EEG BASED AUTOMATED IDENTIFICATION OF SCHIZOPHRENIA FROM FBSE-EWT TECHNIQUE

M.Tech. Thesis

By

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DISCIPLINE OF ELECTRICAL ENGINEERING

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EEG BASED AUTOMATED IDENTIFICATION OF SCHIZOPHRENIA FROM FBSE-EWT TECHNIQUE

A THESIS

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **EEG BASED AUTOMATED IDENTIFICATION OF SCHIZOPHRENIA FROM FBSE-EWT TECHNIQUE** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the DISCIPLINE OF ELECTRICAL ENGINEERING, Indian Institute of Technology **Indore**, is an authentic record of my own work carried out during the time period from July 2019 to June 2020 under the supervision of Prof. Ram Bilas Pachori, Professor, Discipline of Electrical Engineering, IIT Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Manoj
28/06/2020

Signature of the student with date
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This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

28.06.2020

Signature of the Supervisor of
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Abstract

Monitoring of the brain's activity usually done by analyzing electroencephalogram (EEG) signals, EEG signals are helpful to predict abnormal behavior of the brain. The purpose of this thesis is to develop an efficient method for diagnosis of schizophrenia. Already there are many existing techniques for the classification of EEG signals. In previous studies, EEG signal has been analysed for many applications and for diagnosis of many diseases using empirical wavelet transform (EWT) and Fourier-Bessel series expansion (FBSE) techniques. The proposed method uses FBSE-EWT as a combined tool to analyse and detect the important characteristic of the EEG signals. In our method, we have used this FBSE-EWT technique to decompose EEG signal into sub-bands. Here FBSE uses Bessel functions as bases, Bessel function are non-stationary signals which are suitable for analyzing non-stationary signals like EEG. Now after getting sub-bands we have applied Hilbert spectral analysis method for getting time-frequency representation (TFR) of these sub-bands. Here, these TFRs have been fed as input to the convolution neural network (CNN) classifier and this classifier has been obtained a maximum accuracy of 100% in classifying normal and schizophrenia disease classes of EEG signal.

Contents

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List of abbreviations

EEG	Electroencephalogram
WHO	World health organization
CNN	Convolution neural network
TF	Time-frequency
TFR	Time-frequency representation
FBSE	Fourier-Bessel series expansion
EWT	Empirical wavelet transform
MRI	Magnetic resonance imaging
ADC	Analog to digital converter
ANOVA	Analysis of variance
AM	Amplitude modulation
FM	Frequency modulation
FFT	Fast Fourier transform
IMF	Intrinsic mode function
ROC	Receiver operating characteristic
TP	True positive
FP	False positive
TN	True negative
FN	False negative

Chapter 1

Introduction

Human brains are complex in nature, it stores highly non-linear and non-stationary behavior. The electrical activity of brain of human body is generally determined from electroencephalogram (EEG) signals, and these signals are time-varying and non-linear signals [1], [2]. The EEG signals contained a lot of information related to brain and for brain related disorders, like sleep disorders [3], depression [4], Parkinson's disease [5], coma [6], brain death [7], tumour [8], stroke [9], classification of emotions [10], schizophrenia [11] etc. Malfunction of the brain by any disorder affects the brains usual activity. Schizophrenia is a mental disorder which influences the behavior as well as thinking ability. Report of world health organization (WHO) has proved that schizophrenia is a serious health issue, which affected more than 20 million people all across the world [12]. Yet, WHO has also said that it is treatable and early or post detection of this disease will be helpful to recognize its seriousness and stages. Diagnosis and therapy of schizophrenia is necessary in human, since it produces major inconvenience related to memory, thinking ability, reasoning, and other normal activities. If left untreated it may create major issues that will damage the human thinking and behavioral abilities in its later stages [13]. Early as well as post diagnosis of schizophrenia may help while implanting possible therapy methods to cure or reduce its bad effects. Recently many methods have been developed and applied by investigators to investigate schizophrenia based on EEG signals.

EEG signals are recorded using suitable electrodes placed on the certain fixed places of the scalp can be helpful to disclose essential details related to brains normal activities; also inspection of these signals might be helpful to diagnosis the situation of brain [14-16]. Recent researches provide perception of classification using EEG patterns of schizophrenia.

Now day's use of convolution neural network (CNN) is increasing in area of research with very rapid rate. A CNN is a deep learning algorithm which takes images as input and then classify between two classes/objects. In many researches it has been found that CNN has been used to classify between two EEG classes using time-frequency representation (TFR) [17]. A TFR is a view of a signal (frequency as a function of time) represented over both frequency and time.

Many efforts have been devoted over the last few years towards developing efficient techniques for diagnosis of schizophrenia using EEG signals. The scope of this thesis is to examine the potential of Fourier-Bessel series expansion (FBSE) based empirical wavelet transform (EWT) (FBSE-EWT) along with CNN for diagnosis of schizophrenia. This chapter discusses about brief introduction of EEG signals, basic of EEG recording and an overview of the literature on existing methods for diagnosis of schizophrenia from EEG signals.

1.1 Electroencephalogram (EEG)

The EEG is a non-invasive and relatively less expensive method used to monitor the mechanism of the brain. The International Federation of Clinical Neurophysiology defines the EEG as "(1) the science relating to the electrical activity of brain, and (2) the method of acquiring EEG" [18]. EEG has many medical uses which are from scanning arousal states or normal wakefulness to complex medical situation involving seizure attacks or brain abnormality or any other serious problem related to brain and critical thinking. EEG signals are acquired with the electrodes placed on the different places of the scalp (different-different electrode uses different characteristic). Interpretation of this large data (even when data recorded from a single channel) is a challenge; to complete this challenge signal processing and analysis methods are needed. Signal examination and interpretation of these collected brain signals are done by signal processing methods. The most interesting and important thing about EEG is that it is continuous indicator of brain functions so that one can continuously monitor brain's activity. EEG gives excellent temporal resolution significantly better than existing imaging techniques like magnetic resonance imaging (MRI) [19].

EEG signal waves are usually not regular with complex pattern. Conventionally EEG has divided into four spectral bands: alpha, beta, delta, and theta. These bands are briefly explained as;

- Delta (0-4 Hz): The lowest frequency band is delta band, which ranges from zero to four Hz. Normally delta waves are seen while sleeping, or in any critical brain disorder. Normally animals are having more activities in this frequency range.
- Theta (4–7 Hz): Signal waves between 4 to 7 Hz are termed as theta waves. Specially parietal and temporal regions of a child's brain are monitored by these theta waves. In a healthy adult such slow activities are not present, but can be observed during certain stages of sleep or during emotional stress (frustration and disappointment).
- Alpha (8–13 Hz): Frequency range between 8 to 13 Hz represents alpha waves. Signal waves for this region are often acquired from occipital region and also from frontal regions.

- Beta (13–30 Hz): Frequency ranges between 13 to 30 Hz (sometimes up to 50 Hz) are known as beta waves. These waves are generally recorded from frontal region as well as parietal lobes.

1.2 Basic of EEG recording

For acquisition of the EEG signals the signals must be collected from the human's body, which are acquired by electrodes placed on the certain fixed places of the scalp. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal on the electrodes. Because push and pull (movement of electrons) of electrons easily conducts by the metal, the difference between any two electrodes can be measured as a voltage. So these recording of voltages give us EEG. Now because EEG signals are very week in nature (very low voltage signals) so that it can be easily affected by noise so one have to be more careful while recording EEG signal [20]. There is a cap in which electrodes are embedded; this cap is connected to the scalp through a specific gel. Now these electrodes are settled according to the international standards and number of electrodes are depends upon applications and international standards. Each electrode is connected to a one of the input of differential amplifier (one amplifier needed for one electrode) and a reference electrode is connected to the other input of the differential amplifier. This differential amplifier amplifies the voltage between the active electrode and the reference electrode. This amplified signal then passes through an anti-aliasing filter and then discretize through an analog to digital convertor. A simple block diagram for EEG recording is shown in Figure 1.1:

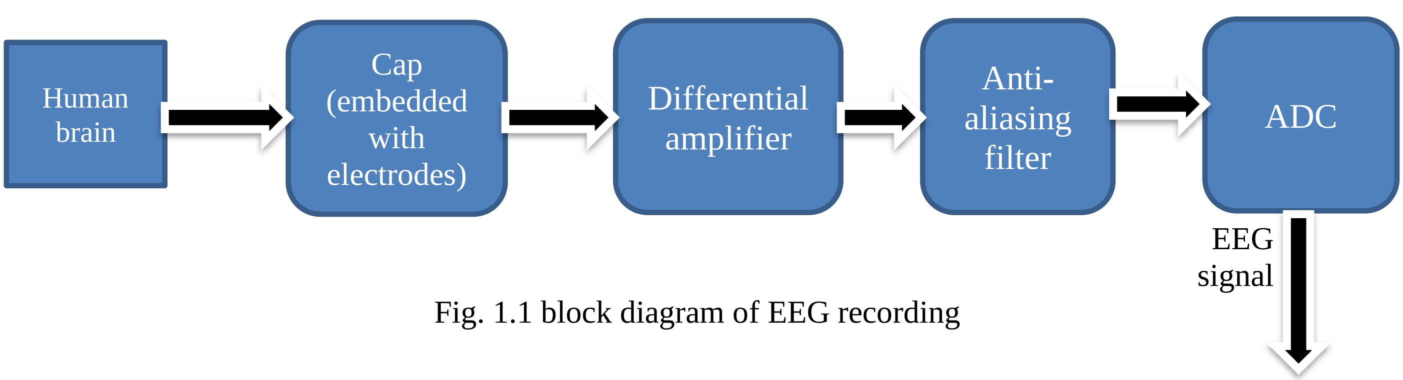


Fig. 1.1 block diagram of EEG recording

1.3 Overview of existing techniques for detection of schizophrenia from EEG signals

In the recent studies classification of schizophrenia has been done based on EEG patterns [21]. The summary of automated detection techniques employed for diagnosis of schizophrenia using EEG signals is as follows:

- Kim et al. [22] acquired EEG signals from gold cup electrodes setup, electrodes settled according to international standards. Participant's eye movements for vertical and horizontal directions were studied. And then after preprocessing, five bands were chosen for analysis purpose. Then by using fast Fourier transform (FFT) spectral power was computed of the EEG for each of the five frequency bands, after which EEG power deviations was studied using analysis of variance method. The receiver operating characteristic (ROC) technique was used to determine the characteristic and the diagnostic performance of a test, utilized in differentiating between healthy subject and schizophrenia patients. The maximum classification accuracy 62% was obtained for delta band in this experiment.
- Dvey-Aharon et al. [23] developed a technique which discuss about TFR based examination of the EEG signal for the diagnosis of schizophrenia. In their work EEG signal was converted into an image by using an approach called as Stockwell approach, and then the feature extraction and classification were done to get good results. Obtained maximum accuracy was between 92 to 93.9%.
- Johannesen et al. [24] collected EEG signals from participants using sixty-four channels system. In this work 60 features per participant were extracted. Participants were required to press one of the two response buttons, using either their right or left index finger. Theta 1 and theta 2, alpha, beta and gamma frequency bands analyzed during a working memory task (i.e. to indicate whether a particular letter was presented in the previous set). Then the brain vision analyser software was used to analyse signals and then segmentation of signals was implemented via four stage of processing. The support vector machine

(SVM) was used as a classifier to classify the classes. Classification accuracy of 84% was obtained using SVM model 1, and classification accuracy of 87% obtained, when SVM model 2 was implemented to classify between normal and schizophrenia in the correct trial data.

- Santos-Mayo et al. [25] analyzed EEG-event related potential (ERP) signals of participants; participants were involved in an ordinary task. Brain signals were recoded using brain vision equipment which was according to 10-20 international standards. Signals were preprocessed using EEG LAB after successful acquisition of EEG [26]. Total of 20 features per subject were extracted out of which sixteen were time-domain features and four were based on frequency-domain. Domination of features was decided using linear discriminant analysis and mutual information feature selection (MIFS) coupled with the double input symmetrical relevance (DISR). The multi-layer perceptron (MLP) and SVM classifier were employed for classification and highest classification rates of 93.4% and 92.23% were achieved.
- Ibanez-Molina et al. [27] used EEG signal to examine schizophrenia. In this, EEG recordings were acquired from participants when they were at relaxed position and were engaged in the reading task. The neuroscan synamps thirty two channel amplifier was used for data recording (i e. for EEG recording), segments were analysed using a moving window method. A total of 80 EEG segments of 2×10^3 ms were evaluated and the higher complexity values were monitored in right frontal regions patients who were relaxed.
- V. Jahmunah et al. [28], developed 11 layer deep CNN model to examine schizophrenia and classifying between normal and schizophrenia. There were two separate neural network models for subject base testing and non-subject base testing. The whole examination was divided into three phase namely training, testing and validation. K-fold validation was used while training. Approximately 86% data were used for training, 7% data for validation and 7% for testing. Accuracy of 81.26% was obtained for subject base testing and 98.07% for non-subject base testing.

1.4 Motivation

EEG signals are weak in nature (i e. in micro volt range) and can be easily affected by noise, so due to this corruption, analysis of EEG signals becomes more difficult also EEG signals are non-stationary signals which are difficult to analyse. In previous studies many researches have been done for diagnosis of schizophrenia but due to non-stationary nature of EEG signal there were some kind of complexity in diagnosis of the disease. In previous studies EWT [62, 66] has been used for analyzing these non-stationary signals, further to enhance this FBSE [53, 67] has been used to analyze non-stationary signals. The motivation came from here, if we can create a technique which can easily analyse the EEG signals and its characteristics and the early diagnosis of schizophrenia can be done so it will be easy to cure a patient from this disease, if one can analyse EEG signals in better manner so that diagnosis will be easy. So here for analyzing non-stationary signals we are using FBSE-EWT [43, 54] method which gives better resolution in terms of frequency also uses EWT filter banks which gives more accurate analysis of EEG signals.

1.5 Contribution of thesis

The purpose of the thesis is to provide better and more adoptable technique for diagnosis of schizophrenia by handling EEG signals more appropriately. In our proposed method we have applied FBSE which results spectral representation with much better frequency resolution of the multicomponent signals. Scale-space method based on boundary detection technique has been applied for estimating boundary frequencies accurately. Based on EWT, filter banks have been generated to decompose non-stationary multi-component signals into narrow-band components. Here we are having Bessel functions as basis function of FBSE which are also non-stationary signals. We have compared results of proposed method with existing techniques in terms of classification accuracy.

1.6 Organization of thesis

The rest of the thesis is organized as follows:

- Chapter 2 presents the detailed description of frequency spectrum using FBSE method, scale-space boundary detection technique for accurately estimating boundary frequencies, and wavelet based filter banks, EWT and FBSE-EWT method.
- Chapter 3 presents database and proposed methodology for diagnosis of schizophrenia from EEG signals using FBSE-EWT method.
- Chapter 4 presents results and discussion section and also we have compared the results with previous existing techniques in terms of classification accuracy.
- Chapter 5 presents the conclusion section also discussed about the future opportunities related to this work.

1.7 Summary

In this chapter we have discussed about EEG signals in detail. About basics of EEG recording and basic components needed for recording EEG signals also discussed about few existing methods. We have discussed difficulties while analyzing EEG signals; existing techniques have some difficulties for analyzing EEG signals due to its non-stationary nature. So our purpose is to analyse EEG signal more accurately and more precisely and to classify between schizophrenia and normal classes more accurately in terms of classification accuracy, sensitivity, specificity.

Chapter 2

FBSE, Scale-Space, EWT and FBSE-EWT

2.1 Introduction

In this chapter we will discuss about FBSE, Scale Space, EWT, Bessel functions and FBSE-EWT method. We will use scale-space method for estimating boundary frequencies which is based boundary detection technique. Scale space boundary detection method works on local minima concept, in this, two local minima will be used for deciding meaningful modes. We will discuss about FBSE method which is used for representing spectral behavior of multicomponent signals also having good frequency resolution of signal components. In this EWT filter banks have been generated to decompose multicomponent signals into narrow-band components. The FBSE uses Bessel function as basis functions, which are damped in nature; due to this FBSE technique becomes suitable for non-stationary signals. Then Hilbert spectral analysis has been used for TFR of the sub-bands.

2.2 FBSE

Many researches have research work using FBSE method, out of which some of them are as follows:

In [29], author discussed about FBSE method for signal processing. The author has shown theory and simulation results related to FBSE method.

In [30], a combination of FBSE and Wigner–Ville distribution (WVD) has been used for TFR of the signal. FBSE decomposes the signal and then WVD is applied for analyzing TFR of the signal.

The FBSE uses Bessel functions as bases because Bessel functions are non-stationary signals, that is Bessel functions are suitable for non-stationary signals like EEG signals, EEG signals are time varying in nature and gives better spectral representation. Suppose $Y(n)$ is a signal then using zero-order Bessel functions, FBSE of $Y(n)$ is as follows [31-33]:

$$Y(n) = \sum_{l=1}^{M} C_l \, J_0\left(\frac{\alpha_l n}{M}\right), \qquad n = 0,1, \dots \dots . . M-1 \tag{2.2.1}$$

Where, C_l is the Fourier-Bessel series coefficient of $Y(n)$which will be express as [31-32]

$$C_l = \frac{2}{M^2\left(J_1(\alpha_l)\right)^2} \sum_{n=0}^{M-1} nY(n) J_0\left(\frac{\alpha_l n}{M}\right) \tag{2.2.2}$$

Where, $J_1(.)$ and $J_0(.)$ denote first-order and zero-order Bessel functions respectively. The positive roots in ascending order of the zero order Bessel function ($J_0(\alpha)$=0) are denoted by α_l with $l = 1,2 \dots \dots . . M$. It should be noted that, order l of the FB series coefficients is related to continuous time frequency f_l (in Hz) where it has peak value, by the following equation [31-32]:

$$\alpha_l \approx \frac{2\pi f_l M}{f_s}, \qquad where\ \alpha_l \approx \alpha_{l-1} + \pi \ \approx l\pi \tag{2.2.3}$$

In above equation, f_s denotes the sampling frequency, the equation (2.2.3) can be expressed as [32,33,34]

$$l \approx \frac{2f_l M}{f_s} \tag{2.2.4}$$

Hence it is clear from above equation that l should be varied from 1 to M to cover complete bandwidth of the analyzed signal.

