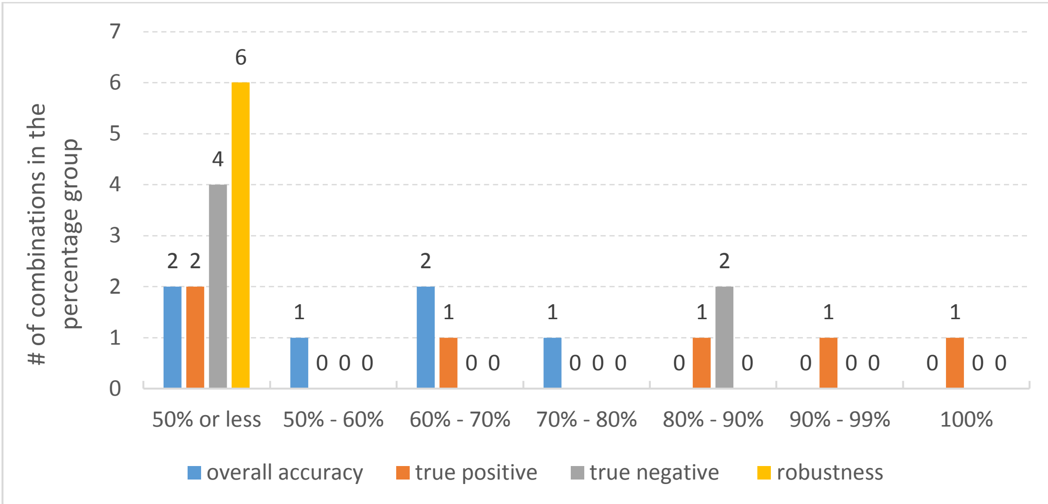

Figure C.11. Equal test-train classification results using a QDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (b).

Table C.11. Top 5 results of equal test-train QDA classification while choosing one PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_1
	68%	94%	33%	27%	PSD_6
	57%	81%	25%	6%	PSD_4
	61%	69%	50%	19%	PSD_2
	50%	25%	83%	8%	PSD_3
In terms of *overall accuracy*	71%	100%	33%	33%	PSD_1
	68%	94%	33%	27%	PSD_6
	61%	69%	50%	19%	PSD_2
	57%	81%	25%	6%	PSD_4
	50%	25%	83%	8%	PSD_3

- Equal test-train when choosing one band at a time – SVM:

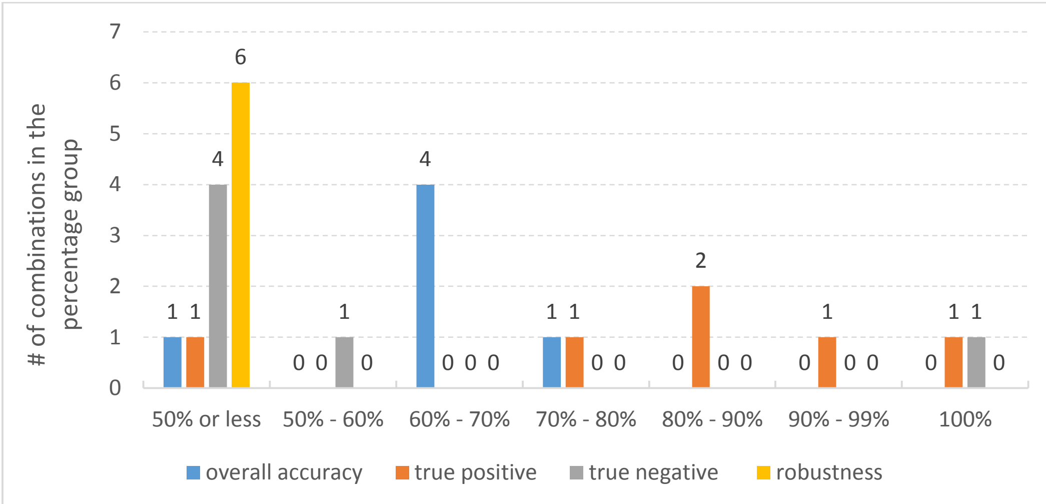

Figure C.12. Equal test-train classification results using a SVM classifier while choosing one PSD bands at a time for the frequency range detailed in point (b).

Table C.12. Top 5 results of equal test-train SVM classification while choosing one PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	61%	100%	8%	8%	PSD_5
	64%	94%	25%	19%	PSD_4
	75%	88%	58%	46%	PSD_1
	68%	88%	42%	29%	PSD_6
	64%	75%	50%	25%	PSD_2
In terms of *overall accuracy*	75%	88%	58%	46%	PSD_1
	68%	88%	42%	29%	PSD_6
	64%	94%	25%	19%	PSD_4
	64%	75%	50%	25%	PSD_2
	61%	100%	8%	8%	PSD_5

- Equal test-train when choosing a combination of two bands at a time – LDA:

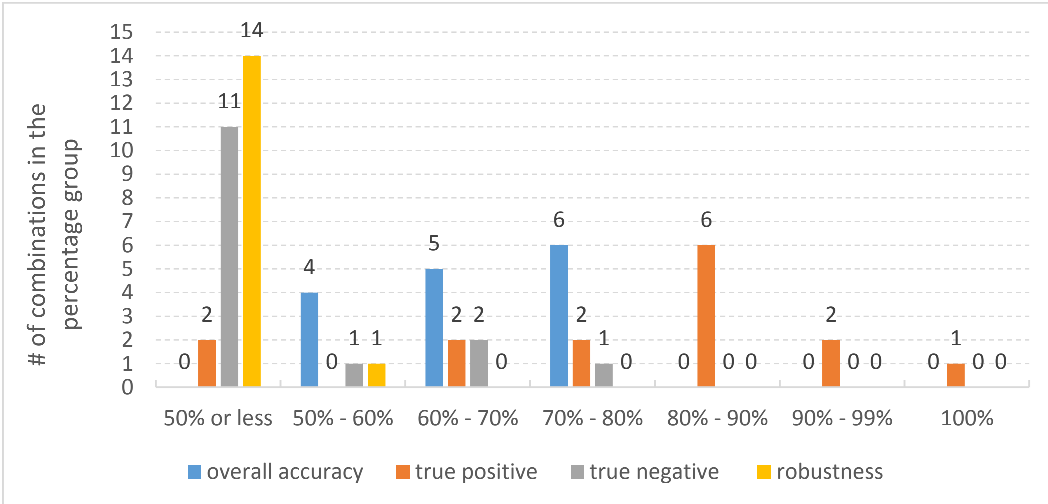

Figure C.13. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (b).

Table C.13. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD$_1$, PSD$_5$
	75%	94%	50%	44%	PSD$_1$, PSD$_3$
	71%	94%	42%	35%	PSD$_1$, PSD$_4$
	79%	88%	67%	54%	PSD$_1$, PSD$_6$
	71%	88%	50%	38%	PSD$_1$, PSD$_2$ PSD$_2$, PSD$_3$
In terms of *overall accuracy*	79%	88%	67%	54%	PSD$_1$, PSD$_6$
	75%	94%	50%	44%	PSD$_1$, PSD$_3$
	71%	100%	33%	33%	PSD$_1$, PSD$_5$
	71%	94%	42%	35%	PSD$_1$, PSD$_4$
	71%	88%	50%	38%	PSD$_1$, PSD$_2$ PSD$_2$, PSD$_3$

- Equal test-train when choosing a combination of two bands at a time – QDA:

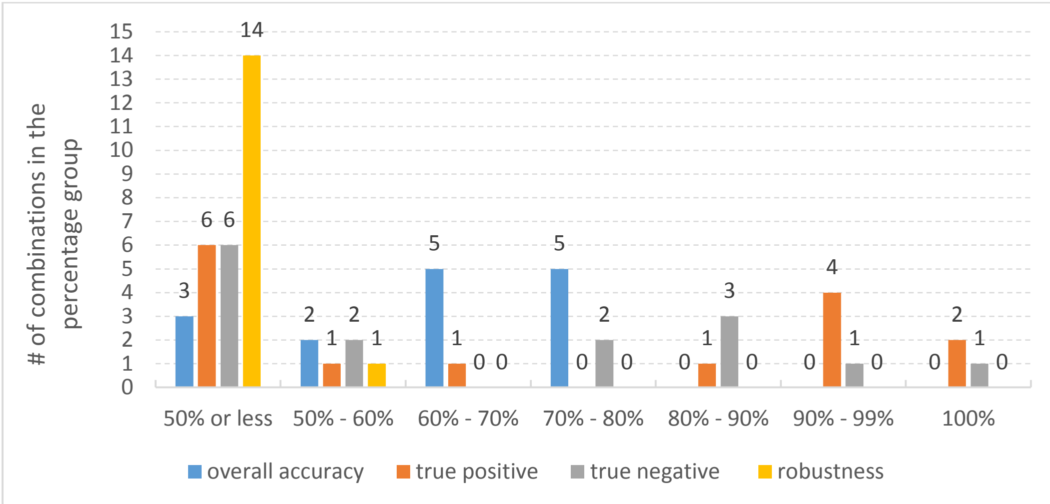

Figure C.14. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (b).

Table C.14. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_1, PSD_2 PSD_1, PSD_4
	79%	94%	58%	52%	PSD_1, PSD_6
	71%	94%	42%	35%	PSD_1, PSD_3
	68%	94%	33%	27%	PSD_1, PSD_5 PSD_2, PSD_6
	-	-	-	-	-
In terms of *overall accuracy*	79%	94%	58%	52%	PSD_1, PSD_6
	71%	100%	33%	33%	PSD_1, PSD_2 PSD_1, PSD_4
	71%	94%	42%	35%	PSD_1, PSD_3
	71%	81%	58%	40%	PSD_4, PSD_6
	-	-	-	-	-

- Equal test-train when choosing a combination of two bands at a time – SVM:

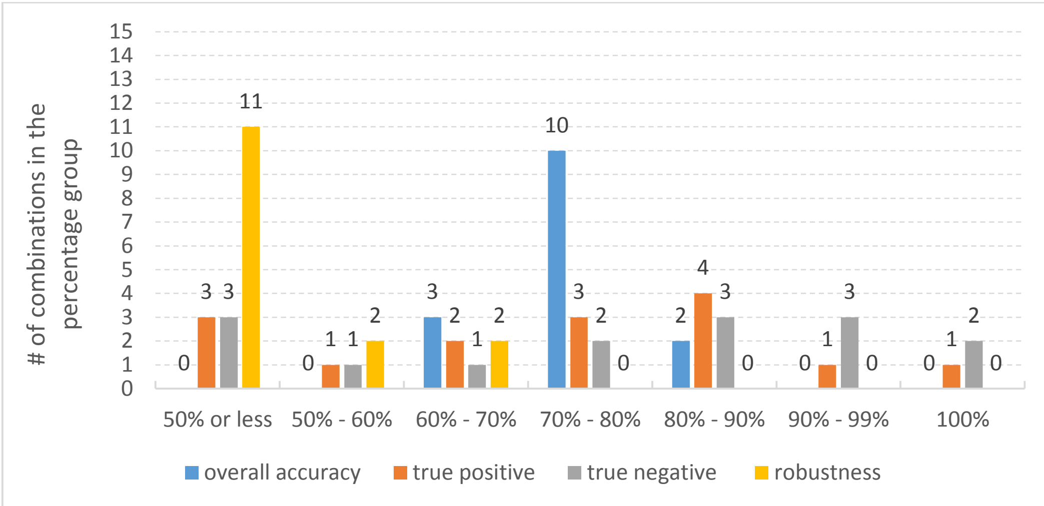

Figure C.15. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (b).

Table C.15. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_2, PSD_6
	71%	94%	42%	35%	PSD_3, PSD_6
	82%	88%	75%	63%	PSD_1, PSD_6
	75%	88%	58%	46%	PSD_2, PSD_3
	68%	88%	42%	29%	PSD_5, PSD_6
In terms of *overall accuracy*	82%	88%	75%	63%	PSD_1, PSD_6
	82%	75%	92%	67%	PSD_1, PSD_5
	79%	75%	83%	58%	PSD_1, PSD_2
	79%	75%	83%	58%	PSD_1, PSD_3
	75%	88%	58%	46%	PSD_2, PSD_3

- Equal test-train when choosing a combination of three bands at a time – LDA:

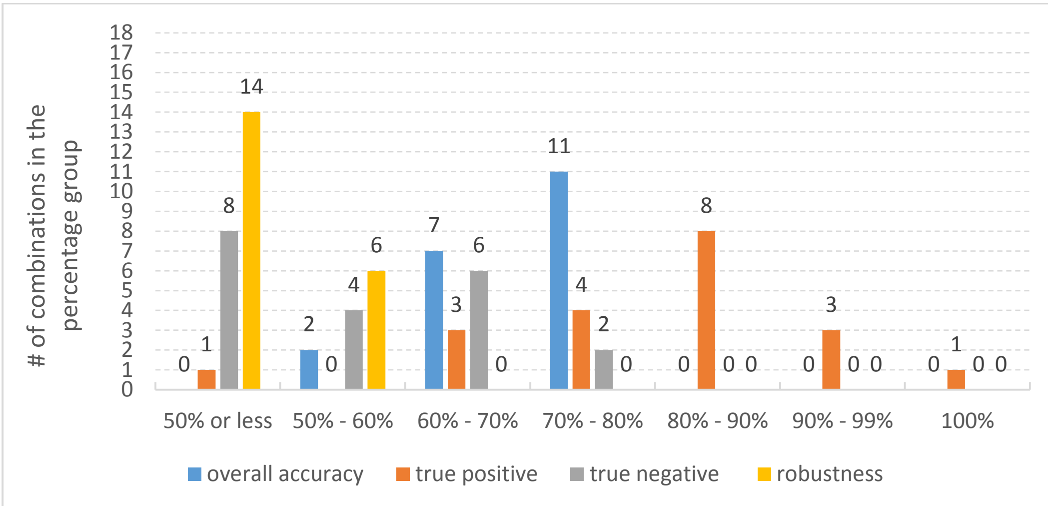

Figure C.16. Equal test-train classification results using a LDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (b).

Table C.16. Top 5 results of equal test-train LDA classification while choosing three PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_1, PSD_3, PSD_5
	79%	94%	58%	52%	PSD_1, PSD_2, PSD_3
	75%	94%	50%	44%	PSD_1, PSD_3, PSD_4
	71%	94%	42%	35%	PSD_1, PSD_2, PSD_4
	79%	88%	67%	54%	PSD_2, PSD_3, PSD_5 PSD_1, PSD_5, PSD_6 PSD_1, PSD_4, PSD_6 PSD_1, PSD_3, PSD_6 PSD_1, PSD_2, PSD_6
In terms of *overall accuracy*	79%	94%	58%	52%	PSD_1, PSD_2, PSD
	79%	88%	67%	54%	PSD_2, PSD_3, PSD_5 PSD_1, PSD_5, PSD_6 PSD_1, PSD_4, PSD_6 PSD_1, PSD_3, PSD_6 PSD_1, PSD_2, PSD_6
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – QDA:

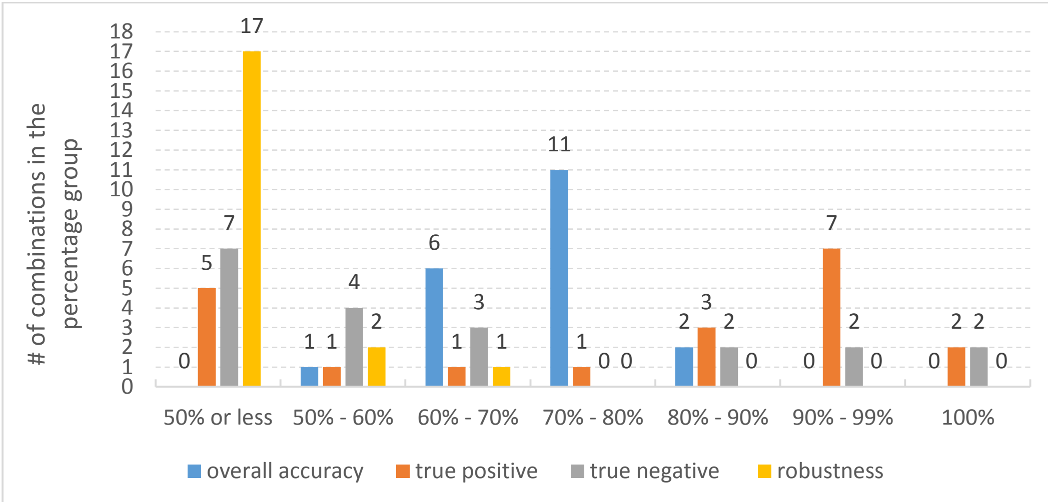

Figure C.17. Equal test-train classification results using a QDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (b).

Table C.17. Top 5 results of equal test-train QDA classification while choosing three PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	100%	58%	58%	PSD_1, PSD_4, PSD_6
	71%	100%	33%	33%	PSD_1, PSD_2, PSD_4
	82%	94%	67%	60%	PSD_1, PSD_3, PSD_6
	79%	94%	58%	52%	PSD_1, PSD_2, PSD_6
	75%	94%	50%	44%	PSD_1, PSD_2, PSD_5 PSD_1, PSD_2, PSD_3
In terms of *overall accuracy*	82%	100%	58%	58%	PSD_1, PSD_4, PSD_6
	82%	94%	67%	60%	PSD_1, PSD_3, PSD_6
	79%	94%	58%	52%	PSD_1, PSD_2, PSD_6
	75%	94%	50%	44%	PSD_1, PSD_2, PSD_5
	75%	94%	50%	44%	PSD_1, PSD_2, PSD_3

- Equal test-train when choosing a combination of three bands at a time – SVM:

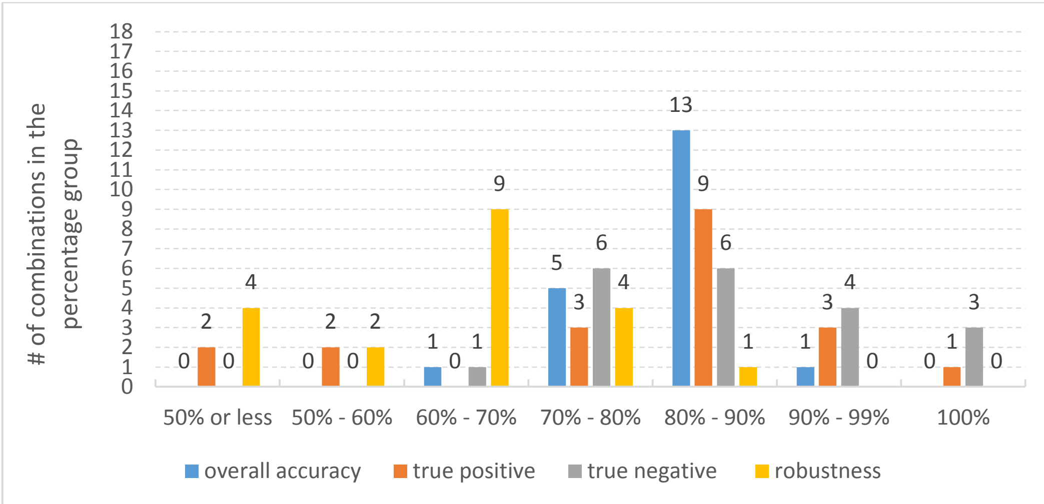

Figure C.18. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (b).