Spectral representation using FBSE method has many advantages over conventional methods like FFT which are as follows:

- FBSE spectral representation has compact representation as compared to conventional spectral representation methods [35-36]. Authors [37] found that due to use of Bessel functions which has decaying amplitude there is effective bandwidth of a signal which is contribution of amplitude modulation bandwidth and frequency modulation bandwidth.
- FBSE spectral representation removes the windowing effect [32]. In order to reduce spectral errors, FFT based spectral representation is implanted with window function. For short duration signals FBSE can analyze signal characteristic without windowing effect.
- In FBSE spectral representation number of coefficients required is equal to length of the signal. While in the conventional FFT spectrum length is the half of the analyzed signal [36]. Hence FBSE's spectral representation has much better resolution than FFT based method.

2.3 Scale-space representation

In [32] author used local maxima concept for boundary detection of signals, but this method was failed to detect accurate boundaries in the case of real time signals. If spectrum consist distinct modes, then only this task gives effective results and one can easily calculate local maxima and detect the boundaries [53]. Again there is a problem with the method [33]; it detects boundary equidistance to two successive maxima. An easy solution of this problem is to use concept of local minima i.e. to use lowest minima concept for deciding the boundaries [47].

When we analyze spectral representation of a signal, so one can conclude that in the same mode a lot of energy is concentrated within a lot of local maxima. Now this situation can be eliminate before the detection task; in the analyzed signal spectrum logarithm must be used to remove the global trend. This process is called as globe trend removing method [72].

Let we have discrete time signal $Y(n)$ and also we have a Gaussian kernel, then the space-space representation of the signal $Y(n)$ will be computed by the convolution of signal $Y(n)$ with the Gaussian kernel, which can be expressed as [32]:

$$\gamma(l,T) = \sum_{n=-L}^{L} Y(l-n)F(n;T) \qquad (2.3.1)$$

Where,

$$F(n;T) = \frac{1}{\sqrt{2\pi T}} e^{\frac{-n^2}{2T}} \qquad (2.3.2)$$

Where $L = X\sqrt{T} + 1$ with $3 \leq X \leq 6$ and T is known as scale parameter. It should be noted that, as the scale-step parameter or scale parameter $\left(\tau = \sqrt{\frac{T}{T_0}}\ ,\ \tau = 1,2,3 \ldots \ldots \ldots \ldots \tau_{\max}\right)$

2.4 EWT method

EWT was proposed in [36] for the analysis of time varying signals or non-stationary signals, it is an adaptive signal decomposition method and is based on formation of adaptive wavelet filters. These filter banks are the decider of the sub-bands, after processing through these wavelet filter banks signal decomposes into sub-bands. These obtained sub-bands have specific center frequencies after EWT and have compact frequency support. Method of the EWT is summarised as follows:

- The frequency spectrum of the signal is obtained by FFT, where the frequency ranges from 0 to π.
- Suppose according to an application one wants *M* number of sub bands then by using EWT boundary detection method frequency spectrum will be segmented into *M* number of segments. Then by using scale-space boundary detection technique we got set of boundary frequencies (W_i) [37].
- Set of band-pass filters is defined by the empirical scaling and wavelet functions. The idea of construction of wavelet filter banks was adopted from the idea of construction of Littlewood-Paley and Mayer’s wavelets [36, 37].

There is an empirical scaling function $B_l(W)$ and wavelet function $\delta_l(W)$, mathematical expressions for these two are as follows:

$$B_l(W) = \begin{cases} 1 & if\ |W| \leq (1-\varepsilon)W_l \\ \cos[\frac{\pi\sigma(\varepsilon,W_l)}{2}] & if\ (1-\varepsilon)W_l \leq |W| \leq (1+\varepsilon)W_l \\ 0 & \text{otherwise} \end{cases} \tag{2.4.1}$$

$$\delta_l(W) = \begin{cases} 1 & \text{if } (1+\varepsilon)W_l \le |W| \le (1-\varepsilon)W_{l+1} \\ \cos[\frac{\pi\sigma(\varepsilon, W_{l+1})}{2}] & \text{if } (1-\varepsilon)W_{l+1} \le |W| \le (1+\varepsilon)W_{l+1} \\ \sin[\frac{\pi\sigma(\varepsilon, W_l)}{2}] & \text{if } (1-\varepsilon)W_l \le |W| \le (1+\varepsilon)W_l \\ 0 & \text{otherwise} \end{cases} \quad (2.4.2)$$

Now in above two expressions used mathematical function $\sigma(\varepsilon, W_l)$ is as follows:

$$\sigma(\varepsilon, W_l) = \omega\left(\frac{(|W| - (1-\varepsilon)W_l}{2\varepsilon W_l}\right) \quad (2.4.3)$$

Where $\omega(x)$ is an arbitrary function and can be defined as [41];

$$\omega(x) = \begin{cases} 0, & \text{if } x \le 0 \\ \text{and } \omega(x) + \omega(1-x) = 1 & \forall\, x \in [0\ 1] \\ 1 & \text{if } x \ge 1 \end{cases} \quad (2.4.4)$$

The condition of tight frame is expressed as;

$$\varepsilon < \min_l\left(\frac{W_{l+1} - W_l}{W_{l+1} + W_l}\right)$$

Now the approximation coefficients of wavelet and scaling functions which are the convolution with the analysed signal v(n) are as follows:

$$\left.\begin{aligned} Y_{v,\delta}(l,t) &= \int v(\mu)\overline{\delta_l(\mu - t)}\, d\mu \\ Y_{v,B}(0,t) &= \int v(\mu)\overline{B_1(\mu - t)}\, d\mu \end{aligned}\right\} \quad (2.4.5)$$

Where $Y_{v,\delta}(l,t)$ denotes the detail coefficients of l^{th} oscillatory level, whereas $Y_{v,B}(0,t)$ denotes the approximation coefficients.

Finally, the reconstructed sub-band signals can be defined as [41],

$$P_0(t) = Y_{v,B}(0,t) * B_1(t) \quad (2.4.6)$$
$$P_l(t) = Y_{v,\delta}(l,t) * \delta_l(t) \quad (2.4.7)$$

Where $P_0(t)$ is the approximate sub-band signal and $P_l(t)$ represents detail sub-band signals of l^{th} level.

2.5 FBSE-EWT method

In this combined FBSE-EWT method [41], first we apply FBSE on the signal. FBSE [53] uses Bessel functions as bases which are non-stationary signals, this non-stationary factor helps FBSE to analyse non-stationary signals due to which FBSE gives better spectral representation having better frequency resolution as compared to other conventional transforms like FFT. FBSE has compact frequency representation as compared to FFT. After that we apply scale-space method based on boundary detection technique for estimating boundary frequencies of FBSE spectrum accurately. Which results the segmentation of spectrum and signal decomposition into sub-bands using filter banks. The EWT [44, 56] mechanism is mainly for developing wavelet filter banks and these filter banks are responsible for getting meaningful modes. After getting sub-bands of the signals we will apply Hilbert spectral analysis to get TFR for each channel of the signal. Here the complete block diagram of FBSE-EWT [41, 43, 54] process is shown in Fig. 2.1:

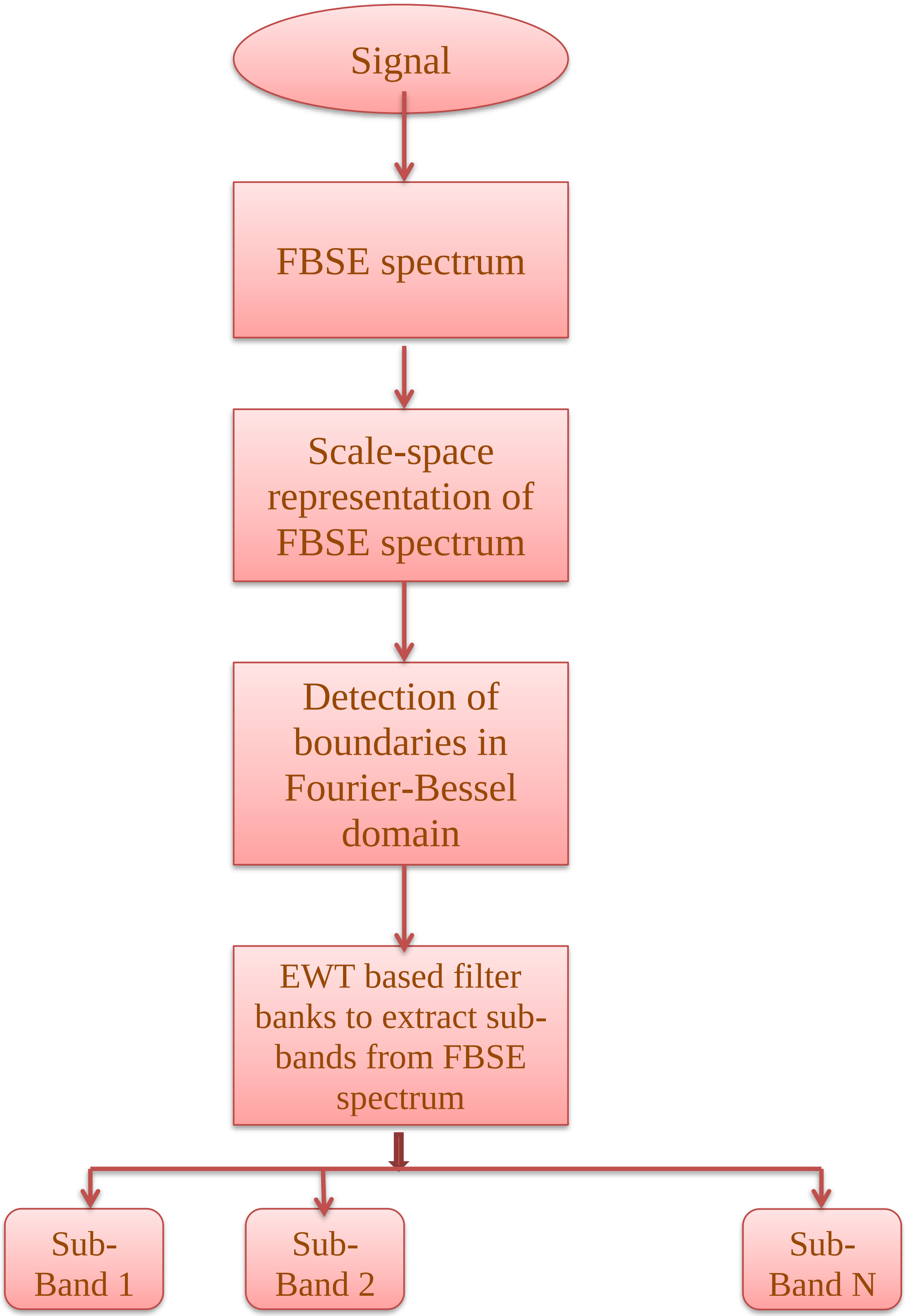


Fig. 2.1 Block diagram of the FBSE-EWT method

2.6 Summary

In this chapter we discussed about FBSE, scale-space representation, EWT filter banks, EWT and the combined process of FBSE-EWT in brief. We use FBSE method for good spectral representation of a well analyzed signal with good frequency resolution. FBSE uses Bessel function as bases; Bessel functions are non-stationary in nature so when we use FBSE for non-stationary signals like EEG then it is suitable for that. FBSE increases frequency resolution two times as compared to FFT. Scale-space representation is responsible for boundary detection for getting modes of the analyzed signal. To decompose a multicomponent signal into sub-bands we use wavelet based filter banks. We discussed about EWT in which we discussed about wavelet and empirical scaling functions and their mathematical expressions. Also we have discussed about mathematical expression for FBSE series and for FBSE coefficient.

Chapter 3

Dataset and proposed method

3.1 Introduction

In this chapter we will discuss about dataset consisting two subjects namely schizophrenia and normal adolescent. In the proposed method we will discuss about how we will get spectral representation after using FBSE. We will use scale space representation for selecting boundaries. Wavelet based filter banks will be used for deciding sub-bands. Detection of boundaries is decided by deciding two local minima. After getting sub-bands we used Hilbert spectral analysis to get TF matrix. Also we used CNN technique for classifying between two classes (schizophrenia and normal adolescent). CNN will use TF matrix and based on different-different features it will classify healthy adolescent subjects and schizophrenia patients with good classification accuracy.

3.2 Dataset

We have used publically available dataset [40]. there are two EEG data collected from two groups of subjects. Subjects are adolescent who have been screened by psychiatrist and divided into two groups namely healthy (39 subjects) and with the symptoms of schizophrenia (45 subjects). Each file is in txt format and contains EEG record for one subject. For one subject there are 16 channels (that means data was collected from 16 different electrode positions). Each channel contains 7680 sample points, and one channel represent 60 seconds of EEG record. Sampling rate is 128 Hz. The topographical positions of channel numbers are shown in Fig. 3.1 [40]:

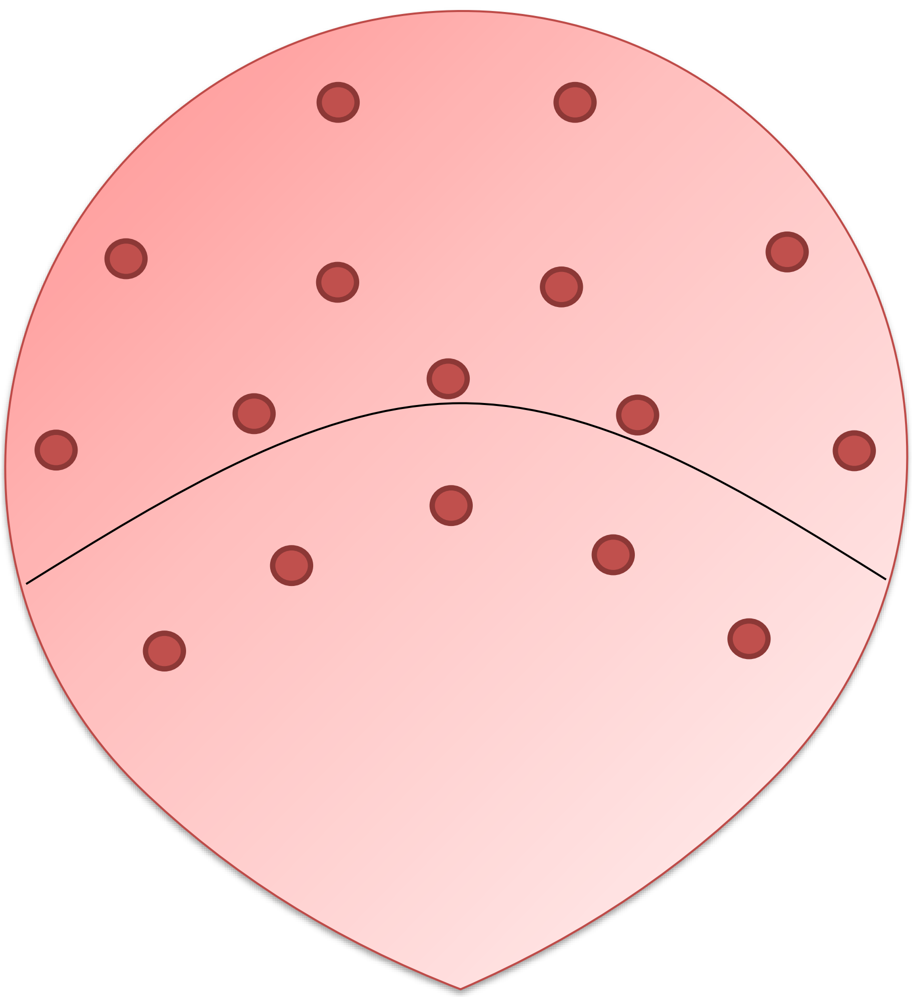


Figure 3.1 positions of electrodes (16 channel model)

In the dataset used 16 channel are F7,F3,F4,F8,T3,C3,Cz,C4,T4,T5,P3,Pz,P4,T6,O1 and O2 are electrodes (every electrode have specific topographical position) which represents channels, from channel 1 to channel 16 respectively.

3.3 Proposed method

In this section we will discuss about our proposed method for analyzing EEG signal and to classify between two classes schizophrenia and healthy adolescent. The block diagram for proposed method is depicted in Fig. 3.2, our proposed method contains following major steps:

Step 1: Apply FBSE-EWT method for analyzing EEG signal, this will decompose signal into *N* number of sub-bands (in our case we used 10 sub-bands).

Step 2: After sub-band decomposition (there are 16 channels for each subjects and each channel will be decomposed into 10 sub-bands) we will use Hilbert spectral analysis technique to get the TF matrix.

Step 3: Once we get TFR (there is one TF matrix for one channel ie. For each subject there are 16 TF matrices) we apply CNN which can classify between two classes with good accuracy.

First we have applied FBSE, which gives spectral representation of the EEG signal with almost doubled frequency resolution as compared to FFT method. It uses Bessel function which are non-stationary that are suitable for non-stationary signals like EEG signal. FBSE spectrum has compact representation and avoids windowing. We have used scale-space boundary detection technique for selecting the boundaries after that wavelet based filter banks have been applied for extracting sub-bands. After extraction of sub-bands we have used Hilbert spectral analysis to get TFR of signals and this TF matrix has been used as input for CNN, which classified the classes based on predefined features obtained by the network.