Table C.18. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	93%	100%	83%	83%	PSD_1, PSD_4, PSD_5
	89%	94%	83%	77%	PSD_1, PSD_3, PSD_4
	86%	94%	75%	69%	PSD_1, PSD_4, PSD_6
	82%	94%	67%	60%	PSD_2, PSD_3, PSD_6
	86%	88%	83%	71%	PSD_2, PSD_4, PSD_6 PSD_1, PSD_3, PSD_5
In terms of *overall accuracy*	93%	100%	83%	83%	PSD_1, PSD_4, PSD_5
	89%	94%	83%	77%	PSD_1, PSD_3, PSD_4
	86%	94%	75%	69%	PSD_1, PSD_4, PSD_6
	86%	88%	83%	71%	PSD_2, PSD_4, PSD_6 PSD_1, PSD_3, PSD_5
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – LDA:

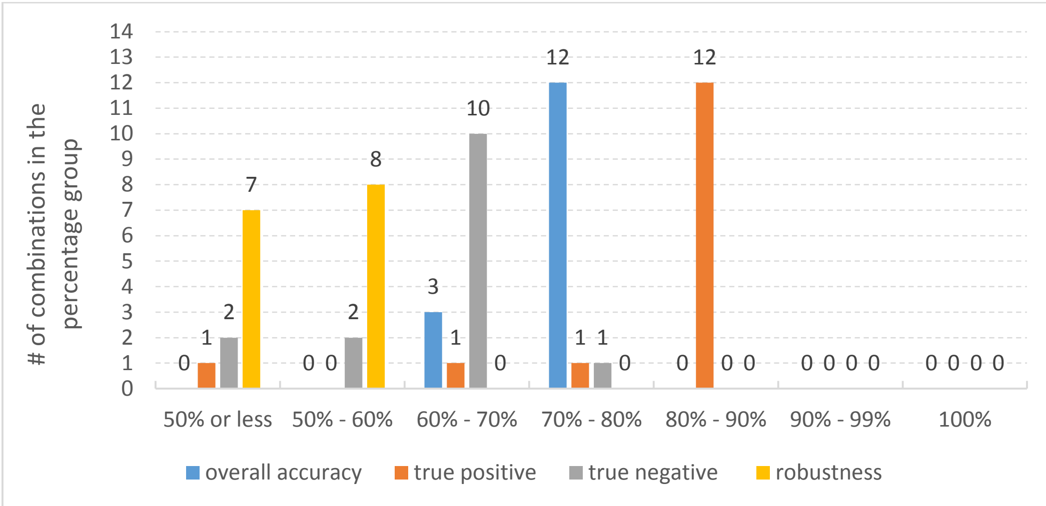

Figure C.19. Equal test-train classification results using a LDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (b).

Table C.19. Top 5 results of equal test-train LDA classification while choosing four PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	88%	67%	54%	PSD_2, PSD_3, PSD_5, PSD_6 PSD_2, PSD_3, PSD_4, PSD_5 PSD_1, PSD_4, PSD_5, PSD_6 PSD_1, PSD_3, PSD_5, PSD_6 PSD_1, PSD_3, PSD_4, PSD_6 PSD_1, PSD_2, PSD_5, PSD_6 PSD_1, PSD_2, PSD_4, PSD_6 PSD_1, PSD_2, PSD_3, PSD_6
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	88%	67%	54%	PSD_2, PSD_3, PSD_5, PSD_6 PSD_2, PSD_3, PSD_4, PSD_5 PSD_1, PSD_4, PSD_5, PSD_6 PSD_1, PSD_3, PSD_5, PSD_6 PSD_1, PSD_3, PSD_4, PSD_6 PSD_1, PSD_2, PSD_5, PSD_6 PSD_1, PSD_2, PSD_4, PSD_6 PSD_1, PSD_2, PSD_3, PSD_6
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – QDA:

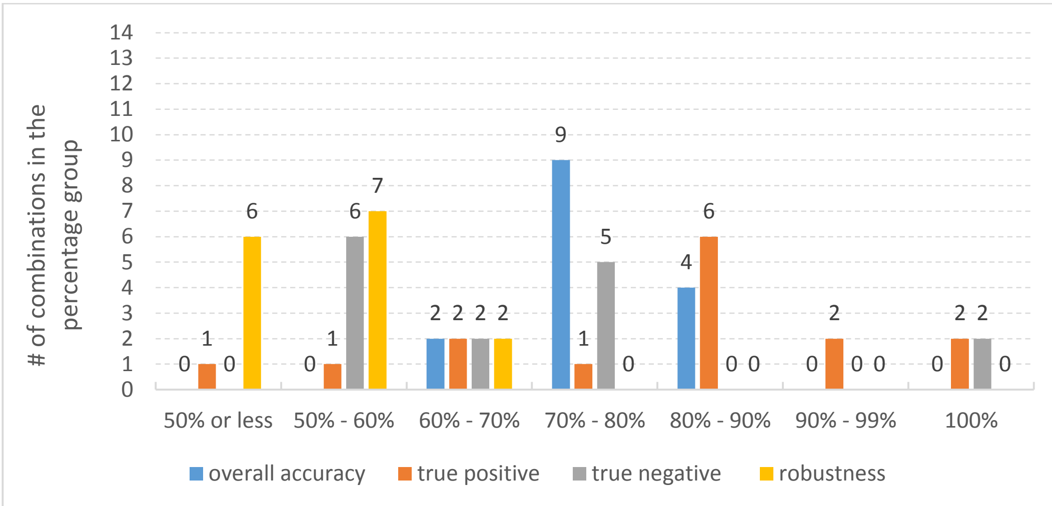

Figure C.20. Equal test-train classification results using a QDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (b).

Table C.20. Top 5 results of equal test-train QDA classification while choosing four PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	100%	58%	58%	PSD_1, PSD_3, PSD_4, PSD_6 PSD_1, PSD_2, PSD_4, PSD_6
	82%	94%	67%	60%	PSD_1, PSD_2, PSD_3, PSD_6
	79%	94%	58%	52%	PSD_2, PSD_3, PSD_4, PSD_6
	82%	88%	75%	63%	PSD_1, PSD_4, PSD_5, PSD_6
	-	-	-	-	-
In terms of *overall accuracy*	82%	100%	58%	58%	PSD_1, PSD_3, PSD_4, PSD_6 PSD_1, PSD_2, PSD_4, PSD_6
	82%	94%	67%	60%	PSD_1, PSD_2, PSD_3, PSD_6
	82%	88%	75%	63%	PSD_1, PSD_4, PSD_5, PSD_6
	79%	94%	58%	52%	PSD_2, PSD_3, PSD_4, PSD_6
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – SVM:

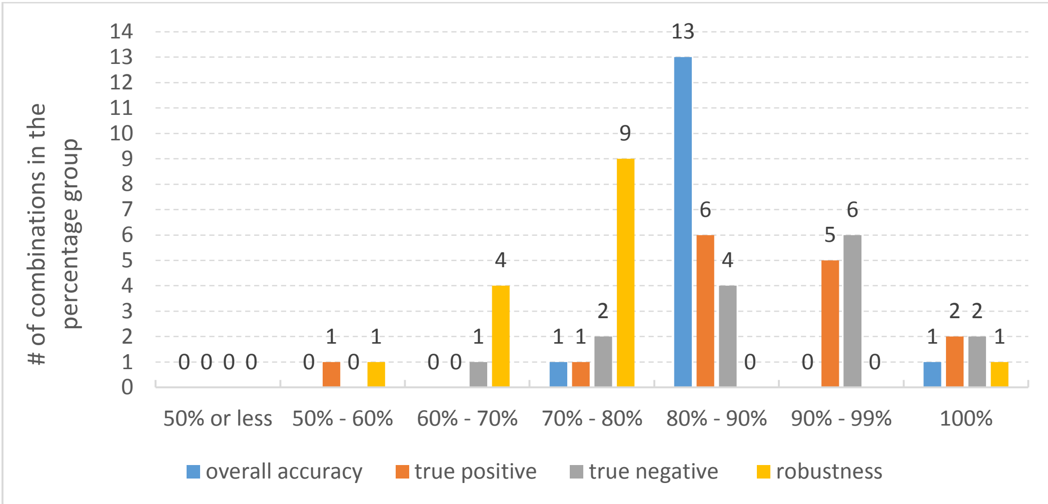

Figure C.21. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (b).

Table C.21. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (b) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	86%	100%	67%	67%	PSD_2, PSD_3, PSD_4, PSD_6
	89%	94%	83%	77%	PSD_1, PSD_3, PSD_4, PSD_6 PSD_1, PSD_2, PSD_4, PSD_6 PSD_1, PSD_2, PSD_3, PSD_6
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	89%	94%	83%	77%	PSD_1, PSD_3, PSD_4, PSD_6 PSD_1, PSD_2, PSD_4, PSD_6 PSD_1, PSD_2, PSD_3, PSD_6
	89%	88%	92%	79%	PSD_2, PSD_3, PSD_4, PSD_5 PSD_1, PSD_2, PSD_3, PSD_5
	-	-	-	-	-
	-	-	-	-	-

c. <u>PSDs in the 0-2.00kHz frequency range along 8 sub-frequencies; 0 – 250Hz, 250Hz – 500Hz, 500Hz – 750Hz, 750Hz – 1.00kHz, 1.00kHz – 1.25kHz, 1.25kHz – 1.50kHz, 1.50kHz – 1.75kHz, and 1.75kHz – 2.00kHz</u>

- Equal test-train when choosing one band at a time – LDA:

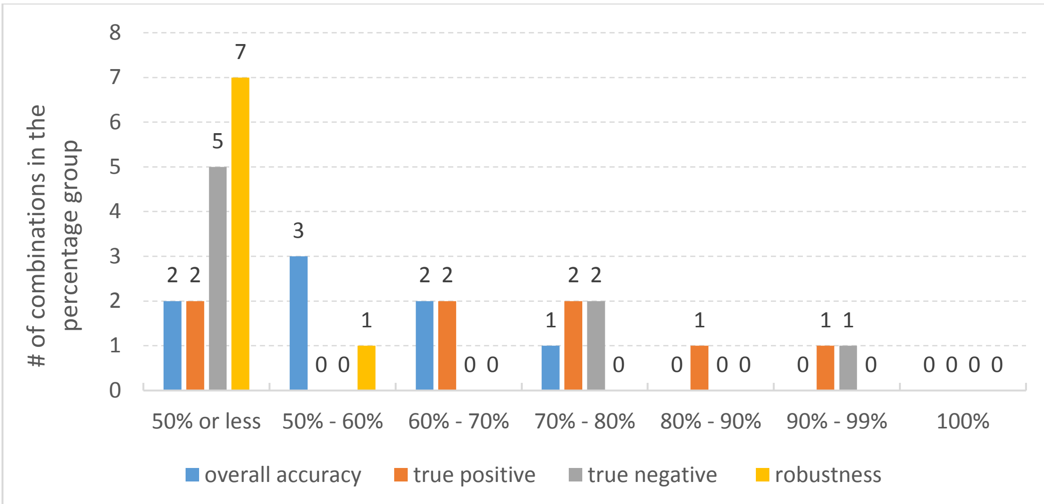

Figure C.22. Equal test-train classification results using a LDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (c).

Table C.22. Top 5 results of equal test-train LDA classification while choosing one PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_1
	68%	88%	42%	29%	PSD_8
	57%	75%	33%	8%	PSD_5 PSD_7
	75%	63%	92%	54%	PSD_3
	-	-	-	-	-
In terms of *overall accuracy*	75%	63%	92%	54%	PSD_3
	68%	94%	33%	27%	PSD_1
	68%	88%	42%	29%	PSD_8
	57%	75%	33%	8%	PSD_5 PSD_7
	-	-	-	-	-

- Equal test-train when choosing one band at a time – QDA:

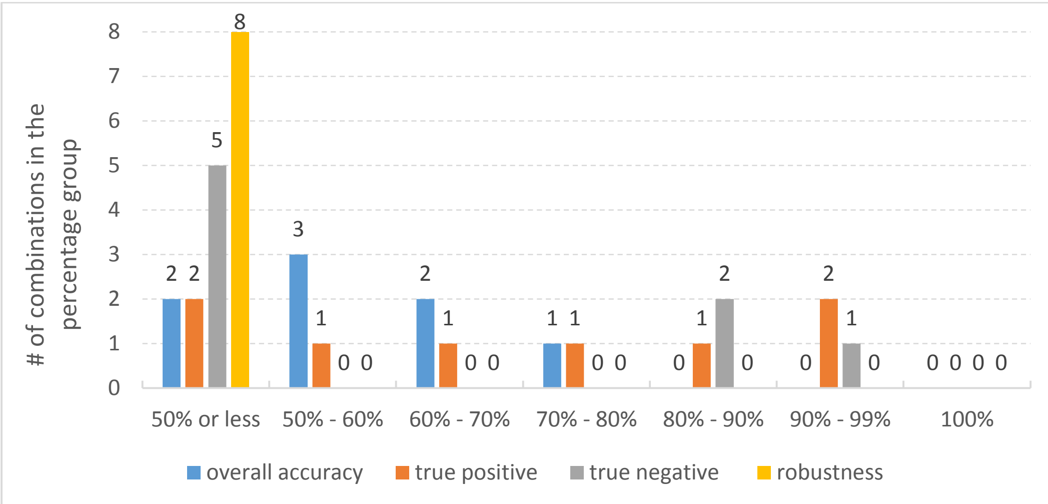

Figure C.23. Equal test-train classification results using a QDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (c).

Table C.23. Top 5 results of equal test-train QDA classification while choosing one PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_1 PSD_8
	57%	81%	25%	6%	PSD_5
	54%	75%	25%	0%	PSD_7
	54%	63%	42%	4%	PSD_2
	-	-	-	-	-
In terms of *overall accuracy*	71%	56%	92%	48%	PSD_3
	68%	94%	33%	27%	PSD_1 PSD_8
	57%	81%	25%	6%	PSD_5
	54%	75%	25%	0%	PSD_7
	-	-	-	-	-

- Equal test-train when choosing one band at a time – SVM:

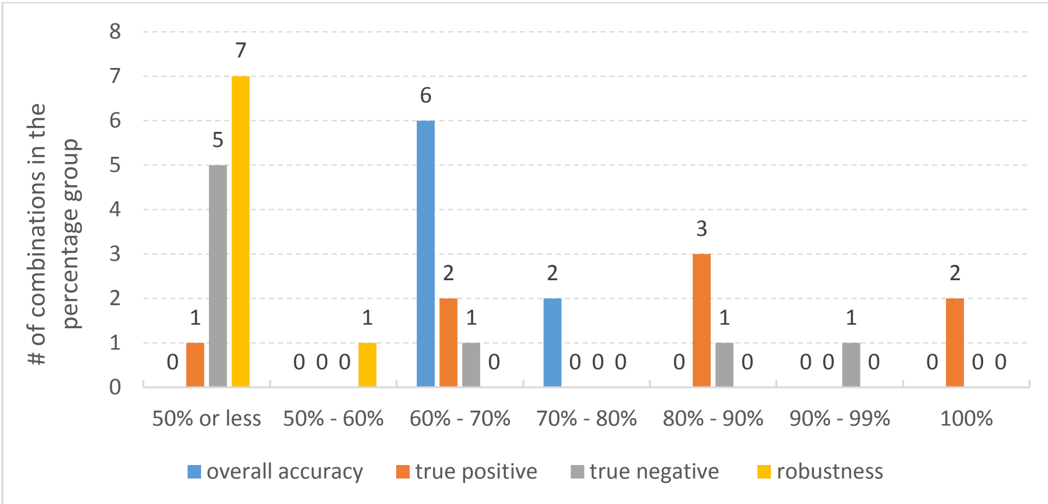

Figure C.24. Equal test-train classification results using a SVM classifier while choosing one PSD bands at a time for the frequency range detailed in point (c).

Table C.24. Top 5 results of equal test-train SVM classification while choosing one PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	100%	25%	25%	PSD_7
	64%	100%	17%	17%	PSD_6
	71%	88%	50%	38%	PSD_1
	68%	88%	42%	29%	PSD_8
	61%	81%	33%	15%	PSD_2
In terms of *overall accuracy*	75%	63%	92%	54%	PSD_3
	71%	88%	50%	38%	PSD_1
	68%	100%	25%	25%	PSD_7
	68%	88%	42%	29%	PSD_8
	64%	100%	17%	17%	PSD_6

- Equal test-train when choosing a combination of two bands at a time – LDA:

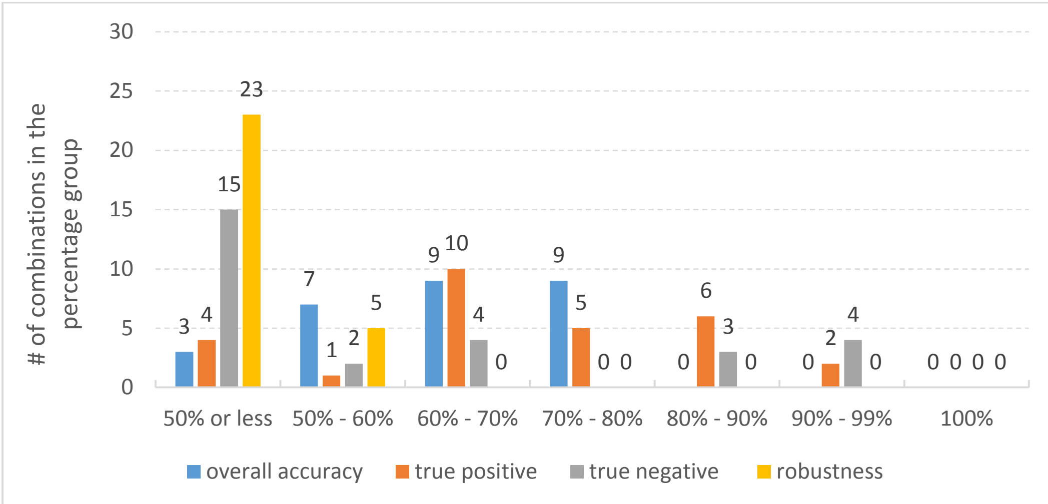

Figure C.25. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (c).

Table C.25. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_1, PSD_4 PSD_1, PSD_6
	71%	88%	50%	38%	PSD_1, PSD_5 PSD_1, PSD_8 PSD_6, PSD_8
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	75%	69%	83%	52%	PSD_1, PSD_3
	75%	63%	92%	54%	PSD_2, PSD_3 PSD_3, PSD_5 PSD_3, PSD_6 PSD_3, PSD_7
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of two bands at a time – QDA:

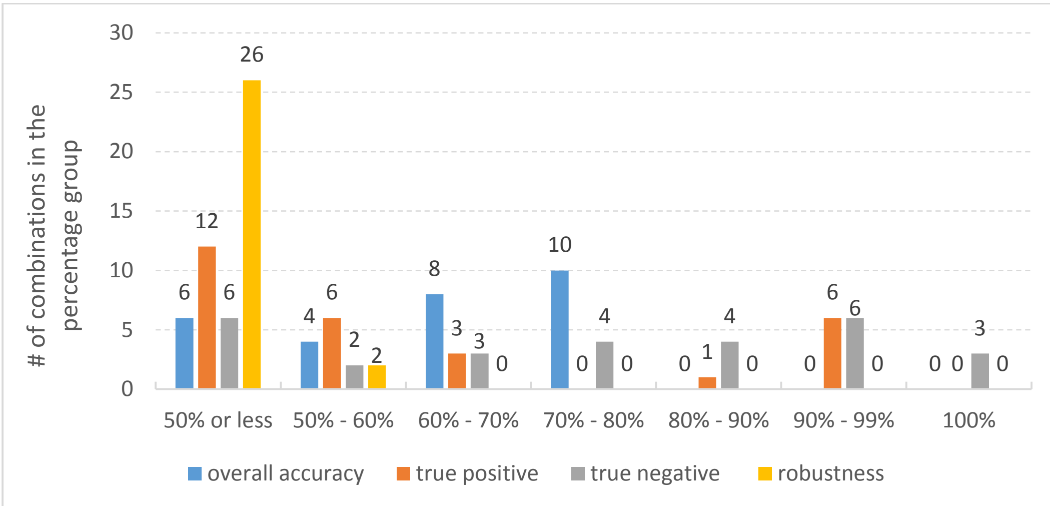

Figure C.26. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (c).