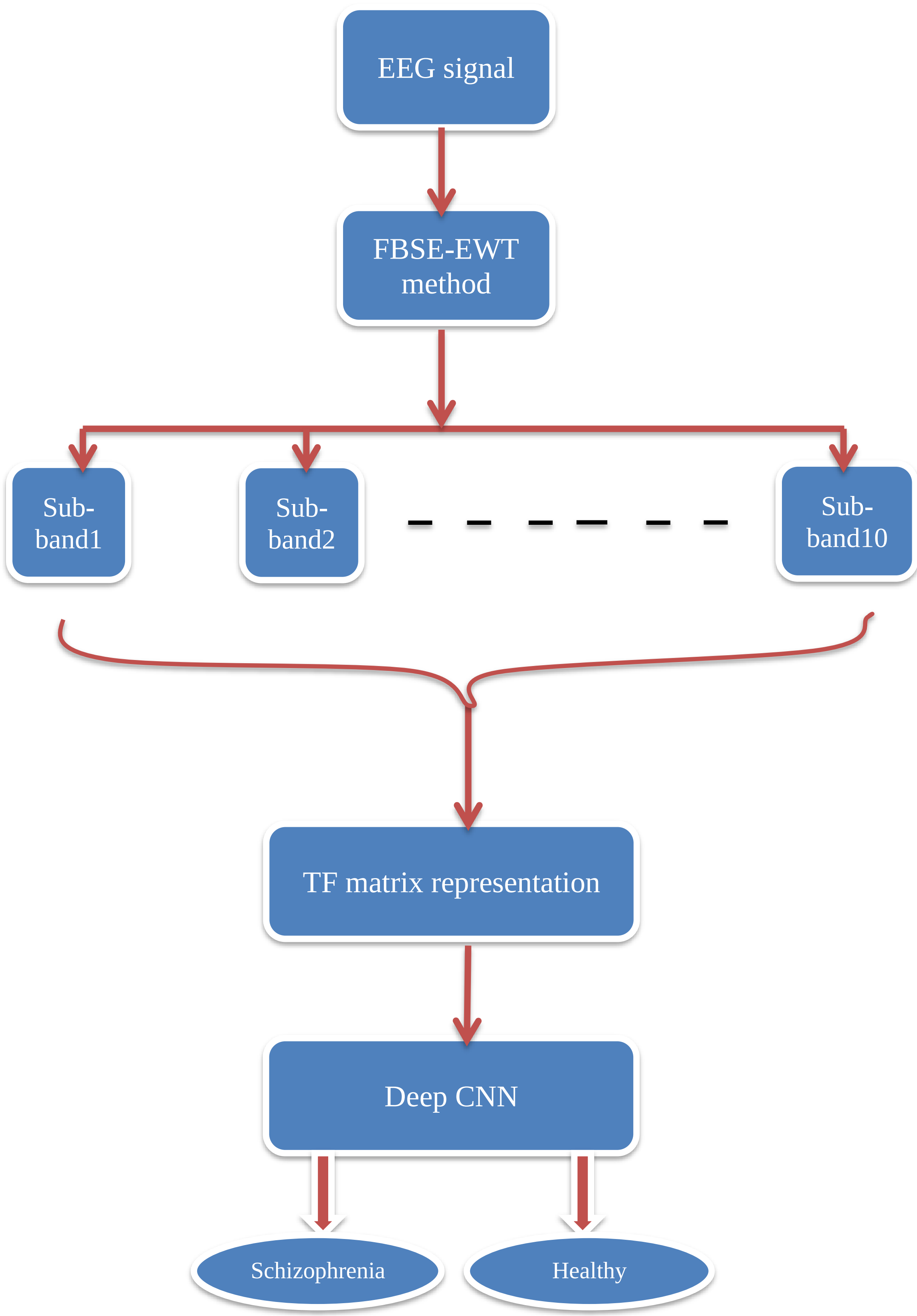


Fig. 3.2 block diagram for proposed method

3.3.1 Decomposition of EEG signal into sub-bands using FBSE-EWT method

This sub-band decomposition technique using FBSE-EWT [45] has following major steps:

Step 1: Apply FBSE method to the EEG signal to get spectral representation of the signal with good frequency representation.

Step 2: Apply scale-space boundary detection method on the FBSE spectrum to select the boundaries of the sub-bands.

Step 3: EWT based filter banks will be applied to get sub-bands of the signals.

Step 4: As per requirement or suitability of the work select the number of bands (in our case N =10 bands) and after processing signal will be decomposed into sub-bands.

First of all we applied FBSE to the signal to get the spectrum of the signal, in FBSE the number of coefficient of spectral representation are equal to the length of the signal, whereas the spectrum length is the half of the signal length in Fourier representation. Hence the frequency resolution of the spectrum is two times as compared to conventional FFT techniques. In this method the scale-space representation technique is the deciding factor for boundaries, it uses local minima concept to differentiate between sub-bands. Then wavelet based filter banks have been used to decide number of sub-bands. In our dataset we have 39 subjects for healthy and 45 subjects for schizophrenia, data for each subject having 16 channels (every channel contains 7680 sample point) and each channel will be decomposed into 10 sub-bands so after decomposition of EEG signal of a single subject the intrinsic mode function (IMF) will have 7680×16×10 matrix.

3.3.2 TF matrix representation

After decomposition of analysed signal into sub-bands they are required to convert into TF matrix format which will behave as input to the neural network. For TFR we used Hilbert spectral analysis [80].

Hilbert spectral analysis is a signal analysis method applying the Hilbert transform to compute the instantaneous frequency of signals according to the relation [80]

$$\omega = \frac{d\varphi(t)}{dt} \tag{3.3.2.1}$$

Where $\varphi(t)$ is instantaneous angle and ω is the instantaneous frequency in radians.

After performing Hilbert transform on each signal, we can express the data in the following form [80, 81]:

$$Z(t) = \sum_{i=1}^{m} b_i\,(t) e^{j\int \omega_i(t)\,dt} \tag{3.3.2.2}$$

Above equation gives both frequency and amplitude of each component as a function of time. Also we can represent the amplitude and instantaneous frequency as a function of time in three dimensional planes. This frequency-time distribution gives TF matrix representation.

3.3.3 Convolution neural network (CNN)

CNN is a deep learning algorithm which can take in an input, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from other [73]. Preprocessing required in CNN is much lesser than the other classification algorithm. Initially with the primitive methods hand-engineered filter were required but CNN has all these ability to learn about these filters/characteristics. A CNN is able to successfully capture the spatial and temporal dependencies in an image through the application of relevant filters [73, 77]. Hence the network can be trained to understand the sophistication of the image in better way. Here CNN provides a network which reduces the images into a form in which it is easier to process, without losing quality features which may be deciding factor for differentiating the classes. Important thing is to design an architecture which is not only good at learning features but also is scalable to massive datasets.

For understanding the process of features extraction using CNN we are going to take a simple example, which will show how convolution works in CNN.

3.3.3.1 Convolution layer- The kernel

For example we have an matrix with matrix dimension = 5(height)× 5(breadth)× 1(number of channels) is having 5×5 matrix this resembles our 5×5×1 input matrix. The second matrix resembles our 3×3×1 Kernel/Filter, K (we have selected K = 3×3×1). And the third section is convolved features section. The kernel shifts 9 times because of the stride length = (non-strided), every time performing a matrix multiplication operation between K and the portion P of the matrix over which the kernel is hovering.

Now in the case of matrix with the multiple channels, the kernel has the same depth as the input matrix. Matrix multiplication is performed between Kn and In stack ([K1, I1]; [K2, I2]; [K3, I3]) and all the results are summed with the bias to give us a squashed one depth channel convoluted feature output [42].

The objective of the convolution operation is to extract the high level features such as edges, from the input matrix. CNN need not be limited to only one convolution layer. Conventionally the first convolution layer is responsible for capturing the low-level features such as edges, color, gradient orientation etc. and further added layers are responsible for high-level features as well, giving us a network which has the wholesome understanding of the matrices in the dataset similar to how we would [73, 42].

There are two types of results for this convolution operation; one in which convolved feature reduced dimensionally as compared to input matrix and other in which convolved feature’s dimensionality is either increased or remains the same. For both the above cases one has to apply valid padding and same padding respectively.

3.3.3.2 Polling layer

Size of convolved feature matrix is reduced by using polling layer, this dimensionality reduction results less computational power requirement for feature extraction process. Furthermore it is responsible for extracting dominating features which are rotational and positional invariant, thus maintaining the process of effectively training the model. Two types of polling are possible; namely max poling and average poling [42, 77, 73]. Max poling gives the maximum value out of all the values (which are covered by the kernel) as a result. On the other hand average poling gives the average value of all values which are covered by the kernel.

Max polling techniques also work as noise suppressant. It reduces the noise content along with the dimensionality reduction. While average polling only performs the dimensionality reduction, it doesn't affect the noise factor. Hence we observe that the performance of max poling is much better than the average poling [42, 73].

3.3.3.3 Fully connected layer (FC layer)

Using fully connected (FC) layer is a cheap/easy way of recognizing non-linear high-level features from the features which are extracted from the Convolution layer [78, 42]. The FC layer learns all possible non-linear features in that space. Now we have successfully converted our input image into a suitable form for our multi-level perceptron, we shall flatten the image into a column vector[42, 73]. The flattened output is fed to a feed-forward neural-network and back-propagation applied to every iteration of training. Series of epoch possesses for a single iteration, then the model is able to differentiate between high level features and low level features of image and then classify between the classes using Soft-max classification technique [42].

There are some different architectures of CNN's which are listed below:

- LeNet
- AlexNet
- Visual geometry group (VGGNet)
- Residual network (ResNet)   etc.

3.3.3.4 ResNet-50

ResNet-50 is a CNN that is 50 layers deep. In our proposed method we have used ResNet-50. One can load a pre-trained version of the network trained on more than a million images from the ImageNet database [42]. The pre-trained classifies images into many (approx. 1000) object categories, such as mouse, pencil, pen and many other species. As a result this neural network acquired rich feature representation for wide range of objects/images.

3.4 Performance evaluation parameters

3.4.1 Classification accuracy

Classification accuracy basically tells that how efficiently and correctly a classifier can classify between two subject/categories. Classification accuracy is simply the rate of correct classification, either for an independent test set, or using some variation of the cross validation idea [82]. In CNN it is inbuilt function which gives classification accuracy. Mathematically accuracy can be computed by the following:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100\%$$

Where, true positive (TP), true negative (TN), false positive (FP), false negative (FN) are the values are corresponding to exact prediction of particular class and wrong prediction of that particular class of the system.

3.4.2 Sensitivity and specificity

Sensitivity and specificity statistically measures the performance of a classification test.

Sensitivity is a measure of the true positive rate; also we can say measure for the probability of detection, the epidemiological/clinical sensitivity, or the recall. It measures the proportion of actual positives that are correctly identified as such. For example the percentage of fudge bulbs which are correctly identified as corrupted. It is the ratio of the true positive value to the sum of true positive value and false negative value [82].

Specificity is a measure of the true negative rate. It measures the proportion of actual negatives that are correctly identified as such. For example the percentage of functioning bulbs which are correctly identified as active. The mathematical expressions for these parameters are as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\%$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\%$$

Where TP, TN, FP and FN are the same values as in accuracy section.

3.4.3 Confusion matrix

Confusion matrix plots for the true labels (known as targets) versus the predicted labels (known as outputs). Rows on the confusion plot refer to the predicted class (ie. to output class) on the other hand column refers to the target class (ie actual true class). Correctly classified classes are observed by the diagonal while the off diagonal shows the observations of the incorrect classification. Using convolution plot one can easily calculate accuracy, sensitivity and also some other measurable parameters.

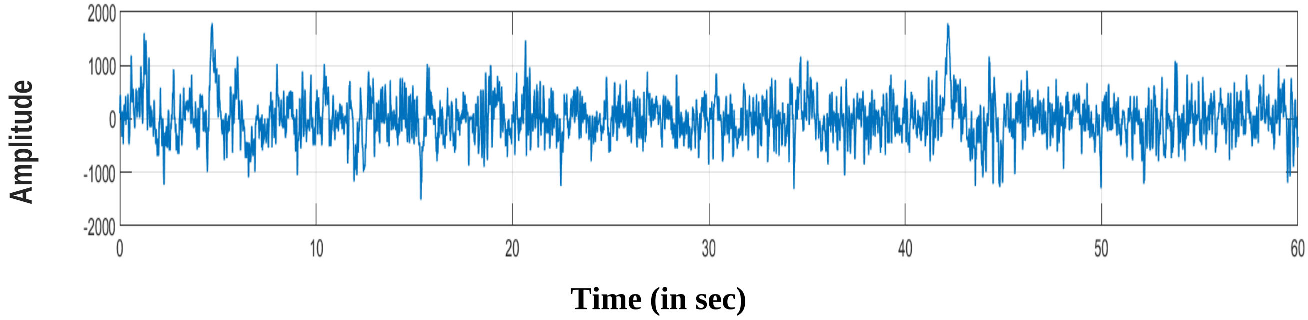
3.4.4 Receiver operating characteristic (ROC) plot

ROC curve is a characteristic plot which tells the characteristic of a classifier system, that is the ROC curve shows how much efficient a classifier is, it is a plot of TP rate versus FP rate. True positive is also called as sensitivity while the false positive rate is known as the probability of false alarm. There is also some threshold value for this ROC curve which varies. If cumulative distribution function (CDF) for both false alarm and detection probability are known, the ROC curve can be drawn by both, CDF of detection probability is represented by Y-axis while the CDF of false alarm represented by X-axis.

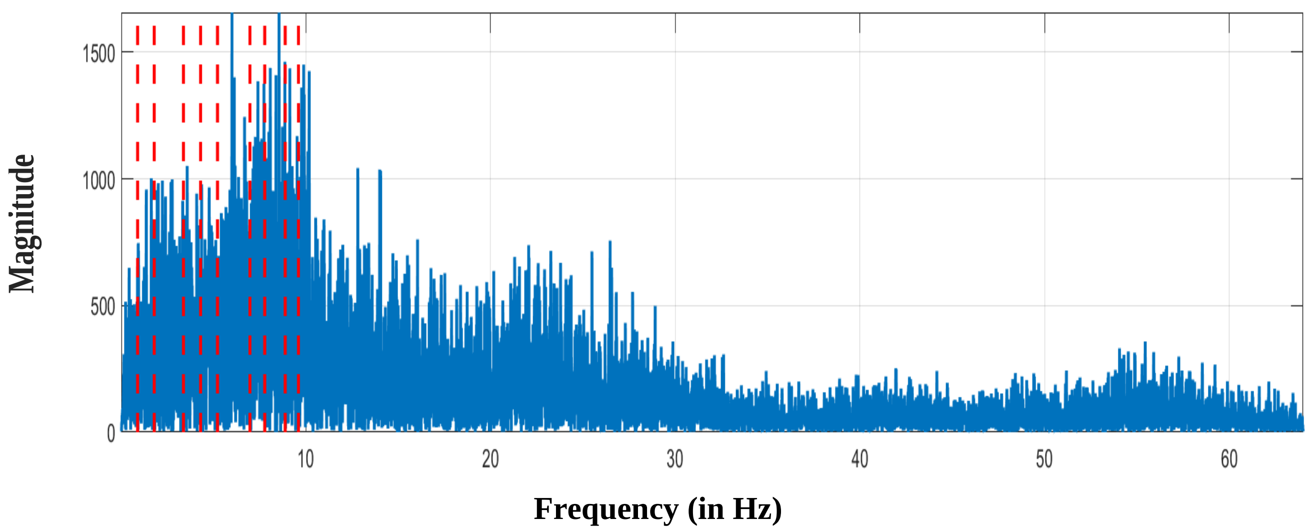
3.5 Overview of the proposed method

We have used FBSE-EWT method for decomposing EEG Signals of both the classes (schizophrenia and normal), the process is as follows:

Step 1: EEG signal of both the classes and then their respective boundaries representation using FBSE-EWT;



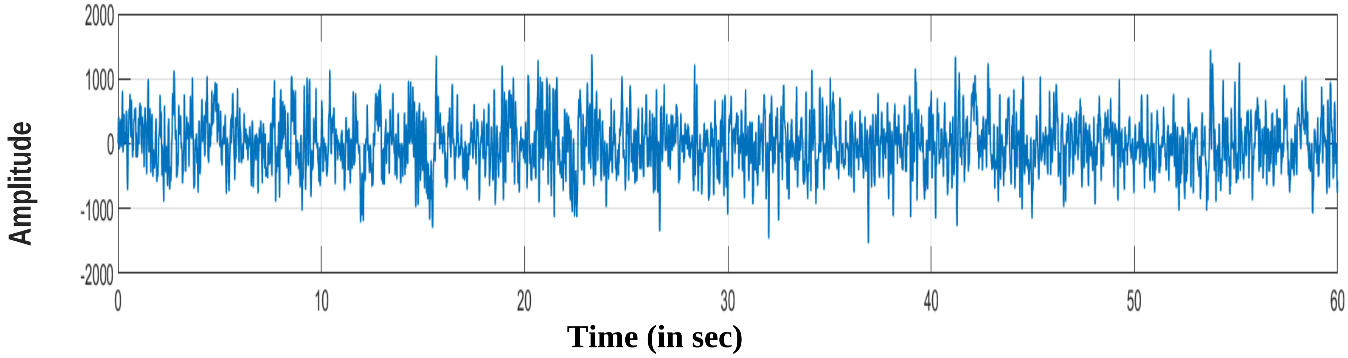
(a)