Table C.26. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_1, PSD_7
	71%	94%	42%	35%	PSD_1, PSD_3 PSD_1, PSD_4 PSD_1, PSD_6
	68%	94%	33%	27%	PSD_1, PSD_2 PSD_1, PSD_5
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_1, PSD_7
	75%	88%	58%	46%	PSD_1, PSD_8
	75%	63%	92%	54%	PSD_3, PSD_7
	75%	56%	100%	56%	PSD_5, PSD_7
	71%	94%	42%	35%	PSD_1, PSD_3 PSD_1, PSD_4 PSD_1, PSD_6

- Equal test-train when choosing a combination of two bands at a time – SVM:

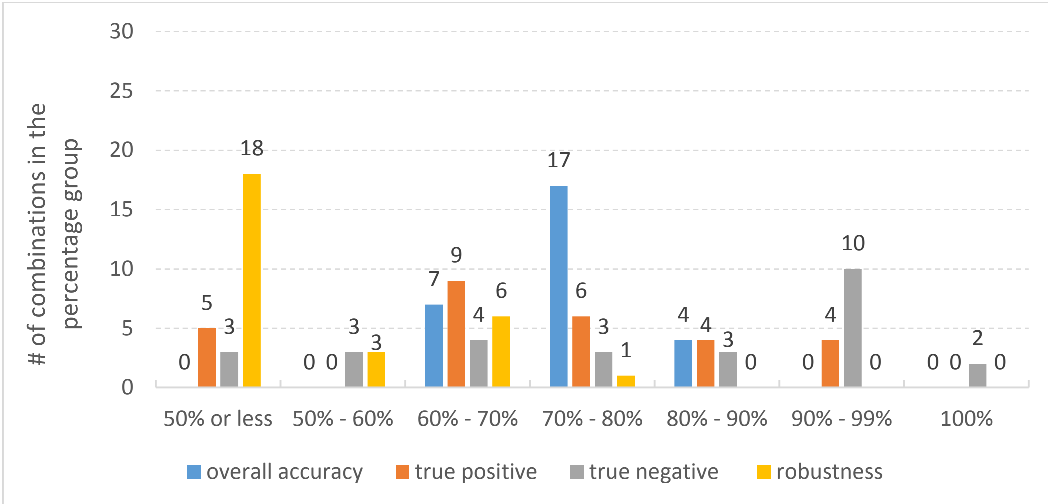

Figure C.27. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (c).

Table C.27. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	89%	94%	83%	77%	PSD_1, PSD_7
	82%	94%	67%	60%	PSD_1, PSD_6
	71%	94%	42%	35%	PSD_6, PSD_8 PSD_7, PSD_8
	75%	88%	58%	46%	PSD_1, PSD_4
	-	-	-	-	-
In terms of *overall accuracy*	89%	94%	83%	77%	PSD_1, PSD_7
	82%	94%	67%	60%	PSD_1, PSD_6
	82%	75%	92%	67%	PSD_3, PSD_4 PSD_3, PSD_5
	79%	69%	92%	60%	PSD_2, PSD_3 PSD_3, PSD_6 PSD_3, PSD_7
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – LDA:

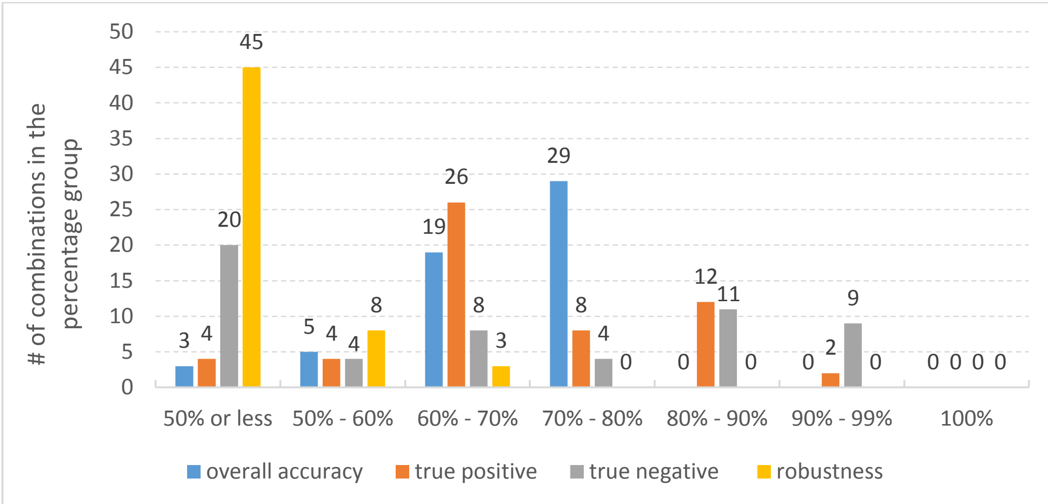

Figure C.28. Equal test-train classification results using a LDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (c).

Table C.28. Top 5 results of equal test-train LDA classification while choosing three PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_1, PSD_5, PSD_8
	68%	94%	33%	27%	PSD_1, PSD_4, PSD_6
	71%	88%	50%	38%	PSD_1, PSD_4, PSD_8 PSD_1, PSD_5, PSD_7 PSD_1, PSD_6, PSD_8 PSD_1, PSD_7, PSD_8
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	75%	83%	58%	PSD_1, PSD_3, PSD_5 PSD_1, PSD_3, PSD_6
	79%	69%	92%	60%	PSD_2, PSD_3, PSD_6 PSD_3, PSD_6, PSD_8 PSD_3, PSD_6, PSD_7
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – QDA:

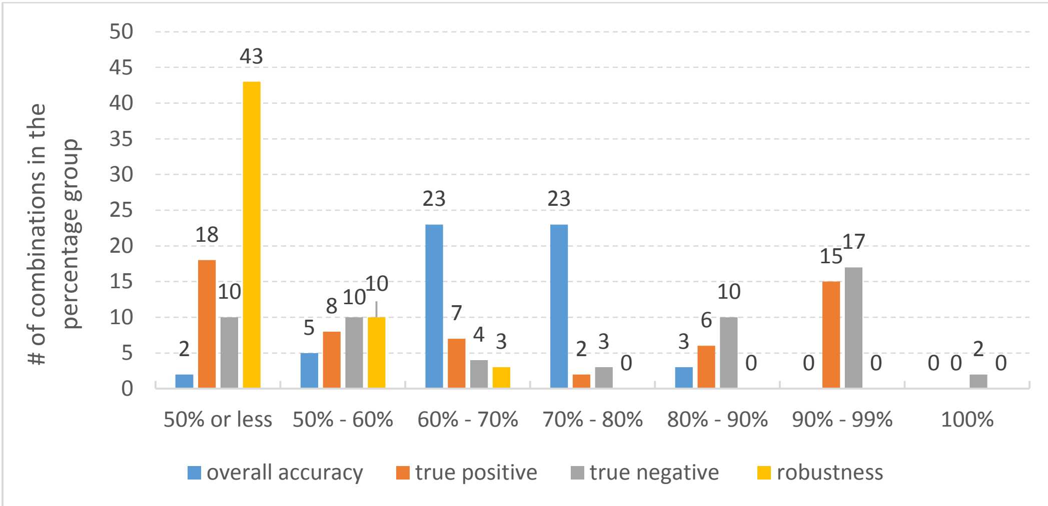

Figure C.29. Equal test-train classification results using a QDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (c).

Table C.29. Top 5 results of equal test-train QDA classification while choosing three PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	94%	67%	60%	PSD_1, PSD_6, PSD_8
	79%	94%	58%	52%	PSD_1, PSD_2, PSD_7 PSD_1, PSD_3, PSD_7 PSD_1, PSD_3, PSD_8 PSD_1, PSD_4, PSD_7 PSD_1, PSD_5, PSD_6 PSD_1, PSD_5, PSD_7 PSD_1, PSD_5, PSD_8 PSD_1, PSD_6, PSD_7
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	82%	94%	67%	60%	PSD_1, PSD_6, PSD_8
	82%	75%	92%	67%	PSD_2, PSD_5, PSD_7 PSD_3, PSD_5, PSD_7
	79%	94%	58%	52%	PSD_1, PSD_2, PSD_7 PSD_1, PSD_3, PSD_7 PSD_1, PSD_3, PSD_8 PSD_1, PSD_4, PSD_7 PSD_1, PSD_5, PSD_6 PSD_1, PSD_5, PSD_7 PSD_1, PSD_5, PSD_8 PSD_1, PSD_6, PSD_7
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – SVM:

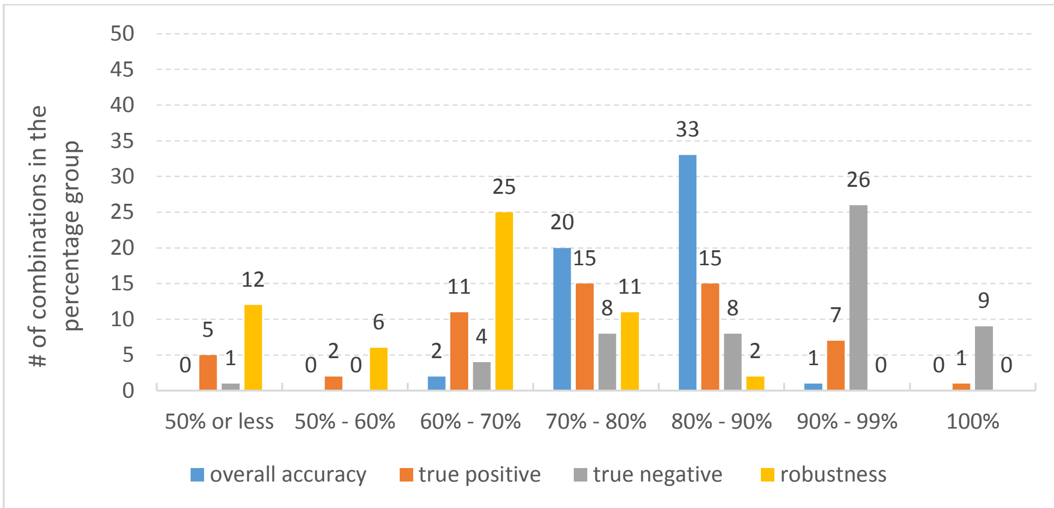

Figure C.30. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (c).

Table C.30. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	93%	100%	83%	83%	PSD_1, PSD_5, PSD_7
	89%	94%	83%	77%	PSD_1, PSD_6, PSD_7
	86%	94%	75%	69%	PSD_1, PSD_3, PSD_8 PSD_1, PSD_4, PSD_5 PSD_1, PSD_4, PSD_7 PSD_1, PSD_5, PSD_6
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	93%	100%	83%	83%	PSD_1, PSD_5, PSD_7
	89%	94%	83%	77%	PSD_1, PSD_6, PSD_7
	89%	81%	100%	81%	PSD_3, PSD_5, PSD_7
	86%	94%	75%	69%	PSD_1, PSD_3, PSD_8 PSD_1, PSD_4, PSD_5 PSD_1, PSD_4, PSD_7 PSD_1, PSD_5, PSD_6
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – LDA:

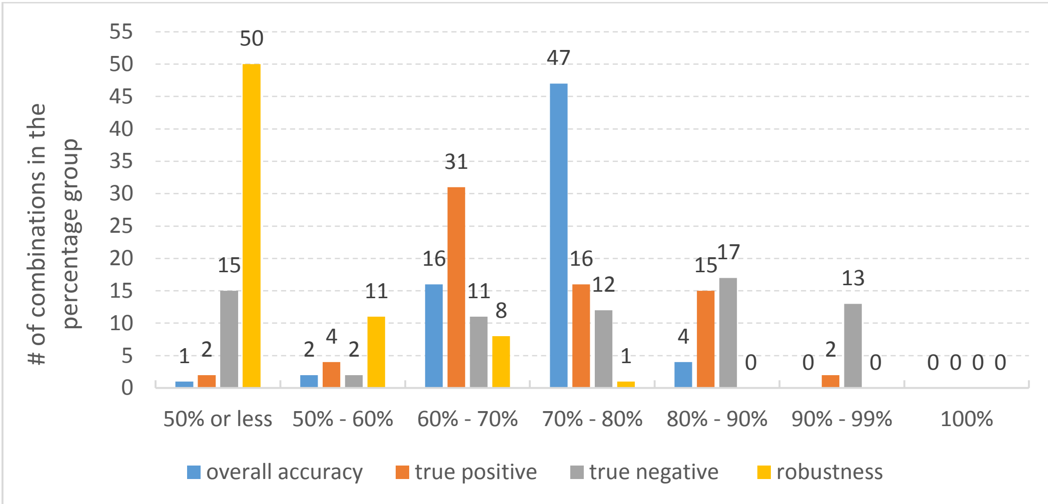

Figure C.31. Equal test-train classification results using a LDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (c).

Table C.31. Top 5 results of equal test-train LDA classification while choosing four PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_1, PSD_5, PSD_6, PSD_8 PSD_1, PSD_4, PSD_5, PSD_8
	71%	88%	50%	38%	PSD_1, PSD_6, PSD_7, PSD_8 PSD_1, PSD_5, PSD_7, PSD_8 PSD_1, PSD_5, PSD_6, PSD_7 PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_4, PSD_6, PSD_8
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	86%	81%	92%	73%	PSD_1, PSD_3, PSD_5, PSD_6
	82%	81%	83%	65%	PSD_1, PSD_2, PSD_5, PSD_7
	82%	75%	92%	67%	PSD_1, PSD_2, PSD_3, PSD_6 PSD_1, PSD_2, PSD_3, PSD_5
	79%	75%	83%	58%	PSD_1, PSD_2, PSD_3, PSD_4 PSD_1, PSD_3, PSD_6, PSD_7 PSD_1, PSD_3, PSD_4, PSD_5 PSD_1, PSD_2, PSD_3, PSD_7
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – QDA:

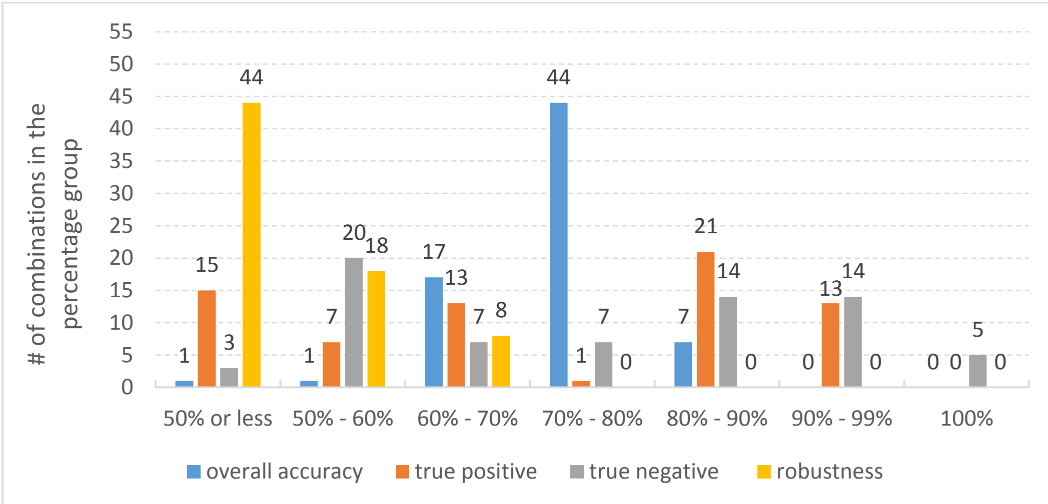

Figure C.32. Equal test-train classification results using a QDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (c).

Table C.32. Top 5 results of equal test-train QDA classification while choosing four PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	86%	94%	75%	69%	PSD_1, PSD_6, PSD_7, PSD_8
	82%	94%	67%	60%	PSD_1, PSD_5, PSD_7, PSD_8 PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_4, PSD_5, PSD_8 PSD_1, PSD_4, PSD_5, PSD_7
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	86%	94%	75%	69%	PSD_1, PSD_6, PSD_7, PSD_8
	82%	94%	67%	60%	PSD_1, PSD_5, PSD_7, PSD_8 PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_4, PSD_5, PSD_8 PSD_1, PSD_4, PSD_5, PSD_7
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – SVM:

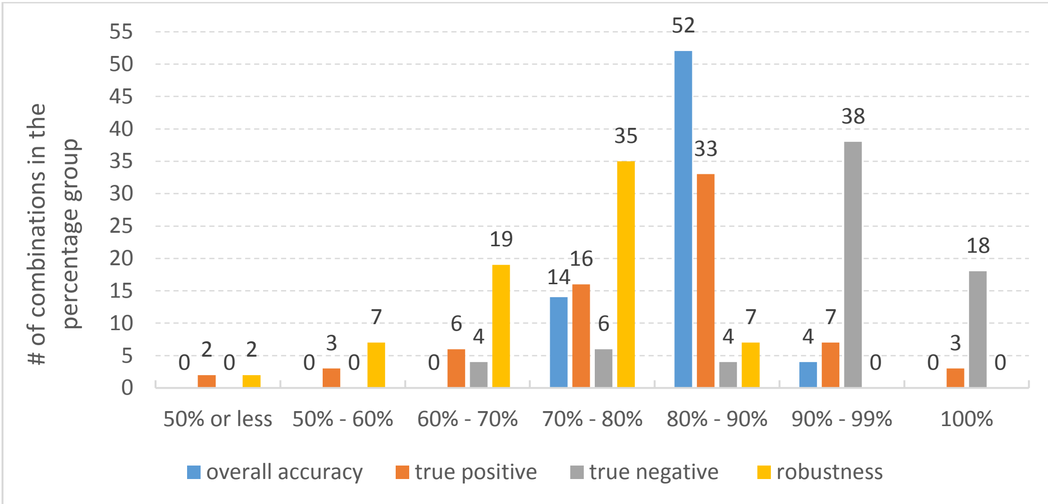

Figure C.33. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (c).

Table C.33. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (c) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	93%	100%	83%	83%	PSD_1, PSD_5, PSD_6, PSD_7
	89%	100%	75%	75%	PSD_1, PSD_4, PSD_5, PSD_6 PSD_1, PSD_3, PSD_4, PSD_8
	93%	94%	92%	85%	PSD_1, PSD_3, PSD_4, PSD_7 PSD_1, PSD_3, PSD_4, PSD_5
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	93%	100%	83%	83%	PSD_1, PSD_5, PSD_6, PSD_7
	93%	94%	92%	85%	PSD_1, PSD_3, PSD_4, PSD_7 PSD_1, PSD_3, PSD_4, PSD_5
	93%	88%	100%	88%	PSD_1, PSD_3, PSD_5, PSD_7
	89%	100%	75%	75%	PSD_1, PSD_4, PSD_5, PSD_6 PSD_1, PSD_3, PSD_4, PSD_8
	-	-	-	-	-

d. PSDs in the 0 – 3.00kHz frequency range along 7 sub-frequencies; 0 – 250Hz, 0 – 500Hz, 500Hz – 1.00kHz, 1.00kHz – 1.50kHz, 1.50kHz – 2.00kHz, 2.00kHz – 2.50kHz, and 2.50kHz – 3.00kHz

- Equal test-train when choosing one band at a time – LDA:

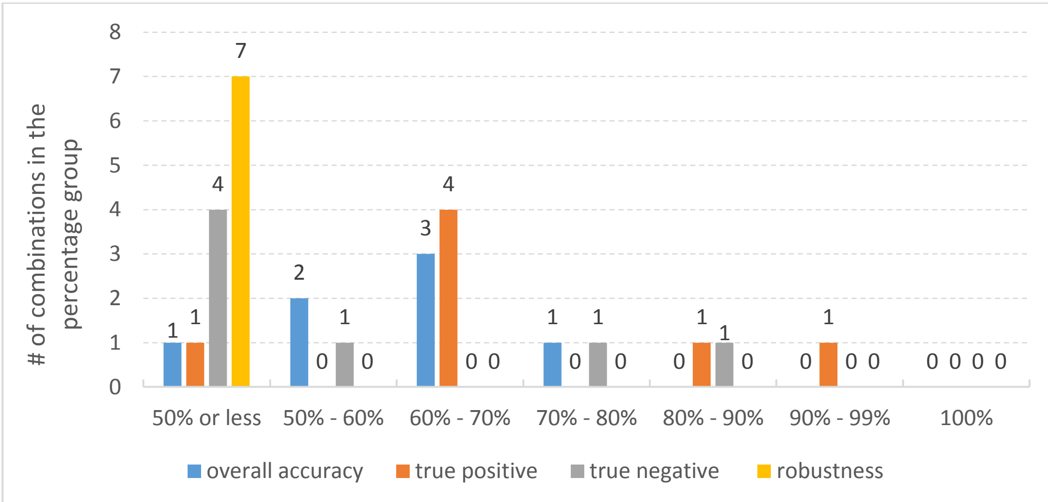

Figure C.34. Equal test-train classification results using a LDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (d).

Table C.34. Top 5 results of equal test-train LDA classification while choosing one PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_0
	61%	88%	25%	13%	PSD_5
	64%	69%	58%	27%	PSD_1
	57%	69%	42%	10%	PSD_4
	71%	63%	83%	46%	PSD_2
In terms of *overall accuracy*	71%	63%	83%	46%	PSD_2
	68%	94%	33%	27%	PSD_0
	64%	69%	58%	27%	PSD_1
	61%	88%	25%	13%	PSD_5
	57%	69%	42%	10%	PSD_4

- Equal test-train when choosing one band at a time – QDA:

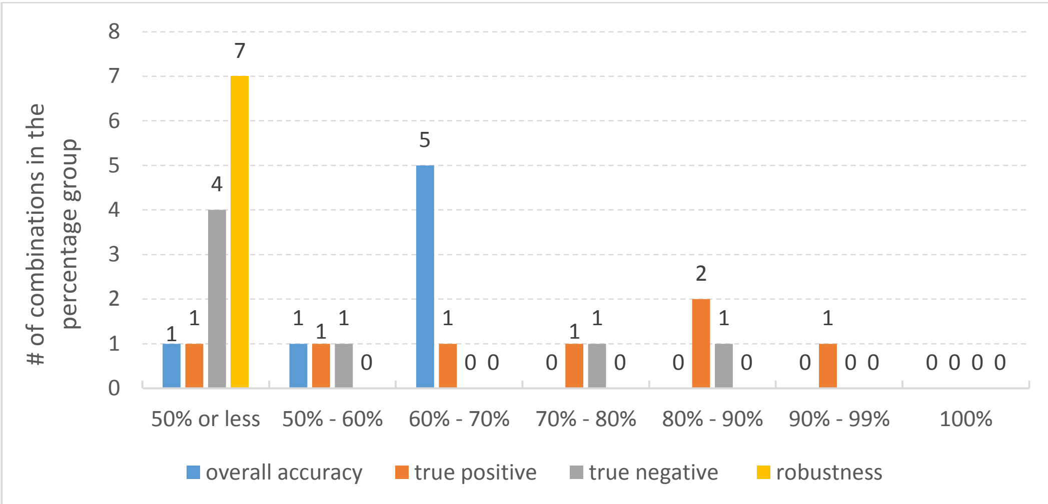

Figure C.35. Equal test-train classification results using a QDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (d).

Table C.35. Top 5 results of equal test-train QDA classification while choosing one PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_0
	61%	88%	25%	13%	PSD_5
	54%	88%	8%	-4%	PSD_6
	61%	75%	42%	17%	PSD_4
	64%	69%	58%	27%	PSD_1
In terms of *overall accuracy*	68%	94%	33%	27%	PSD_0
	68%	56%	83%	40%	PSD_2
	64%	69%	58%	27%	PSD_1
	61%	88%	25%	13%	PSD_5
	61%	75%	42%	17%	PSD_4

- Equal test-train when choosing one band at a time – SVM:

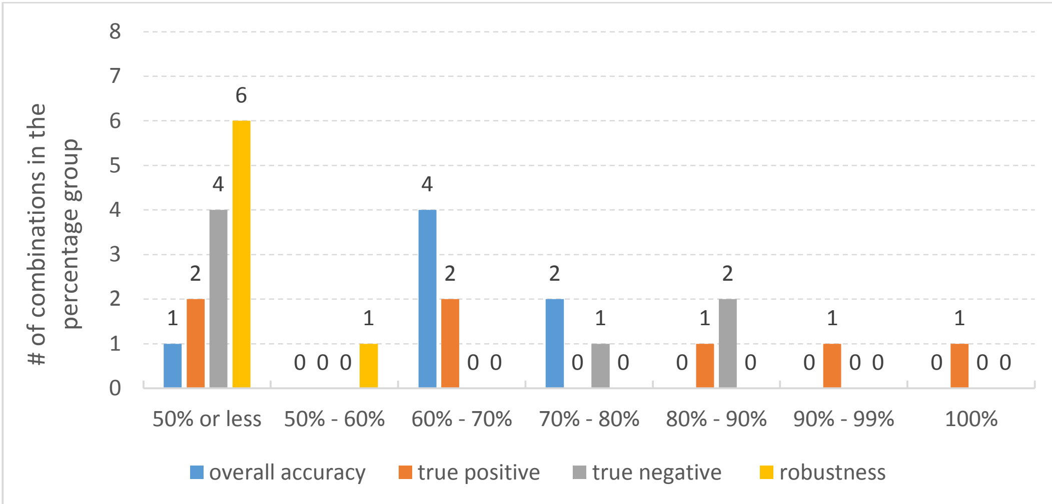

Figure C.36. Equal test-train classification results using a SVM classifier while choosing one PSD bands at a time for the frequency range detailed in point (d).

Table C.36. Top 5 results of equal test-train SVM classification while choosing one PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	100%	25%	25%	PSD_4
	75%	94%	50%	44%	PSD_0
	68%	81%	50%	31%	PSD_1
	75%	69%	83%	52%	PSD_2
	61%	69%	50%	19%	PSD_5
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_0
	75%	69%	83%	52%	PSD_2
	68%	100%	25%	25%	PSD_4
	68%	81%	50%	31%	PSD_1
	64%	50%	83%	33%	PSD_3

- Equal test-train when choosing a combination of two bands at a time – LDA:

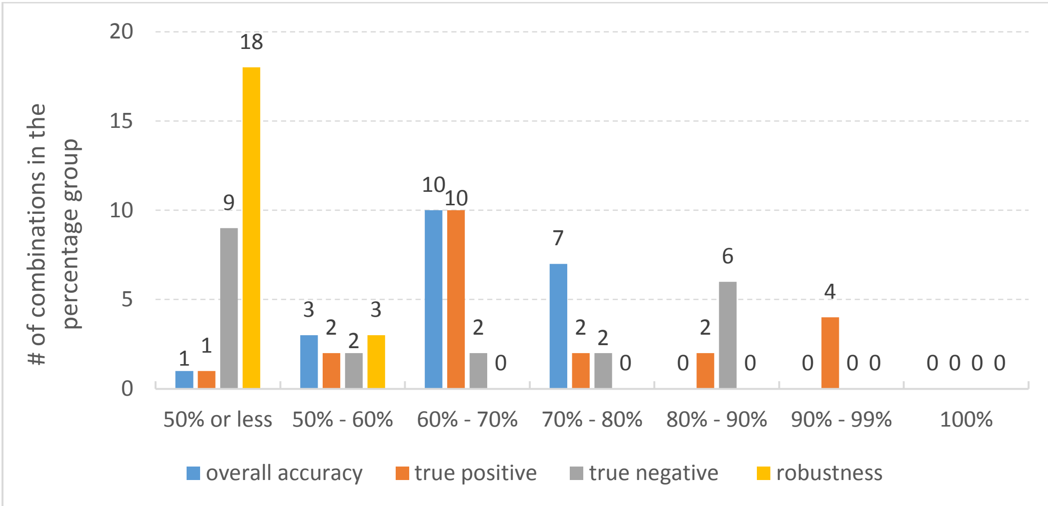

Figure C.37. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (d).

Table C.37. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_0, PSD_4
	71%	94%	42%	35%	PSD_0, PSD_5
	68%	94%	33%	27%	PSD_0, PSD_3 PSD_0, PSD_6
	61%	81%	33%	15%	PSD_5, PSD_6
	-	-	-	-	-
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_0, PSD_4
	75%	69%	83%	52%	PSD_1, PSD_5 PSD_2, PSD_3 PSD_2, PSD_5
	71%	94%	42%	35%	PSD_0, PSD_5
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of two bands at a time – QDA:

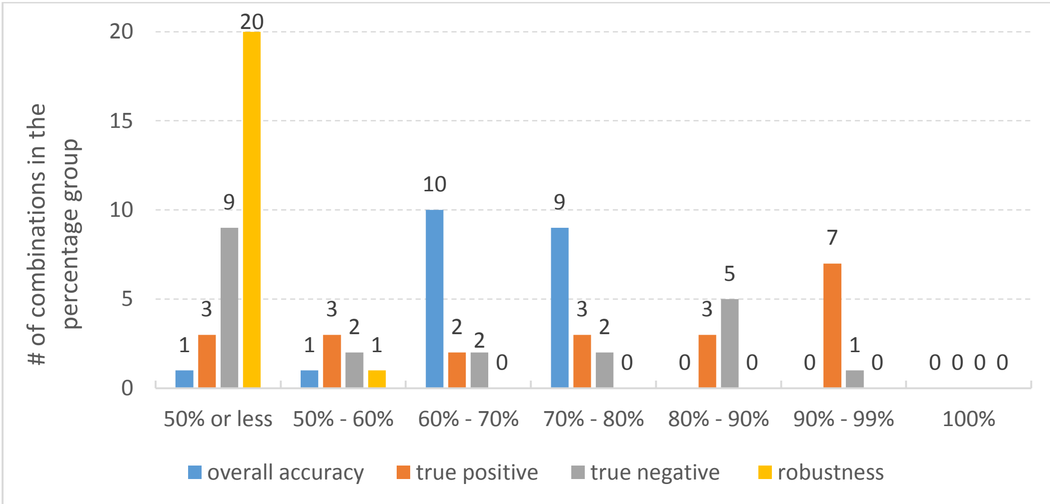

Figure C.38. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (d).

Table C.38. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	94%	58%	52%	PSD_0, PSD_5
	71%	94%	42%	35%	PSD_0, PSD_2 PSD_0, PSD_3 PSD_0, PSD_6
	68%	94%	33%	27%	PSD_0, PSD_1 PSD_0, PSD_4
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	94%	58%	52%	PSD_0, PSD_5
	71%	94%	42%	35%	PSD_0, PSD_2 PSD_0, PSD_3 PSD_0, PSD_6
	71%	81%	58%	40%	PSD_2, PSD_5
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of two bands at a time – SVM:

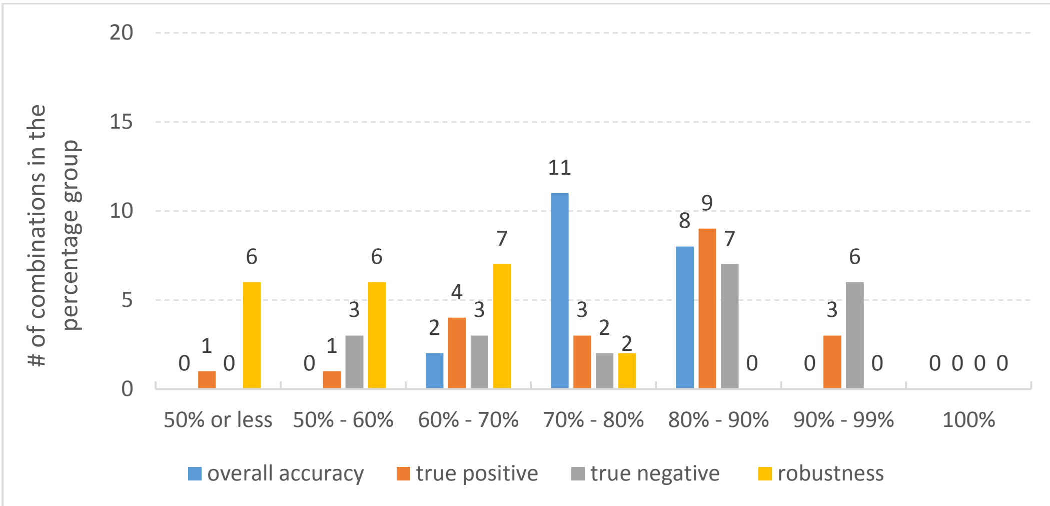

Figure C.39. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (d).

Table C.39. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	86%	94%	75%	69%	PSD_0, PSD_5
	79%	94%	58%	52%	PSD_0, PSD_4 PSD_0, PSD_6
	86%	88%	83%	71%	PSD_2, PSD_6
	79%	88%	67%	54%	PSD_0, PSD_3
	-	-	-	-	-
In terms of *overall accuracy*	86%	94%	75%	69%	PSD_0, PSD_5
	86%	88%	83%	71%	PSD_2, PSD_6
	86%	81%	92%	73%	PSD_2, PSD_4
	82%	81%	83%	65%	PSD_1, PSD_4 PSD_1, PSD_5 PSD_2, PSD_3 PSD_2, PSD_5
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – LDA:

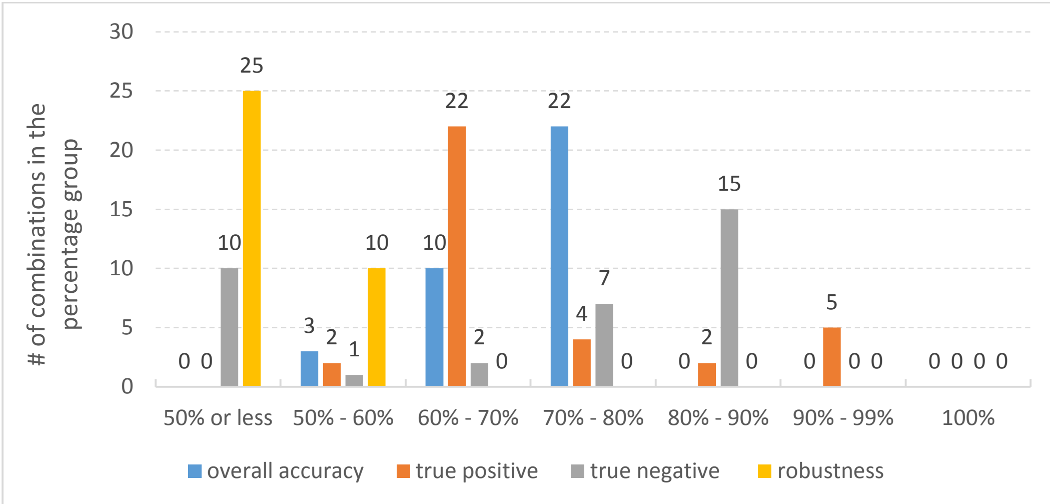

Figure C.40. Equal test-train classification results using a LDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (d).

Table C.40. Top 5 results of equal test-train LDA classification while choosing three PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD$_0$, PSD$_3$, PSD$_4$ PSD$_0$, PSD$_3$, PSD$_5$ PSD$_0$, PSD$_4$, PSD$_5$ PSD$_0$, PSD$_4$, PSD$_6$
	71%	94%	42%	35%	PSD$_0$, PSD$_5$, PSD$_6$
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	75%	83%	58%	PSD$_0$, PSD$_1$, PSD$_5$
	75%	94%	50%	44%	PSD$_0$, PSD$_3$, PSD$_4$ PSD$_0$, PSD$_3$, PSD$_5$ PSD$_0$, PSD$_4$, PSD$_5$ PSD$_0$, PSD$_4$, PSD$_6$
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – QDA:

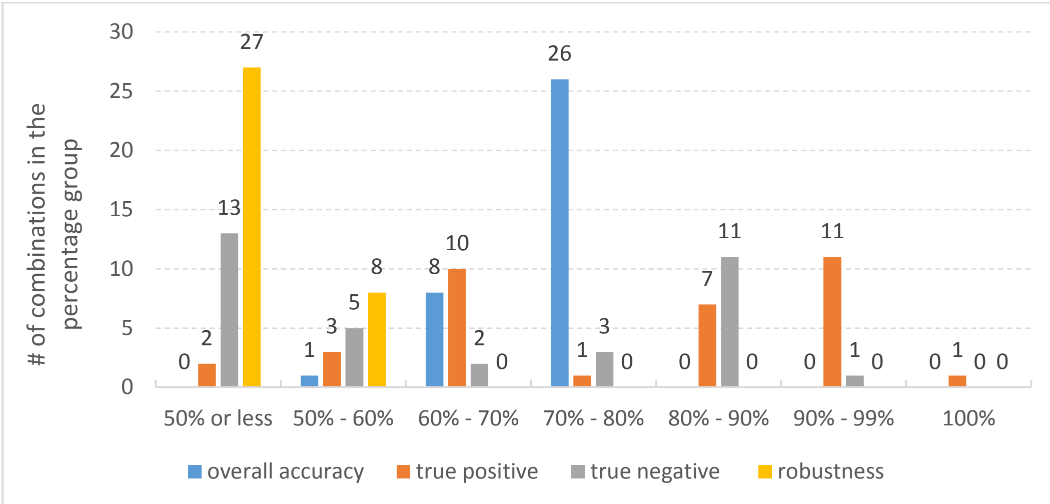

Figure C.41. Equal test-train classification results using a QDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (d).