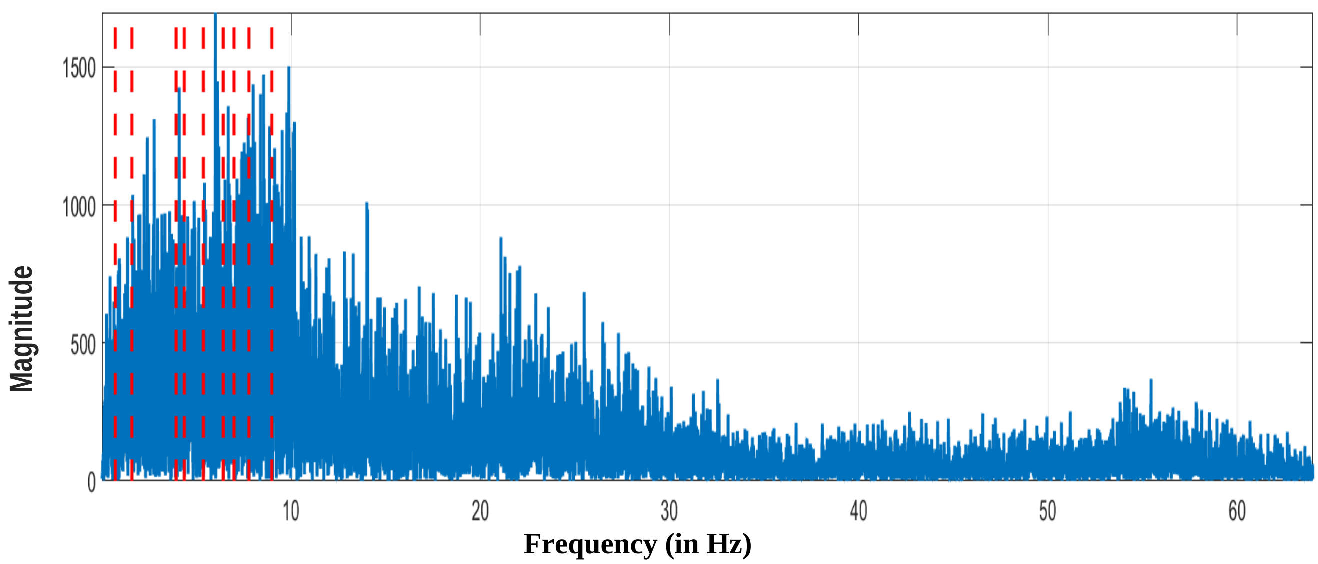
(b)

Figure 3.3 (a) EEG signal representation for healthy class (channel 1) (b) EWT boundaries using FBSE method for healthy class (channel 1)

When we used FBSE on the input EEG signal, we got spectral representation of the input EEG signal. Fig. 3.3 (a) shows simple signal representations of the EEG signal. Also because of scale-space boundary detection method we got the boundary frequencies of the input EEG signal. Fig. 3.3 (b) shows the boundaries for the input EEG signal.



(a)



(b)

Figure 3.4 (a) EEG signal representation for schizophrenia class (channel 1) (b) EWT boundaries using FBSE method for schizophrenia class (channel 1)

Step 2: after getting FBSE spectrum, EWT filter banks have been applied, which results the sub-bands decomposition of input EEG signal. Fig. 3.5 and Fig. 3.6 are showing IMF's (or sub-bands) obtained by using FBSE-EWT method for healthy adolescent and symptoms with schizophrenia respectively.