Table C.41. Top 5 results of equal test-train QDA classification while choosing three PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	100%	50%	50%	PSD_0, PSD_5, PSD_6
	79%	94%	58%	52%	PSD_0, PSD_1, PSD_5 PSD_0, PSD_2, PSD_5 PSD_0, PSD_3, PSD_5 PSD_0, PSD_4, PSD_5
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	100%	50%	50%	PSD_0, PSD_5, PSD_6
	79%	94%	58%	52%	PSD_0, PSD_1, PSD_5 PSD_0, PSD_2, PSD_5 PSD_0, PSD_3, PSD_5 PSD_0, PSD_4, PSD_5
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – SVM:

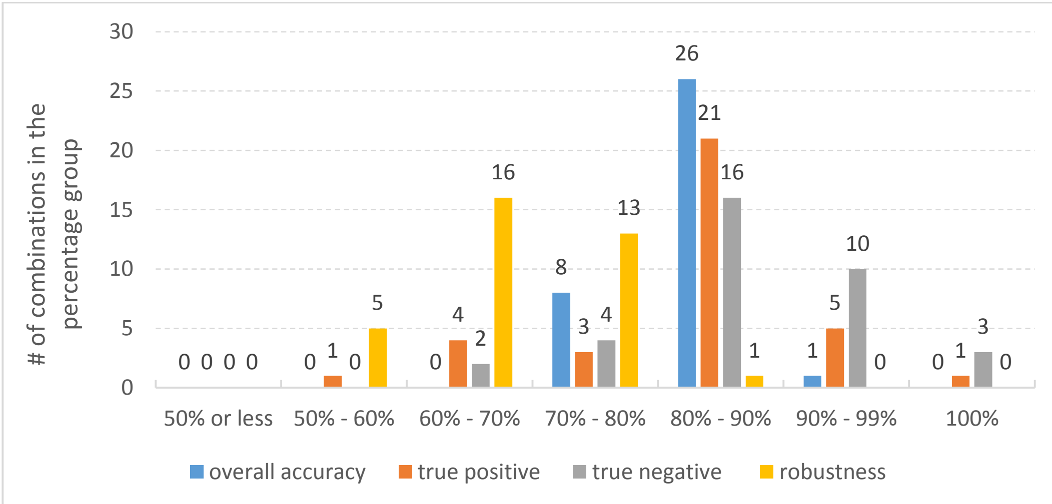

Figure C.42. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (d).

Table C.42. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	93%	100%	83%	83%	PSD_0, PSD_2, PSD_4
	89%	94%	83%	77%	PSD_2, PSD_5, PSD_6
	86%	94%	75%	69%	PSD_0, PSD_3, PSD_5 PSD_0, PSD_5, PSD_6
	82%	94%	67%	60%	PSD_0, PSD_3, PSD_4 PSD_0, PSD_4, PSD_6
	-	-	-	-	-
In terms of *overall accuracy*	93%	100%	83%	83%	PSD_0, PSD_2, PSD_4
	89%	94%	83%	77%	PSD_2, PSD_5, PSD_6
	89%	88%	92%	79%	PSD_1, PSD_4, PSD_6 PSD_1, PSD_3, PSD_6 PSD_1, PSD_2, PSD_4 PSD_2, PSD_4, PSD_6 PSD_2, PSD_3, PSD_6
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – LDA:

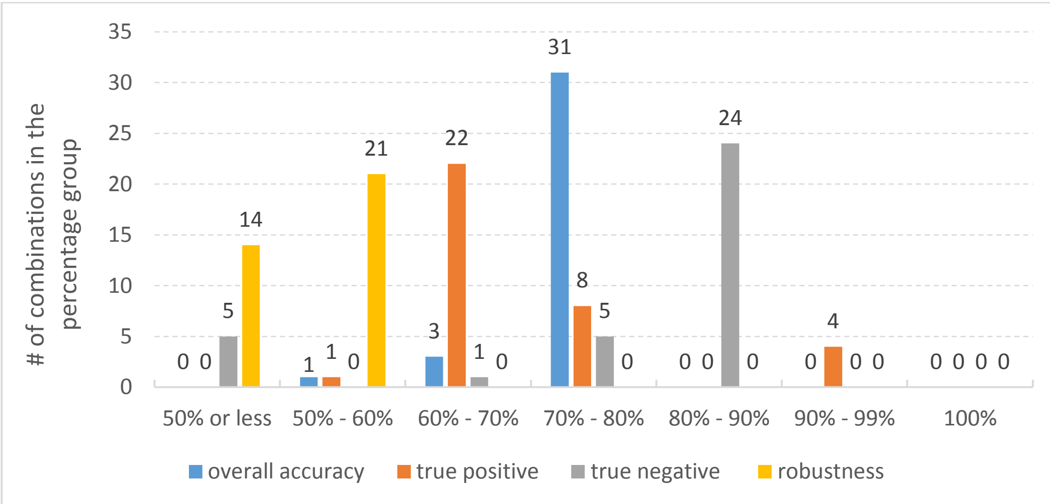

Figure C.43. Equal test-train classification results using a LDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (d).

Table C.43. Top 5 results of equal test-train LDA classification while choosing four PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_4, PSD_5, PSD_6, PSD_0 PSD_3, PSD_5, PSD_6, PSD_0 PSD_3, PSD_4, PSD_6, PSD_0 PSD_3, PSD_4, PSD_5, PSD_0
	79%	75%	83%	58%	PSD_2, PSD_3, PSD_5, PSD_0 PSD_1, PSD_5, PSD_6, PSD_0 PSD_1, PSD_4, PSD_5, PSD_0 PSD_1, PSD_3, PSD_5, PSD_0 PSD_1, PSD_3, PSD_4, PSD_0 PSD_1, PSD_2, PSD_5, PSD_0
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	75%	83%	58%	PSD_2, PSD_3, PSD_5, PSD_0 PSD_1, PSD_5, PSD_6, PSD_0 PSD_1, PSD_4, PSD_5, PSD_0 PSD_1, PSD_3, PSD_5, PSD_0 PSD_1, PSD_3, PSD_4, PSD_0 PSD_1, PSD_2, PSD_5, PSD_0
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – QDA:

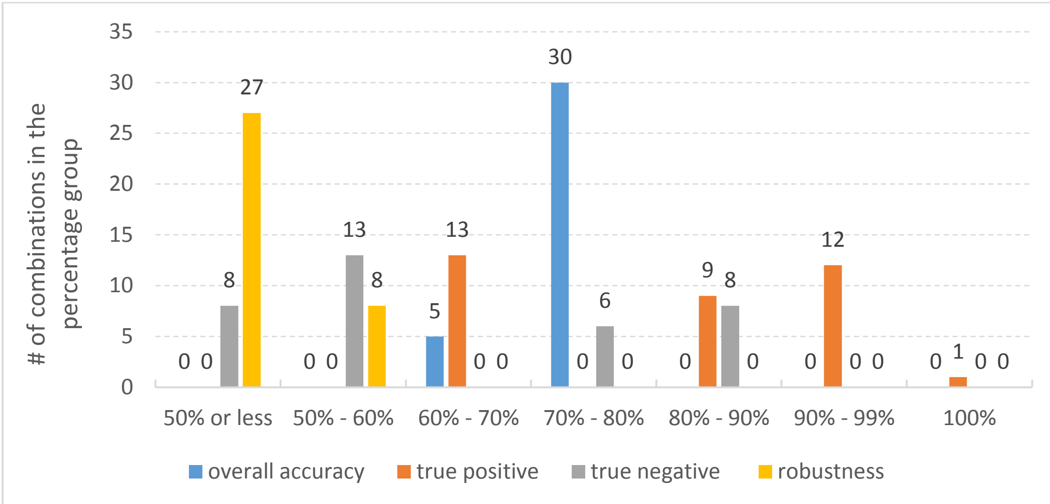

Figure C.44. Equal test-train classification results using a QDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (d).

Table C.44. Top 5 results of equal test-train QDA classification while choosing four PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	100%	50%	50%	PSD_4, PSD_5, PSD_6, PSD_0
	79%	94%	58%	52%	PSD_3, PSD_5, PSD_6, PSD_0 PSD_1, PSD_5, PSD_6, PSD_0 PSD_1, PSD_4, PSD_5, PSD_0 PSD_1, PSD_3, PSD_5, PSD_0 PSD_1, PSD_2, PSD_5, PSD_0 PSD_1, PSD_2, PSD_4, PSD_0
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	79%	100%	50%	50%	PSD_4, PSD_5, PSD_6, PSD_0
	79%	94%	58%	52%	PSD_3, PSD_5, PSD_6, PSD_0 PSD_1, PSD_5, PSD_6, PSD_0 PSD_1, PSD_4, PSD_5, PSD_0 PSD_1, PSD_3, PSD_5, PSD_0 PSD_1, PSD_2, PSD_5, PSD_0 PSD_1, PSD_2, PSD_4, PSD_0
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – SVM:

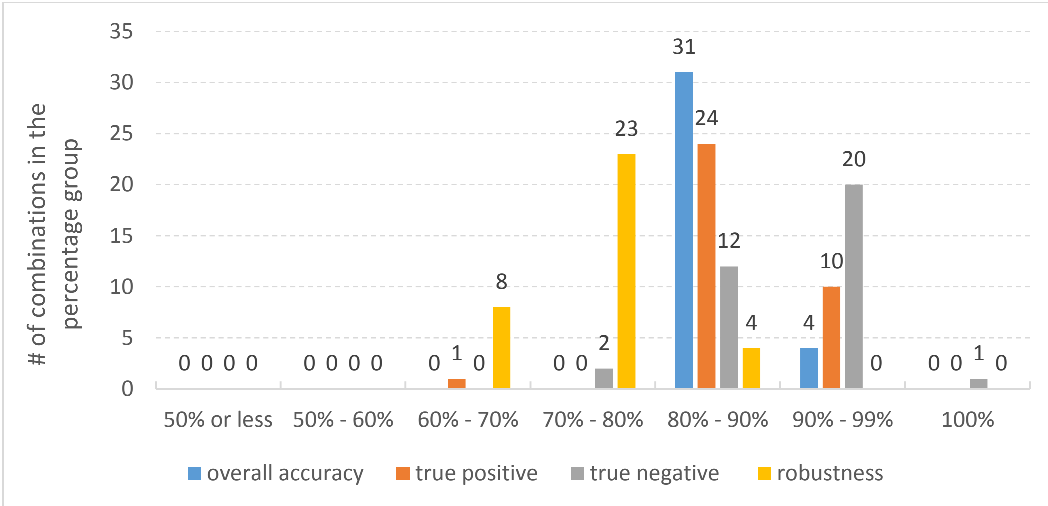

Figure C.45. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (d).

Table C.45. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (d) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	93%	94%	92%	85%	PSD_4, PSD_5, PSD_6, PSD_2 PSD_3, PSD_5, PSD_6, PSD_2 PSD_2, PSD_4, PSD_6, PSD_1 PSD_2, PSD_4, PSD_5, PSD_0
	89%	94%	83%	77%	PSD_2, PSD_5, PSD_6, PSD_1 PSD_4, PSD_5, PSD_6, PSD_0 PSD_3, PSD_5, PSD_6, PSD_0 PSD_2, PSD_5, PSD_6, PSD_0
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	93%	94%	92%	85%	PSD_4, PSD_5, PSD_6, PSD_2 PSD_3, PSD_5, PSD_6, PSD_2 PSD_2, PSD_4, PSD_6, PSD_1 PSD_2, PSD_4, PSD_5, PSD_0
	89%	94%	83%	77%	PSD_2, PSD_5, PSD_6, PSD_1 PSD_4, PSD_5, PSD_6, PSD_0 PSD_3, PSD_5, PSD_6, PSD_0 PSD_2, PSD_5, PSD_6, PSD_0
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

e. PSDs in the 0 – 3.00kHz frequency range along 9 sub-frequencies; 0 – 333Hz, 333Hz – 666Hz, 666Hz – 1.00kHz, 1.00kHz – 1.33kHz, 1.33kHz – 1.67kHz, 1.67kHz – 2.00kHz, 2.00kHz – 2.33kHz, 2.33kHz – 2.67kHz, and 2.67kHz – 3.00kHz

- Equal test-train when choosing one band at a time – LDA:

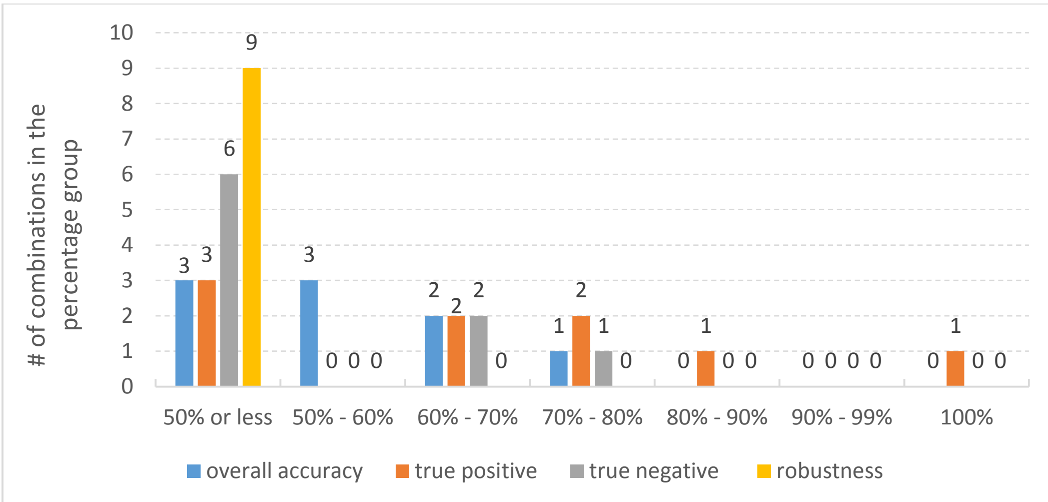

Figure C.46. Equal test-train classification results using a LDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (e).

Table C.46. Top 5 results of equal test-train LDA classification while choosing one PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_1
	64%	81%	42%	23%	PSD_6
	57%	75%	33%	8%	PSD_7 PSD_9
	61%	69%	50%	19%	PSD_2
	-	-	-	-	-
In terms of *overall accuracy*	71%	100%	33%	33%	PSD_1
	64%	81%	42%	23%	PSD_6
	61%	69%	50%	19%	PSD_2
	57%	75%	33%	8%	PSD_7 PSD_9
	-	-	-	-	-

- Equal test-train when choosing one band at a time – QDA:

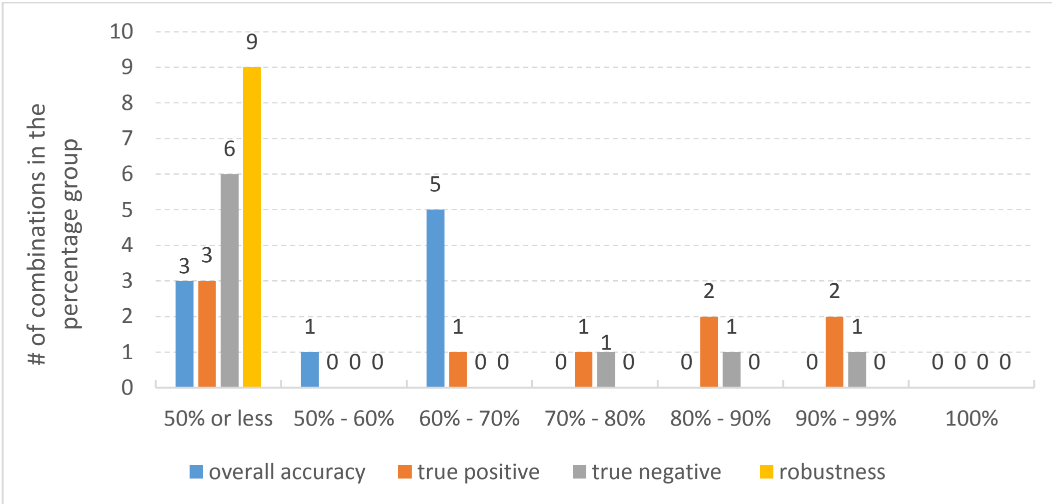

Figure C.47. Equal test-train classification results using a QDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (e).

Table C.47. Top 5 results of equal test-train QDA classification while choosing one PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_1
	64%	94%	25%	19%	PSD_7
	61%	88%	25%	13%	PSD_8
	64%	81%	42%	23%	PSD_6
	46%	75%	8%	-17%	PSD_9
In terms of *overall accuracy*	68%	94%	33%	27%	PSD_1
	64%	94%	25%	19%	PSD_7
	64%	81%	42%	23%	PSD_6
	61%	88%	25%	13%	PSD_8
	61%	69%	50%	19%	PSD_2

- Equal test-train when choosing one band at a time – SVM:

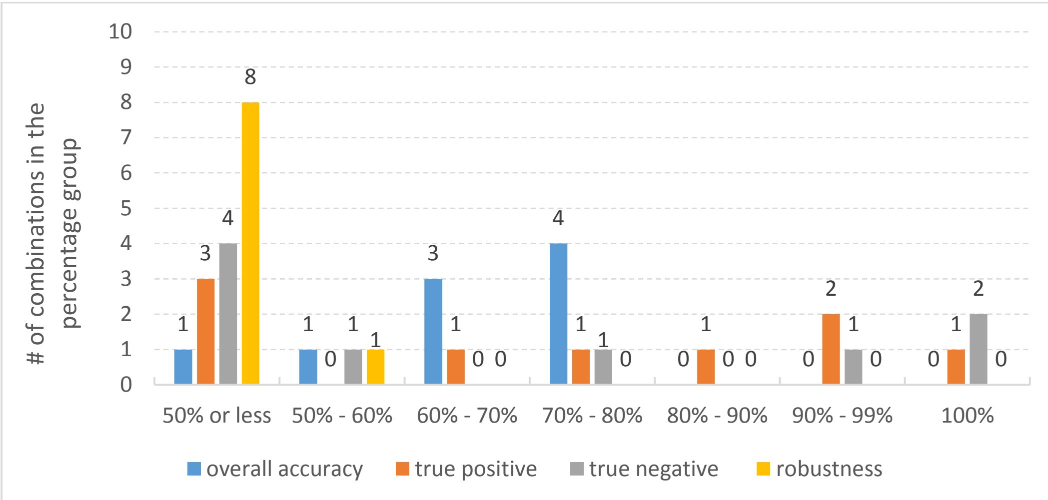

Figure C.48. Equal test-train classification results using a SVM classifier while choosing one PSD bands at a time for the frequency range detailed in point (e).

Table C.48. Top 5 results of equal test-train SVM classification while choosing one PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	100%	25%	25%	PSD_7
	79%	94%	58%	52%	PSD_1
	71%	94%	42%	35%	PSD_6
	61%	88%	25%	13%	PSD_4
	75%	75%	75%	50%	PSD_9
In terms of *overall accuracy*	79%	94%	58%	52%	PSD_1
	75%	75%	75%	50%	PSD_9
	71%	94%	42%	35%	PSD_6
	71%	50%	100%	50%	PSD_8
	68%	100%	25%	25%	PSD_7

- Equal test-train when choosing a combination of two bands at a time – LDA:

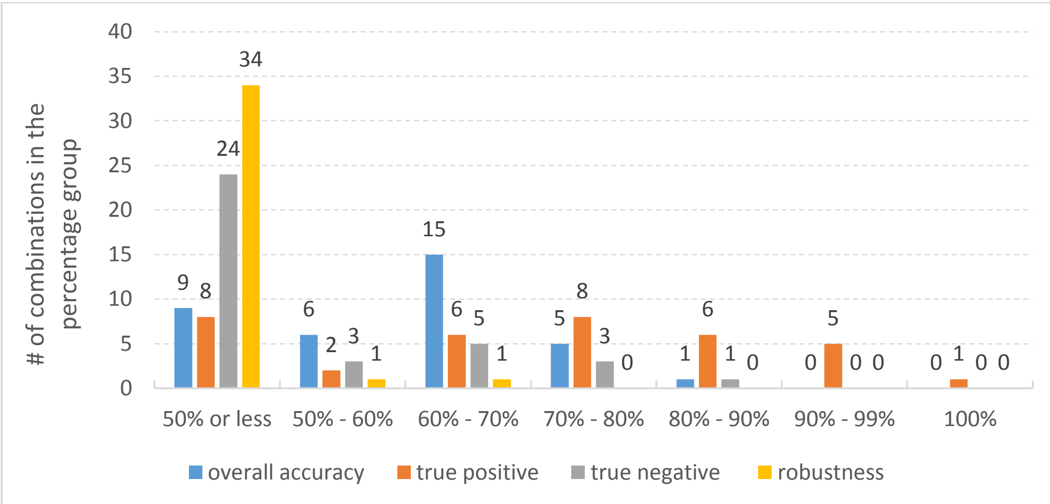

Figure C.49. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (e).

Table C.49. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	100%	42%	42%	PSD_1, PSD_9
	82%	94%	67%	60%	PSD_1, PSD_7
	75%	94%	50%	44%	PSD_1, PSD_3
	71%	94%	42%	35%	PSD_1, PSD_2
	68%	94%	33%	27%	PSD_1, PSD_4 PSD_1, PSD_5
In terms of *overall accuracy*	82%	94%	67%	60%	PSD_1, PSD_7
	79%	88%	67%	54%	PSD_1, PSD_6
	75%	100%	42%	42%	PSD_1, PSD_9
	75%	94%	50%	44%	PSD_1, PSD_3
	71%	94%	42%	35%	PSD_1, PSD_2

- Equal test-train when choosing a combination of two bands at a time – QDA:

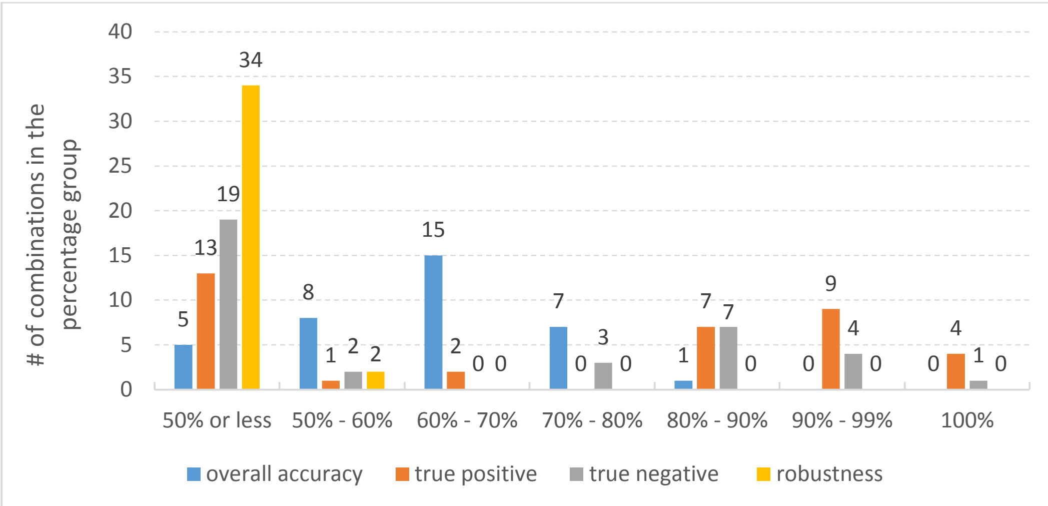

Figure C.50. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (e).

Table C.50. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	100%	58%	58%	PSD_1, PSD_8
	75%	100%	42%	42%	PSD_1, PSD_6
	75%	100%	42%	42%	PSD_1, PSD_9
	71%	100%	33%	33%	PSD_1, PSD_2
	79%	94%	58%	52%	PSD_1, PSD_7
In terms of *overall accuracy*	82%	100%	58%	58%	PSD_1, PSD_8
	79%	94%	58%	52%	PSD_1, PSD_7
	75%	100%	42%	42%	PSD_1, PSD_6
	75%	100%	42%	42%	PSD_1, PSD_9
	71%	100%	33%	33%	PSD_1, PSD_2

- Equal test-train when choosing a combination of two bands at a time – SVM:

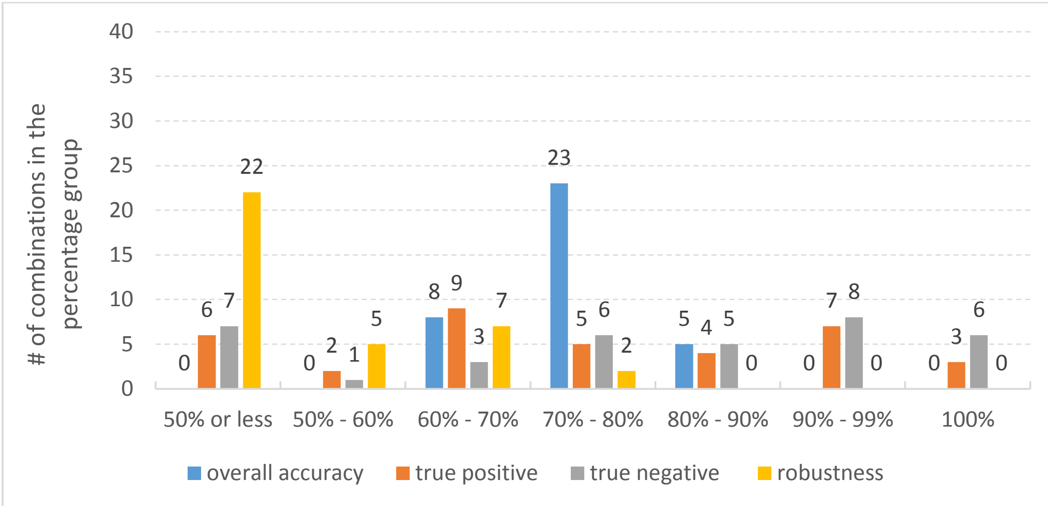

Figure C.51. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (e).

Table C.51. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	79%	100%	50%	50%	PSD_2, PSD_6
	75%	100%	42%	42%	PSD_3, PSD_6 PSD_6, PSD_7
	89%	94%	83%	77%	PSD_1, PSD_8 PSD_1, PSD_9
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	89%	94%	83%	77%	PSD_1, PSD_8 PSD_1, PSD_9
	86%	94%	75%	69%	PSD_1, PSD_6 PSD_1, PSD_7
	82%	69%	100%	69%	PSD_6, PSD_8
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – LDA:

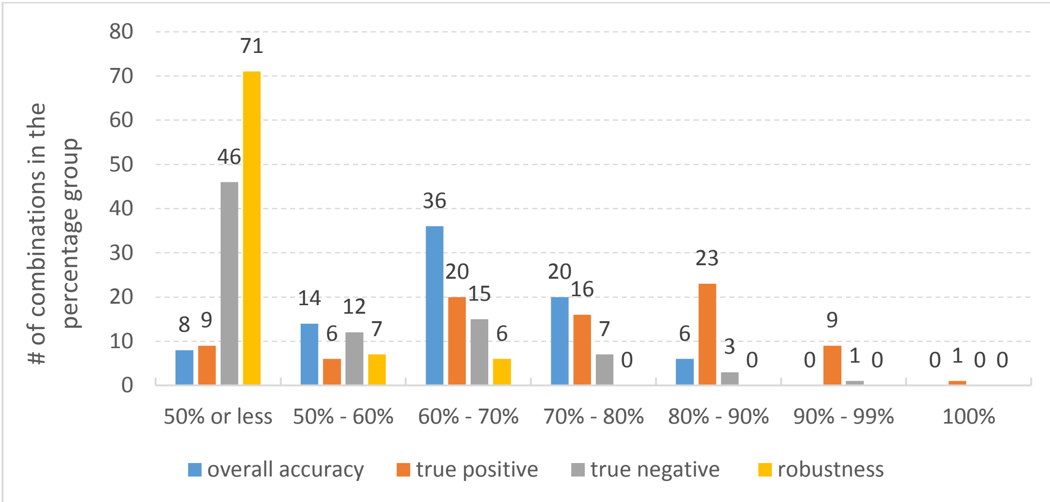

Figure C.52. Equal test-train classification results using a LDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (e).

Table C.52. Top 5 results of equal test-train LDA classification while choosing three PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	71%	100%	33%	33%	PSD_1, PSD_2, PSD_9
	82%	94%	67%	60%	PSD_1, PSD_2, PSD_7 PSD_1, PSD_3, PSD_7 PSD_1, PSD_4, PSD_7 PSD_1, PSD_5, PSD_7 PSD_1, PSD_7, PSD_8
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	82%	94%	67%	60%	PSD_1, PSD_2, PSD_7 PSD_1, PSD_3, PSD_7 PSD_1, PSD_4, PSD_7 PSD_1, PSD_5, PSD_7 PSD_1, PSD_7, PSD_8
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – QDA:

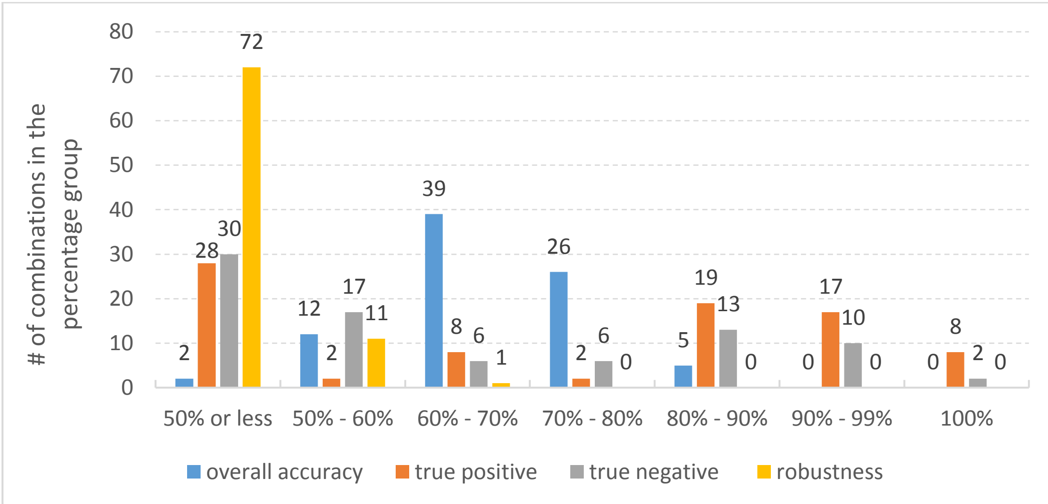

Figure C.53. Equal test-train classification results using a QDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (e).

Table C.53. Top 5 results of equal test-train QDA classification while choosing three PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	100%	58%	58%	PSD_1, PSD_2, PSD_8 PSD_1, PSD_6, PSD_8 PSD_1, PSD_7, PSD_9 PSD_1, PSD_8, PSD_9
	75%	100%	42%	42%	PSD_1, PSD_2, PSD_4 PSD_1, PSD_2, PSD_9 PSD_1, PSD_6, PSD_9
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	82%	100%	58%	58%	PSD_1, PSD_2, PSD_8 PSD_1, PSD_6, PSD_8 PSD_1, PSD_7, PSD_9 PSD_1, PSD_8, PSD_9
	82%	94%	67%	60%	PSD_1, PSD_5, PSD_6
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – SVM:

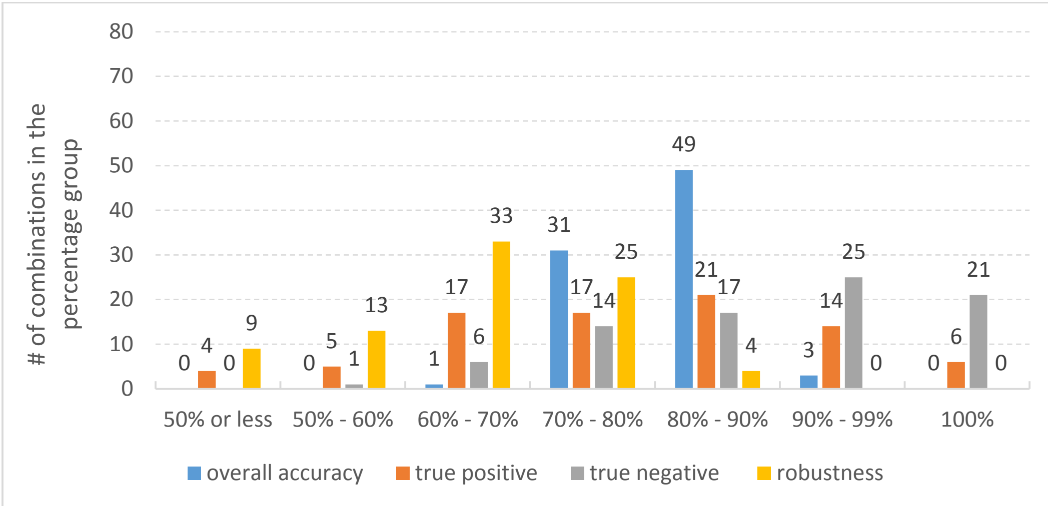

Figure C.54. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (e).

Table C.54. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	93%	100%	83%	83%	PSD_1, PSD_4, PSD_9
	89%	100%	75%	75%	PSD_1, PSD_2, PSD_6 PSD_1, PSD_6, PSD_7 PSD_1, PSD_6, PSD_8 PSD_1, PSD_7, PSD_9
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	93%	100%	83%	83%	PSD_1, PSD_4, PSD_9
	93%	94%	92%	85%	PSD_1, PSD_4, PSD_5 PSD_1, PSD_8, PSD_9
	89%	100%	75%	75%	PSD_1, PSD_2, PSD_6 PSD_1, PSD_6, PSD_7 PSD_1, PSD_6, PSD_8 PSD_1, PSD_7, PSD_9
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – LDA:

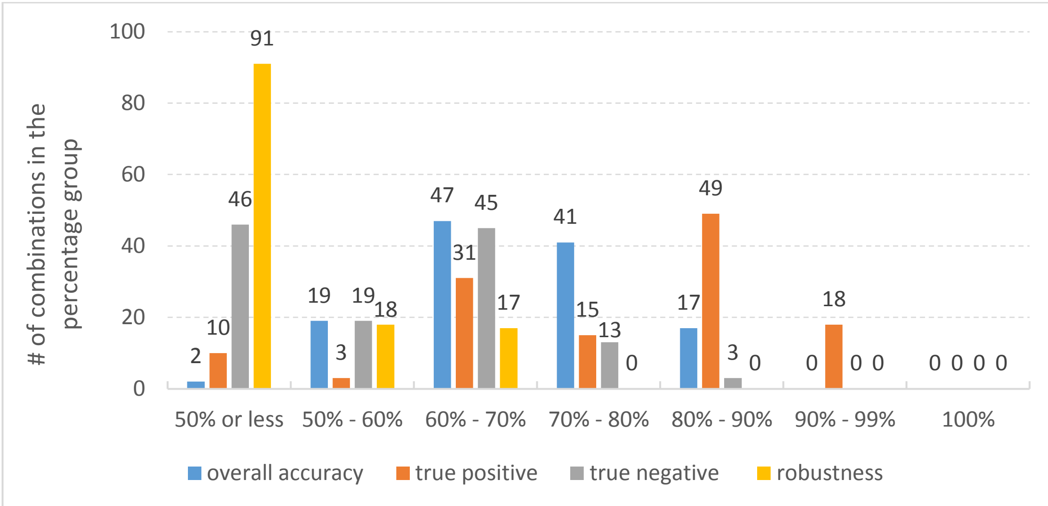

Figure C.55. Equal test-train classification results using a LDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (e).

Table C.55. Top 5 results of equal test-train LDA classification while choosing four PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	94%	67%	60%	PSD_1, PSD_5, PSD_7, PSD_9 PSD_1, PSD_5, PSD_7, PSD_8 PSD_1, PSD_4, PSD_7, PSD_9 PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_4, PSD_5, PSD_7 PSD_1, PSD_3, PSD_7, PSD_8 PSD_1, PSD_3, PSD_5, PSD_7 PSD_1, PSD_3, PSD_4, PSD_7 PSD_1, PSD_2, PSD_7, PSD_9 PSD_1, PSD_2, PSD_7, PSD_8 PSD_1, PSD_2, PSD_5, PSD_7 PSD_1, PSD_2, PSD_4, PSD_7 PSD_1, PSD_2, PSD_3, PSD_7 PSD_1, PSD_2, PSD_3, PSD_5
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	82%	94%	67%	60%	PSD_1, PSD_5, PSD_7, PSD_9 PSD_1, PSD_5, PSD_7, PSD_8 PSD_1, PSD_4, PSD_7, PSD_9 PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_4, PSD_5, PSD_7 PSD_1, PSD_3, PSD_7, PSD_8 PSD_1, PSD_3, PSD_5, PSD_7 PSD_1, PSD_3, PSD_4, PSD_7 PSD_1, PSD_2, PSD_7, PSD_9 PSD_1, PSD_2, PSD_7, PSD_8 PSD_1, PSD_2, PSD_5, PSD_7 PSD_1, PSD_2, PSD_4, PSD_7 PSD_1, PSD_2, PSD_3, PSD_7 PSD_1, PSD_2, PSD_3, PSD_5
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – QDA:

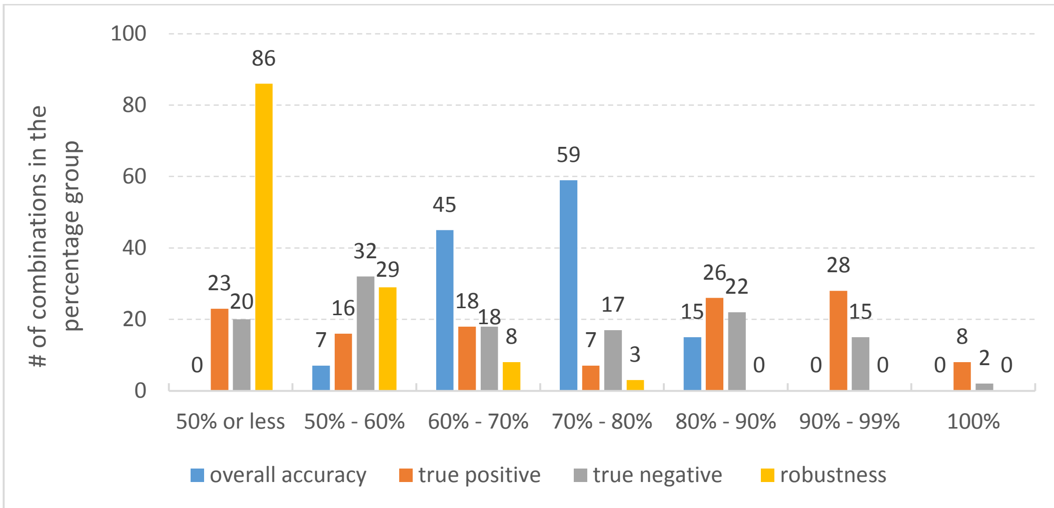

Figure C.56. Equal test-train classification results using a QDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (e).

Table C.56. Top 5 results of equal test-train QDA classification while choosing four PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	86%	100%	67%	67%	PSD_1, PSD_2, PSD_4, PSD_8
	82%	100%	58%	58%	PSD_1, PSD_6, PSD_8, PSD_9 PSD_1, PSD_4, PSD_7, PSD_9 PSD_1, PSD_2, PSD_8, PSD_9 PSD_1, PSD_2, PSD_6, PSD_8
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	86%	100%	67%	67%	PSD_1, PSD_2, PSD_4, PSD_8
	86%	94%	75%	69%	PSD_1, PSD_3, PSD_4, PSD_7 PSD_1, PSD_2, PSD_5, PSD_8 PSD_1, PSD_2, PSD_3, PSD_4
	86%	88%	83%	71%	PSD_1, PSD_4, PSD_5, PSD_8 PSD_1, PSD_4, PSD_5, PSD_7 PSD_1, PSD_3, PSD_5, PSD_8
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – SVM:

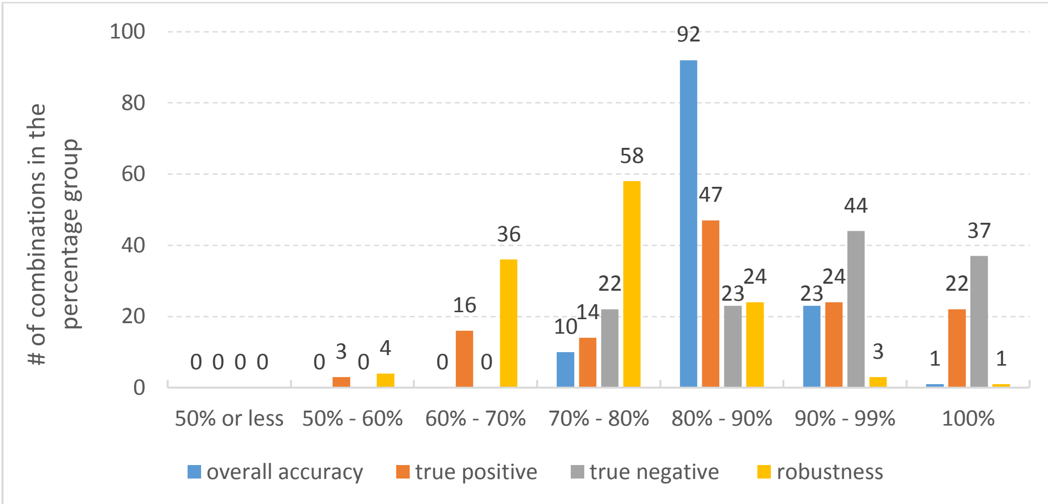

Figure C.57. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (e).

Table C.57. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (e) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	96%	100%	92%	92%	PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_3, PSD_4, PSD_9 PSD_1, PSD_2, PSD_3, PSD_4
	93%	100%	83%	83%	PSD_1, PSD_4, PSD_5, PSD_9 PSD_1, PSD_3, PSD_6, PSD_7 PSD_1, PSD_2, PSD_4, PSD_9 PSD_1, PSD_2, PSD_4, PSD_7 PSD_1, PSD_2, PSD_4, PSD_6 PSD_1, PSD_2, PSD_3, PSD_7 PSD_1, PSD_2, PSD_3, PSD_6
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	100%	100%	100%	100%	PSD_1, PSD_3, PSD_4, PSD_5
	96%	100%	92%	92%	PSD_1, PSD_4, PSD_7, PSD_8 PSD_1, PSD_3, PSD_4, PSD_9 PSD_1, PSD_2, PSD_3, PSD_4
	93%	100%	83%	83%	PSD_1, PSD_4, PSD_5, PSD_9 PSD_1, PSD_3, PSD_6, PSD_7 PSD_1, PSD_2, PSD_4, PSD_9 PSD_1, PSD_2, PSD_4, PSD_7 PSD_1, PSD_2, PSD_4, PSD_6 PSD_1, PSD_2, PSD_3, PSD_7 PSD_1, PSD_2, PSD_3, PSD_6
	-	-	-	-	-
	-	-	-	-	-

f. *<u>PSDs in the 0 – 3.00kHz frequency range along 12 sub-frequencies; 0 – 250Hz, 250Hz – 500Hz, 500Hz – 750Hz, 750Hz – 1.00kHz, 1.00kHz – 1.25kHz, 1.25kHz – 1.50kHz, 1.50kHz – 1.75kHz, 1.75kHz – 2.00kHz, 2.00kHz – 2.25kHz, 2.25kHz – 2.50kHz, 2.50kHz – 2.75kHz, and 2.75kHz – 3.00kHz</u>*

- Equal test-train when choosing one band at a time – LDA:

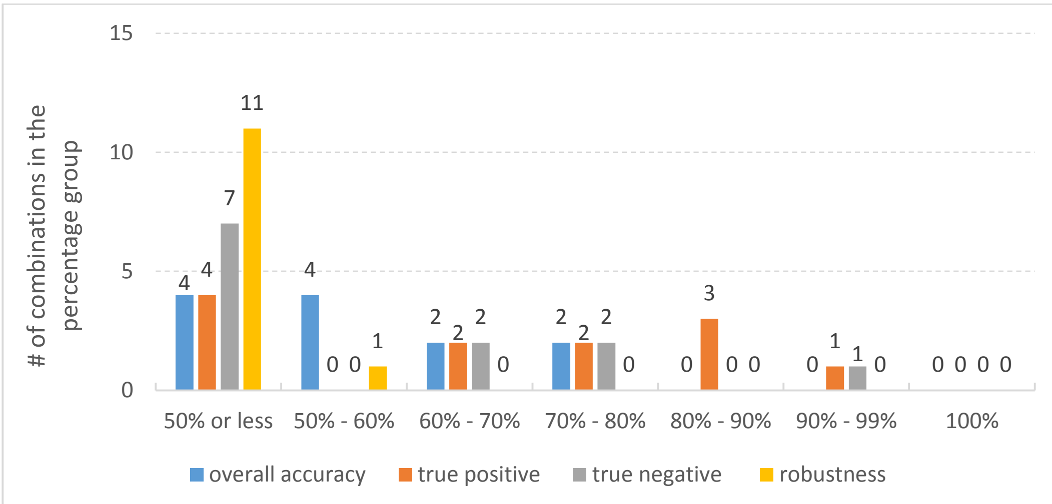

Figure C.58. Equal test-train classification results using a LDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (f).

Table C.58. Top 5 results of equal test-train LDA classification while choosing one PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_1
	71%	88%	50%	38%	PSD_8
	64%	81%	42%	23%	PSD_9
	57%	81%	25%	6%	PSD_{10}
	57%	75%	33%	8%	PSD_7 PSD_{12}
In terms of *overall accuracy*	75%	63%	92%	54%	PSD_3
	71%	88%	50%	38%	PSD_8
	68%	94%	33%	27%	PSD_1
	64%	81%	42%	23%	PSD_9
	57%	81%	25%	6%	PSD_{10}

- Equal test-train when choosing one band at a time – QDA:

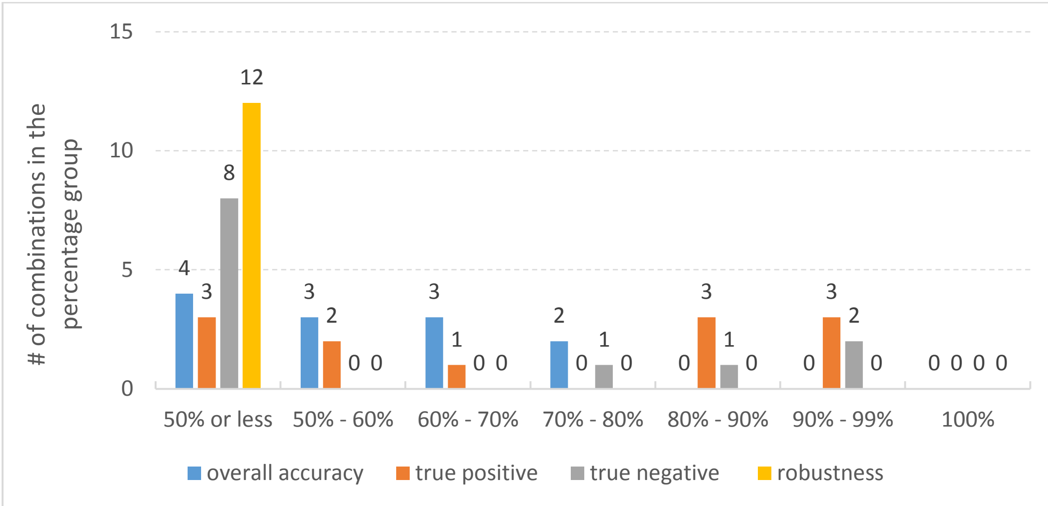

Figure C.59. Equal test-train classification results using a QDA classifier while choosing one PSD bands at a time for the frequency range detailed in point (f).

Table C.59. Top 5 results of equal test-train QDA classification while choosing one PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	94%	33%	27%	PSD_1
	68%	94%	33%	27%	PSD_9
	57%	94%	8%	2%	PSD_{11}
	71%	88%	50%	38%	PSD_8
	61%	88%	25%	13%	PSD_{10}
In terms of *overall accuracy*	71%	88%	50%	38%	PSD_8
	71%	56%	92%	48%	PSD_3
	68%	94%	33%	27%	PSD_1
	68%	94%	33%	27%	PSD_9
	61%	88%	25%	13%	PSD_{10}

- Equal test-train when choosing one band at a time – SVM:

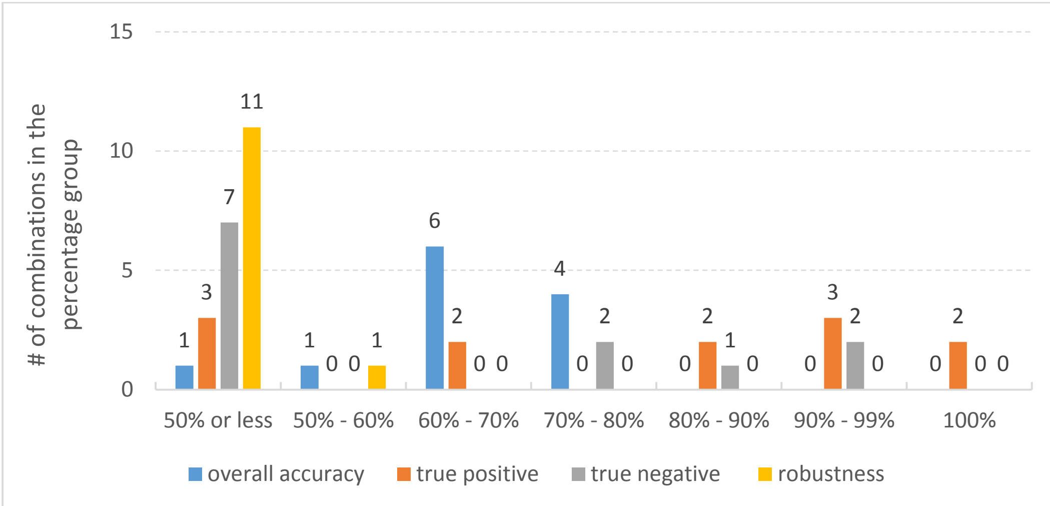

Figure C.60. Equal test-train classification results using a SVM classifier while choosing one PSD bands at a time for the frequency range detailed in point (f).

Table C.60. Top 5 results of equal test-train SVM classification while choosing one PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	68%	100%	25%	25%	PSD_9
	64%	100%	17%	17%	PSD_6
	75%	94%	50%	44%	PSD_1
	71%	94%	42%	35%	PSD_8
	68%	94%	33%	27%	PSD_5
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_1
	75%	63%	92%	54%	PSD_3
	71%	94%	42%	35%	PSD_8
	71%	69%	75%	44%	PSD_{12}
	68%	100%	25%	25%	PSD_9

- Equal test-train when choosing a combination of two bands at a time – LDA:

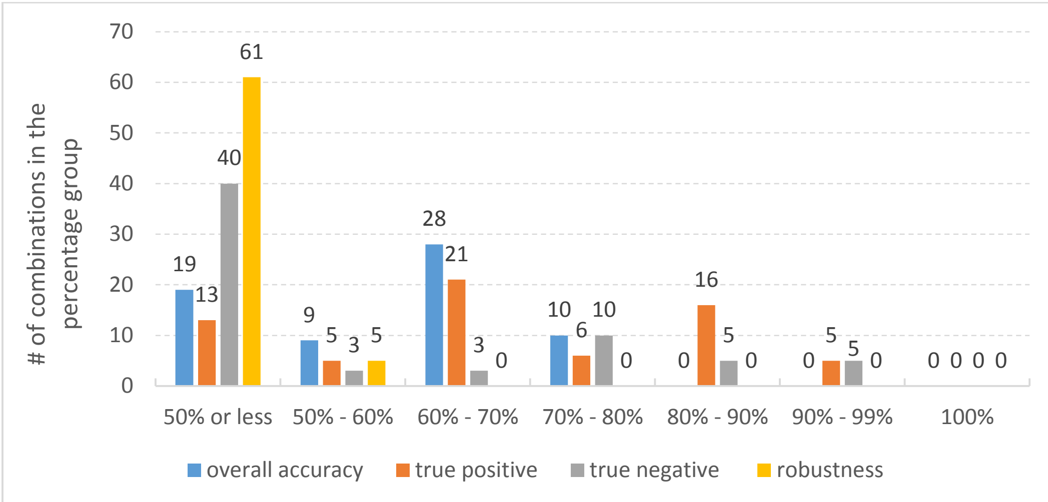

Figure C.61. Equal test-train classification results using a LDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (f).

Table C.61. Top 5 results of equal test-train LDA classification while choosing two PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	94%	50%	44%	PSD_1, PSD_9
	71%	94%	42%	35%	PSD_1, PSD_4
	68%	94%	33%	27%	PSD_1, PSD_6
	68%	94%	33%	27%	PSD_1, PSD_{11}
	64%	94%	25%	19%	PSD_1, PSD_5
In terms of *overall accuracy*	75%	94%	50%	44%	PSD_1, PSD_9
	75%	63%	92%	54%	PSD_2, PSD_3 PSD_3, PSD_6 PSD_3, PSD_7 PSD_3, PSD_{10} PSD_3, PSD_{12}
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of two bands at a time – QDA:

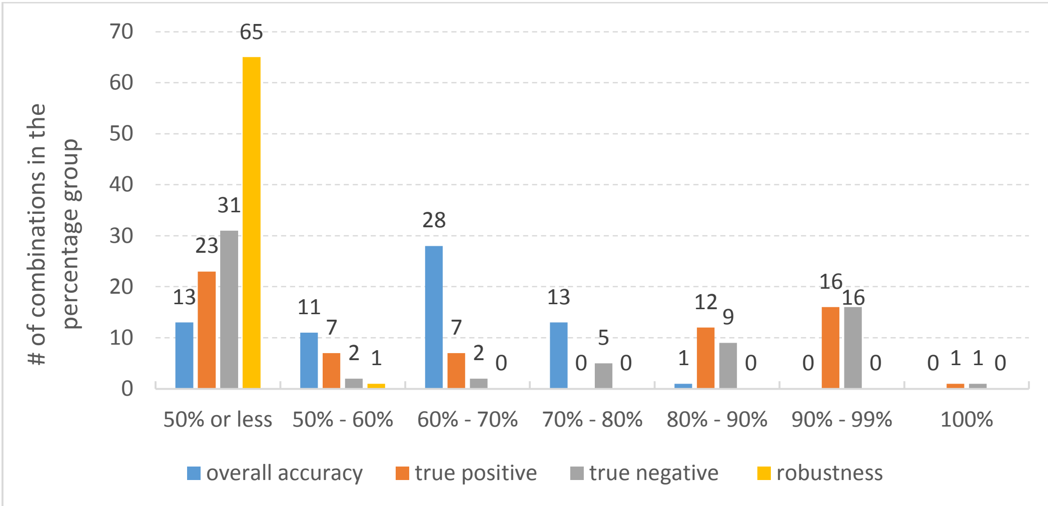

Figure C.62. Equal test-train classification results using a QDA classifier while choosing two PSD bands at a time for the frequency range detailed in point (f).

Table C.62. Top 5 results of equal test-train QDA classification while choosing two PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	100%	58%	58%	PSD_1, PSD_9
	75%	94%	50%	44%	PSD_1, PSD_6
	75%	94%	50%	44%	PSD_2, PSD_9
	71%	94%	42%	35%	PSD_1, PSD_3 PSD_1, PSD_4 PSD_1, PSD_5 PSD_1, PSD_{10} PSD_1, PSD_{12} PSD_3, PSD_9 PSD_7, PSD_9
	-	-	-	-	-
In terms of *overall accuracy*	82%	100%	58%	58%	PSD_1, PSD_9
	75%	94%	50%	44%	PSD_1, PSD_6
	75%	94%	50%	44%	PSD_2, PSD_9
	71%	94%	42%	35%	PSD_1, PSD_3 PSD_1, PSD_4 PSD_1, PSD_5 PSD_1, PSD_{10} PSD_1, PSD_{12} PSD_3, PSD_9 PSD_7, PSD_9
	-	-	-	-	-

- Equal test-train when choosing a combination of two bands at a time – SVM:

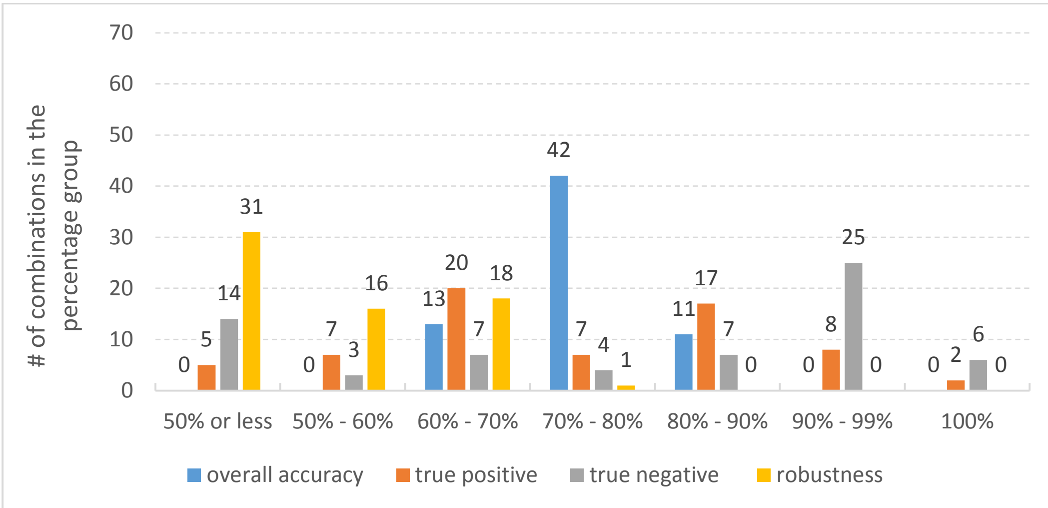

Figure C.63. Equal test-train classification results using a SVM classifier while choosing two PSD bands at a time for the frequency range detailed in point (f).

Table C.63. Top 5 results of equal test-train SVM classification while choosing two PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	75%	100%	42%	42%	PSD_4, PSD_8
	68%	100%	25%	25%	PSD_6, PSD_9
	79%	94%	58%	52%	PSD_1, PSD_9
	75%	94%	50%	44%	PSD_7, PSD_9 PSD_8, PSD_9
	-	-	-	-	-
In terms of *overall accuracy*	86%	88%	83%	71%	PSD_3, PSD_{10}
	82%	88%	75%	63%	PSD_1, PSD_5 PSD_1, PSD_6 PSD_1, PSD_{12}
	82%	81%	83%	65%	PSD_2, PSD_{10} PSD_3, PSD_{11}
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – LDA:

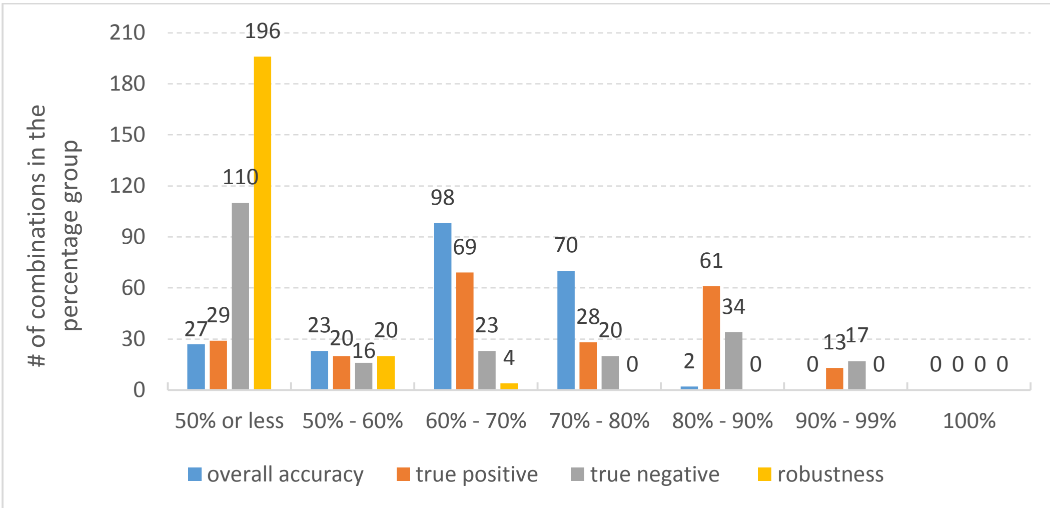

Figure C.64. Equal test-train classification results using a LDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (f).

Table C.64. Top 5 results of equal test-train LDA classification while choosing three PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	94%	67%	60%	PSD_1, PSD_3, PSD_9
	75%	94%	50%	44%	PSD_1, PSD_4, PSD_9 PSD_1, PSD_5, PSD_9 PSD_1, PSD_6, PSD_9 PSD_1, PSD_7, PSD_9 PSD_1, PSD_8, PSD_9 PSD_1, PSD_9, PSD_{11} PSD_1, PSD_9, PSD_{12}
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	82%	94%	67%	60%	PSD_1, PSD_3, PSD_9
	82%	81%	83%	65%	PSD_1, PSD_2, PSD_9
	79%	75%	83%	58%	PSD_1, PSD_2, PSD_8 PSD_1, PSD_3, PSD_6 PSD_1, PSD_3, PSD_8
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – QDA:

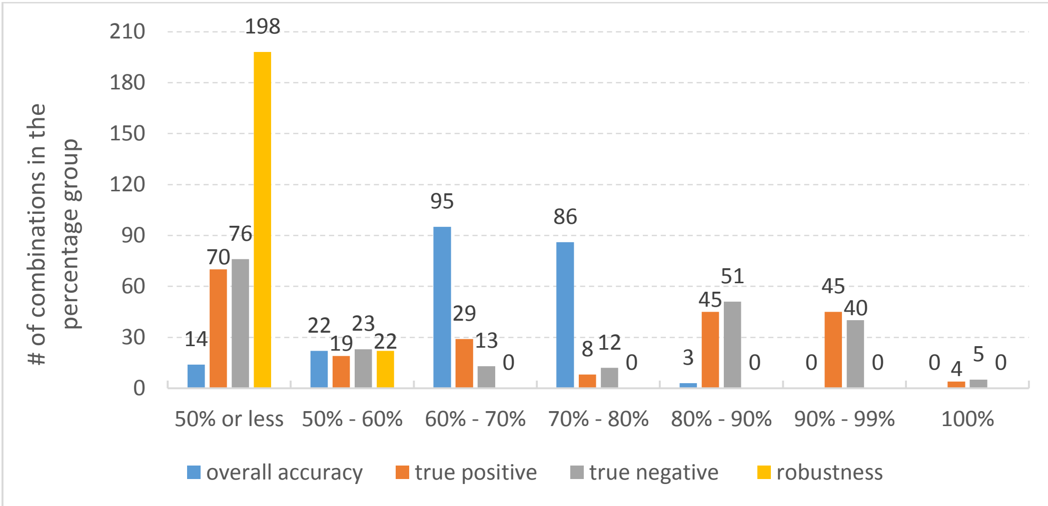

Figure C.65. Equal test-train classification results using a QDA classifier while choosing three PSD bands at a time for the frequency range detailed in point (f).

Table C.65. Top 5 results of equal test-train QDA classification while choosing three PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	82%	100%	58%	58%	PSD_1, PSD_9, PSD_{10} PSD_1, PSD_9, PSD_{11} PSD_1, PSD_9, PSD_{12}
	79%	100%	50%	50%	PSD_1, PSD_{10}, PSD_{12}
	79%	94%	58%	52%	PSD_1, PSD_3, PSD_9 PSD_1, PSD_4, PSD_9 PSD_1, PSD_2, PSD_9 PSD_1, PSD_5, PSD_9 PSD_1, PSD_6, PSD_{10} PSD_1, PSD_7, PSD_9 PSD_1, PSD_8, PSD_9 PSD_2, PSD_9, PSD_{11} PSD_3, PSD_9, PSD_{11}
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	82%	100%	58%	58%	PSD_1, PSD_9, PSD_{10} PSD_1, PSD_9, PSD_{11} PSD_1, PSD_9, PSD_{12}
	79%	100%	50%	50%	PSD_1, PSD_{10}, PSD_{12}
	79%	94%	58%	52%	PSD_1, PSD_3, PSD_9 PSD_1, PSD_4, PSD_9 PSD_1, PSD_2, PSD_9 PSD_1, PSD_5, PSD_9 PSD_1, PSD_6, PSD_{10} PSD_1, PSD_7, PSD_9 PSD_1, PSD_8, PSD_9 PSD_2, PSD_9, PSD_{11} PSD_3, PSD_9, PSD_{11}
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of three bands at a time – SVM:

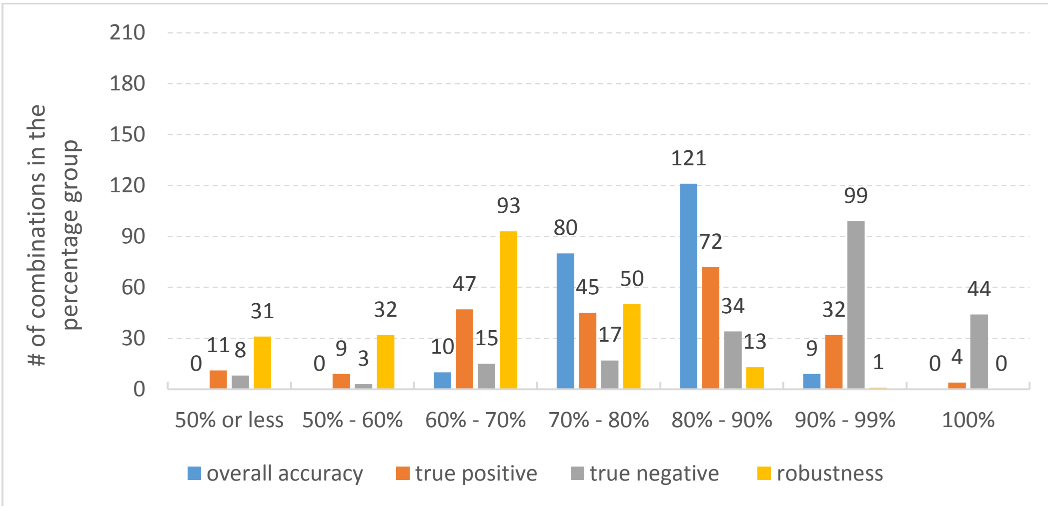

Figure C.66. Equal test-train classification results using a SVM classifier while choosing three PSD bands at a time for the frequency range detailed in point (f).

Table C.66. Top 5 results of equal test-train SVM classification while choosing three PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	96%	100%	92%	92%	PSD_3, PSD_5, PSD_{10}
	86%	100%	67%	67%	PSD_1, PSD_5, PSD_8
	82%	100%	58%	58%	PSD_1, PSD_5, PSD_9
	75%	100%	42%	42%	PSD_6, PSD_7, PSD_8
	93%	94%	92%	85%	PSD_2, PSD_3, PSD_{10} PSD_2, PSD_3, PSD_{11} PSD_1, PSD_3, PSD_9 PSD_3, PSD_4, PSD_{10} PSD_3, PSD_{10}, PSD_{11} PSD_3, PSD_{10}, PSD_{12}
In terms of *overall accuracy*	96%	100%	92%	92%	PSD_3, PSD_5, PSD_{10}
	93%	94%	92%	85%	PSD_2, PSD_3, PSD_{10} PSD_2, PSD_3, PSD_{11} PSD_1, PSD_3, PSD_9 PSD_3, PSD_4, PSD_{10} PSD_3, PSD_{10}, PSD_{11} PSD_3, PSD_{10}, PSD_{12}
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – LDA:

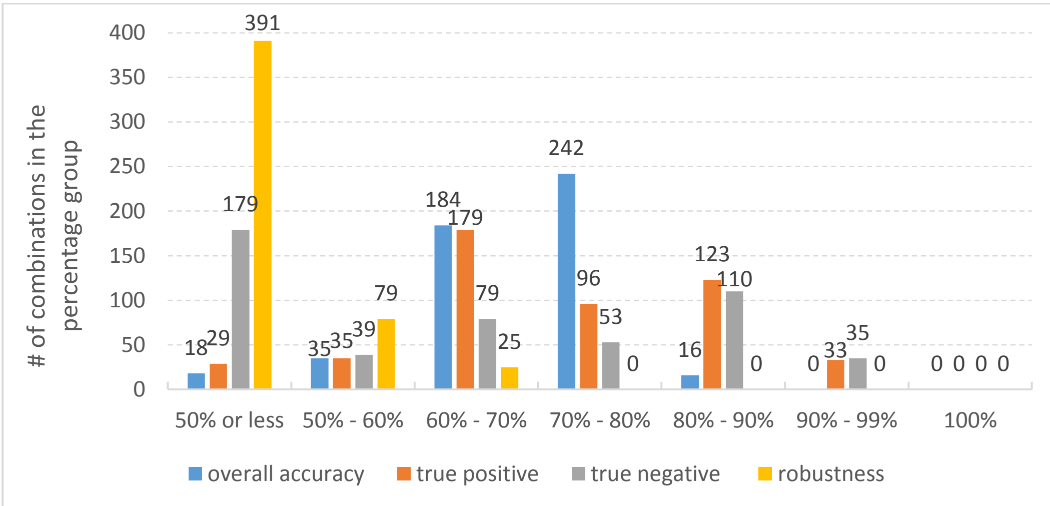

Figure C.67. Equal test-train classification results using a LDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (f).

Table C.67. Top 5 results of equal test-train LDA classification while choosing four PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	86%	94%	75%	69%	PSD_1, PSD_3, PSD_9, PSD_{11} PSD_1, PSD_3, PSD_5, PSD_9
	82%	94%	67%	60%	PSD_1, PSD_3, PSD_9, PSD_{10} PSD_1, PSD_3, PSD_8, PSD_9 PSD_1, PSD_3, PSD_9, PSD_{12} PSD_1, PSD_3, PSD_7, PSD_9
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	86%	94%	75%	69%	PSD_1, PSD_3, PSD_9, PSD_{11} PSD_1, PSD_3, PSD_5, PSD_9
	82%	94%	67%	60%	PSD_1, PSD_3, PSD_9, PSD_{10} PSD_1, PSD_3, PSD_8, PSD_9 PSD_1, PSD_3, PSD_9, PSD_{12} PSD_1, PSD_3, PSD_7, PSD_9
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – QDA:

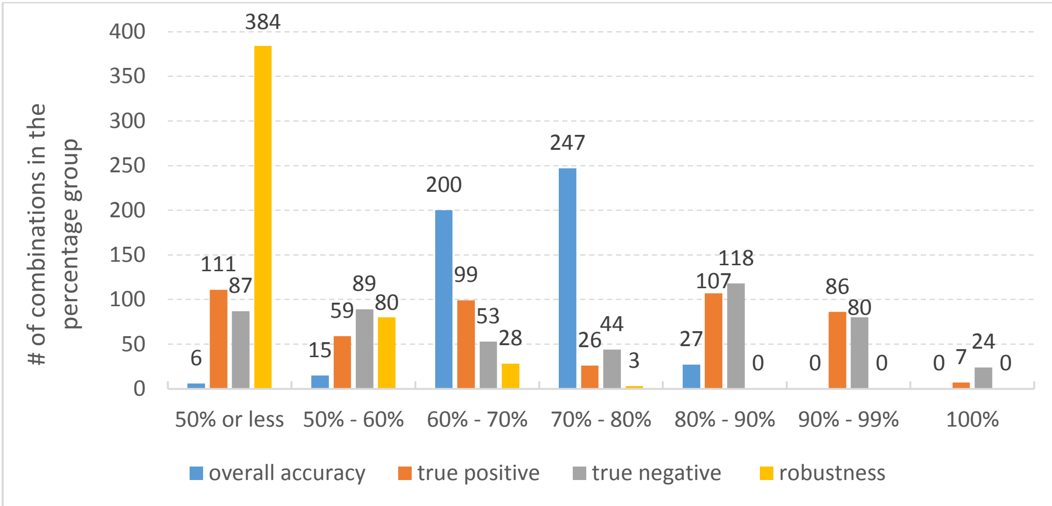

Figure C.68. Equal test-train classification results using a QDA classifier while choosing four PSD bands at a time for the frequency range detailed in point (f).

Table C.68. Top 5 results of equal test-train QDA classification while choosing four PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	86%	100%	67%	67%	PSD_1, PSD_2, PSD_9, PSD_{10}
	82%	100%	58%	58%	PSD_1, PSD_8, PSD_9, PSD_{12} PSD_1, PSD_7, PSD_9, PSD_{10} PSD_1, PSD_9, PSD_{10}, PSD_{11} PSD_1, PSD_3, PSD_9, PSD_{10} PSD_1, PSD_9, PSD_{10}, PSD_{12}
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	86%	100%	67%	67%	PSD_1, PSD_2, PSD_9, PSD_{10}
	86%	88%	83%	71%	PSD_3, PSD_5, PSD_9, PSD_{11}
	86%	75%	100%	75%	PSD_4, PSD_5, PSD_6, PSD_{10} PSD_3, PSD_4, PSD_5, PSD_6
	82%	100%	58%	58%	PSD_1, PSD_8, PSD_9, PSD_{12} PSD_1, PSD_7, PSD_9, PSD_{10} PSD_1, PSD_9, PSD_{10}, PSD_{11} PSD_1, PSD_3, PSD_9, PSD_{10} PSD_1, PSD_9, PSD_{10}, PSD_{12}
	-	-	-	-	-

- Equal test-train when choosing a combination of four bands at a time – SVM:

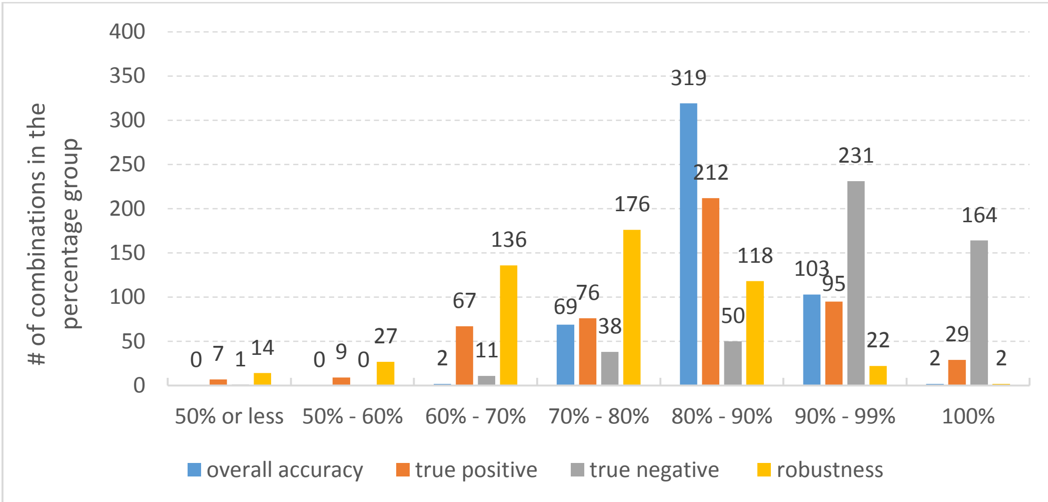

Figure C.69. Equal test-train classification results using a SVM classifier while choosing four PSD bands at a time for the frequency range detailed in point (f).

Table C.69. Top 5 results of equal test-train SVM classification while choosing four PSD bands at a time for the frequency range detailed in point (f) by 1) true positive followed by robustness and 2) overall accuracy.

Reference of top 5 results	*overall accuracy*	*true positive*	*true negative*	*robustness*	Combination details
In terms of *true positive* followed by *robustness*	100%	100%	100%	100%	PSD_3, PSD_5, PSD_7, PSD_{10} PSD_1, PSD_3, PSD_7, PSD_{10}
	96%	100%	92%	92%	PSD_3, PSD_5, PSD_{10}, PSD_{12} PSD_3, PSD_5, PSD_{10}, PSD_{11} PSD_3, PSD_5, PSD_{11}, PSD_{12} PSD_3, PSD_5, PSD_9, PSD_{10} PSD_3, PSD_5, PSD_8, PSD_{10} PSD_3, PSD_5, PSD_6, PSD_{10} PSD_3, PSD_4, PSD_{10}, PSD_{12} PSD_3, PSD_4, PSD_{10}, PSD_{11} PSD_3, PSD_4, PSD_6, PSD_{10} PSD_3, PSD_4, PSD_5, PSD_{10} PSD_2, PSD_3, PSD_9, PSD_{10} PSD_2, PSD_3, PSD_8, PSD_{10} PSD_1, PSD_5, PSD_8, PSD_{10} PSD_1, PSD_3, PSD_9, PSD_{10} PSD_1, PSD_3, PSD_8, PSD_{10} PSD_1, PSD_3, PSD_5, PSD_{10}
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-
In terms of *overall accuracy*	100%	100%	100%	100%	PSD_3, PSD_5, PSD_7, PSD_{10} PSD_1, PSD_3, PSD_7, PSD_{10}
	96%	100%	92%	92%	PSD_3, PSD_5, PSD_{10}, PSD_{12} PSD_3, PSD_5, PSD_{10}, PSD_{11} PSD_3, PSD_5, PSD_{11}, PSD_{12} PSD_3, PSD_5, PSD_9, PSD_{10} PSD_3, PSD_5, PSD_8, PSD_{10} PSD_3, PSD_5, PSD_6, PSD_{10} PSD_3, PSD_4, PSD_{10}, PSD_{12} PSD_3, PSD_4, PSD_{10}, PSD_{11} PSD_3, PSD_4, PSD_6, PSD_{10} PSD_3, PSD_4, PSD_5, PSD_{10} PSD_2, PSD_3, PSD_9, PSD_{10} PSD_2, PSD_3, PSD_8, PSD_{10} PSD_1, PSD_5, PSD_8, PSD_{10} PSD_1, PSD_3, PSD_9, PSD_{10} PSD_1, PSD_3, PSD_8, PSD_{10} PSD_1, PSD_3, PSD_5, PSD_{10}
	-	-	-	-	-
	-	-	-	-	-
	-	-	-	-	-