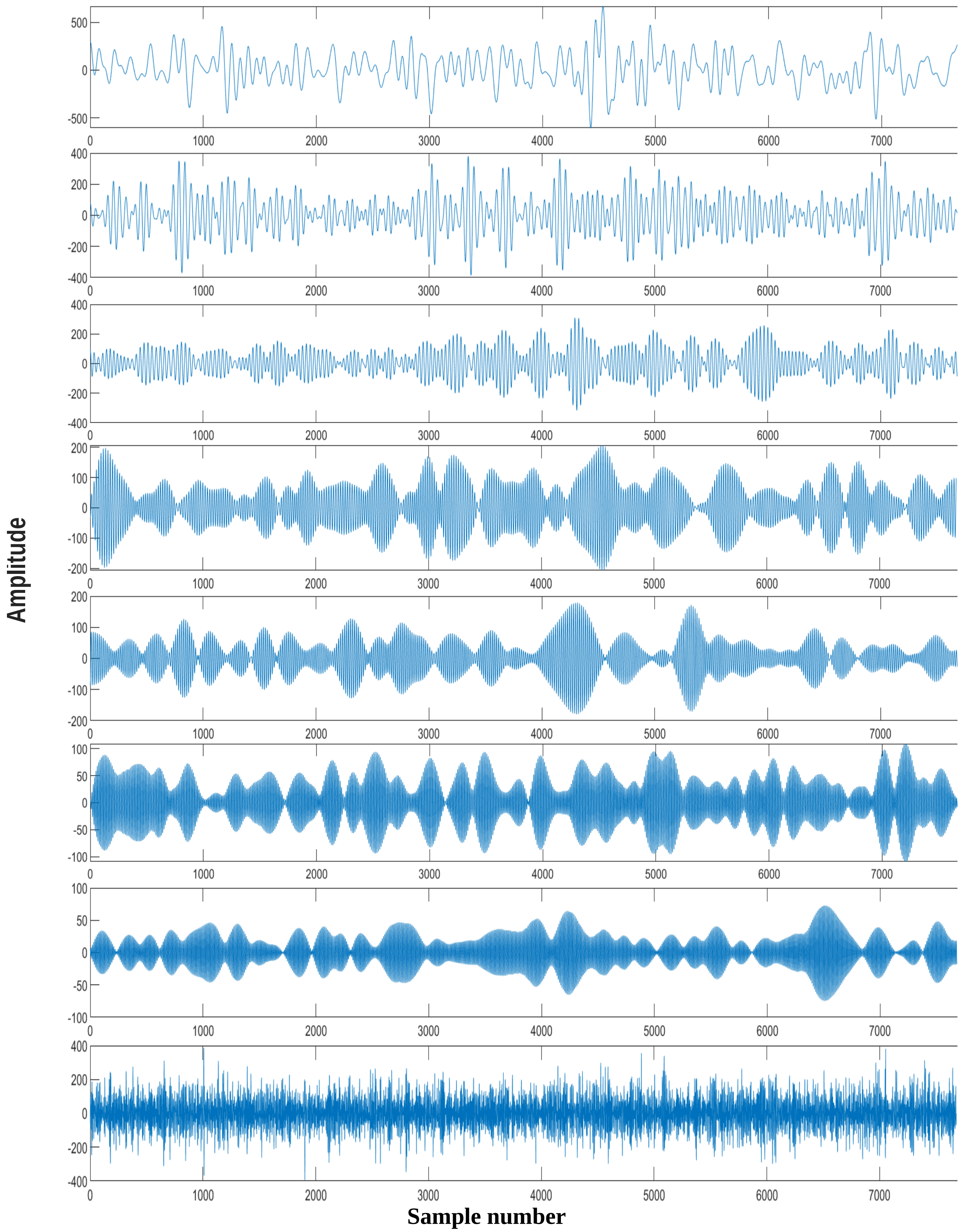


Figure 3.5 IMFs or sub-bands of a healthy adolescent

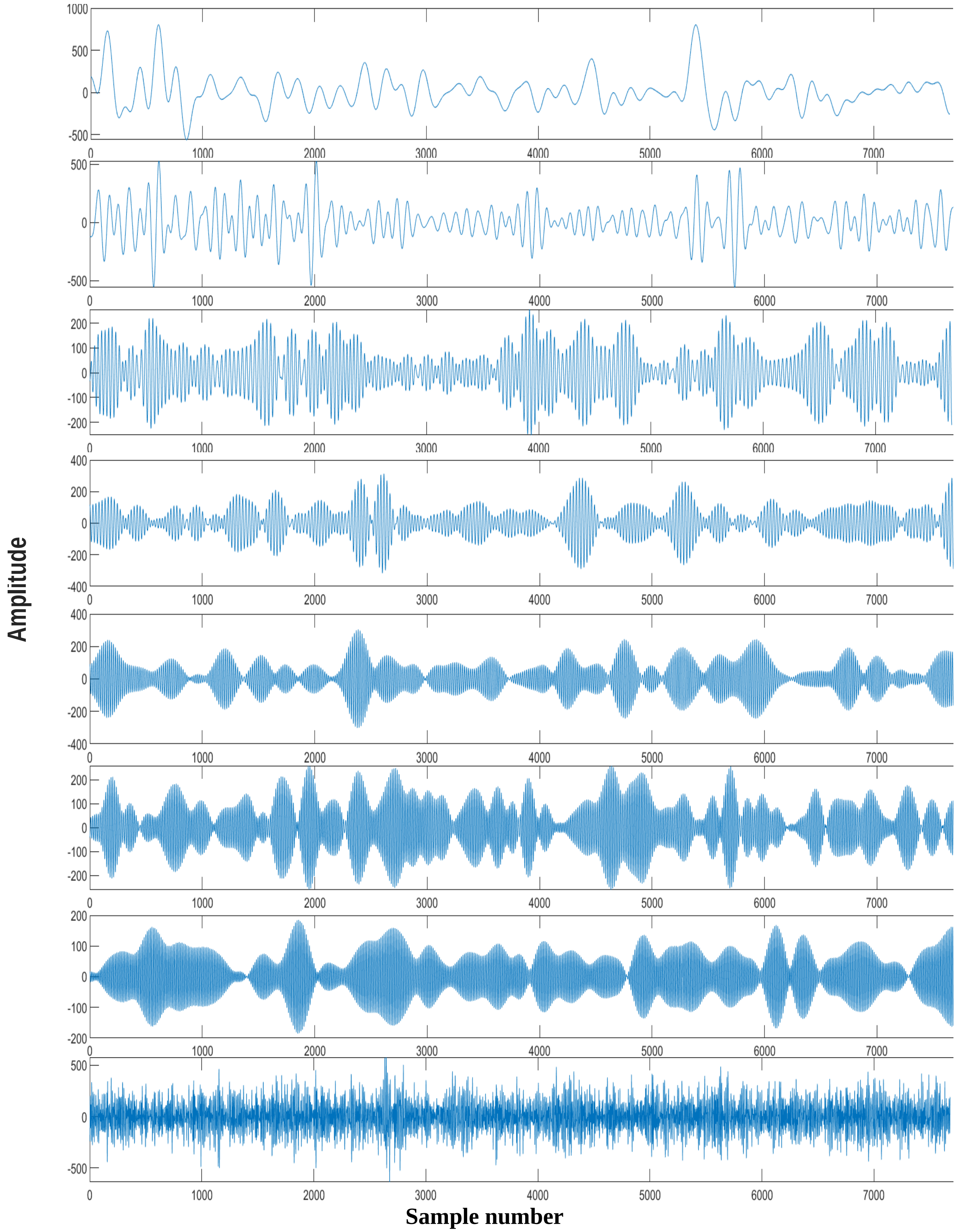
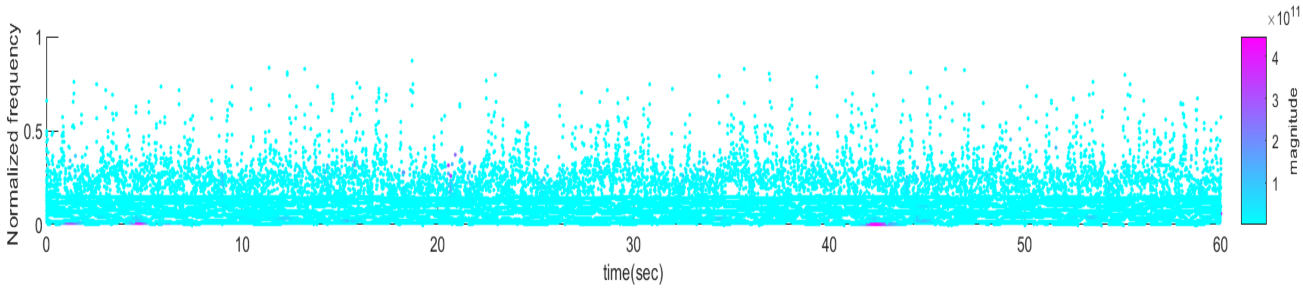
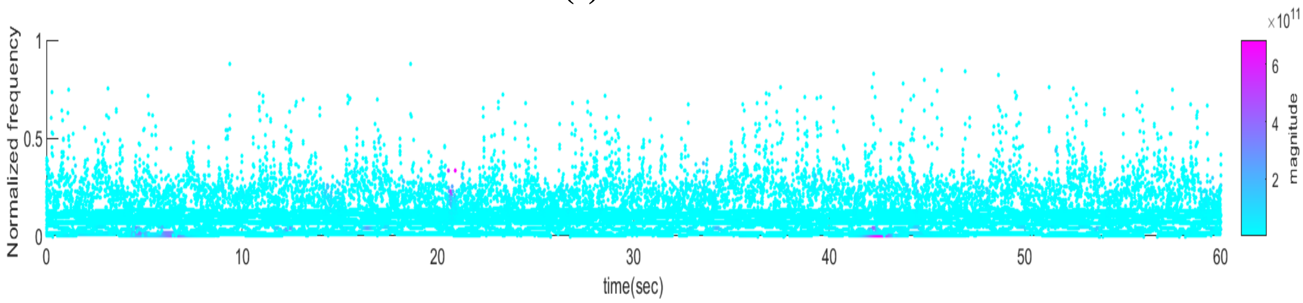


Figure 3.6 IMFs or sub-bands of a schizophrenia patient

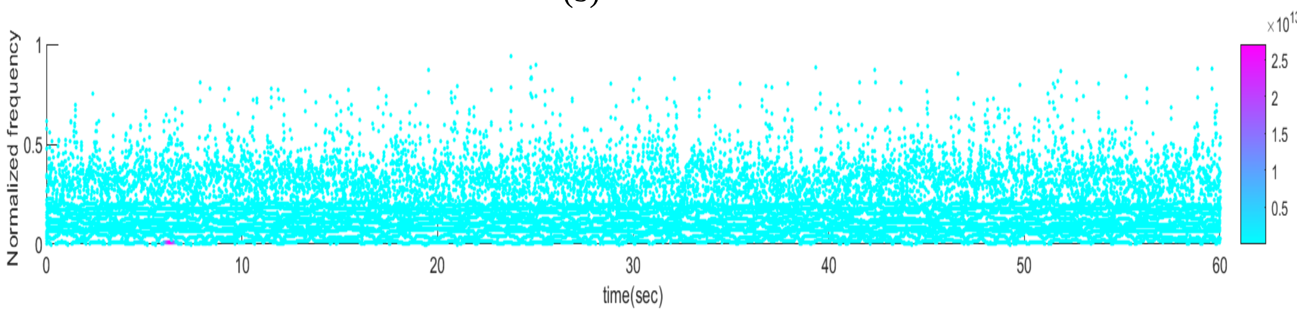
Step 3: Once we got IMFs or sub-bands of the signals we have to find the TFR of the signal, for that we applied Hilbert spectral analysis on the sub-bands and got one TFR for each channel that means there are 16 TFR per channel. Fig. 3.7 shows the TFR for two channels for both schizophrenia and normal classes.



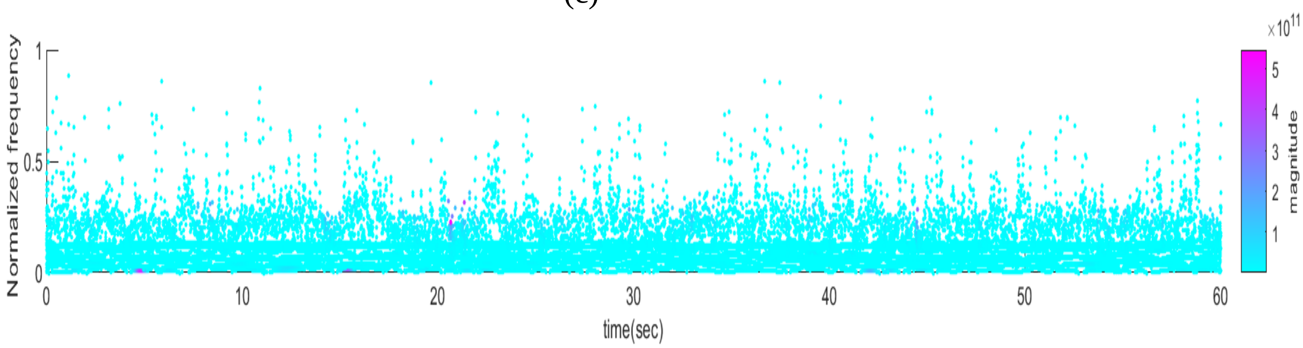
(a)



(b)



(c)



(d)

Figure 3.7 (a) TFR for healthy subject channel 1 (b) TFR for healthy subject channel 2 (c) TFR for schizophrenia affected person channel 1 (d) TFR schizophrenia affected person channel2

Step 4: This TFR will be input for CNN, where CNN will classify between the classes with good accuracy, for that ROC plot and confusion plot will be discuss in the next chapter (in results and discussion).

3.6 Summary

We are using dataset which is publically available also we have proposed a method FBSE-EWT along with CNN for classifying two classes (schizophrenia and healthy). FBSE-EWT method has been used for decomposing EEG signal into sub-bands (ie. into IMFs). We have briefly discussed the FBSE method along with spectrums and filter banks. After getting IMFs we got TFR matrix using Hilbert spectral analysis. We have also discussed about performance evaluation parameters, which will be briefly discussed in the next chapter.

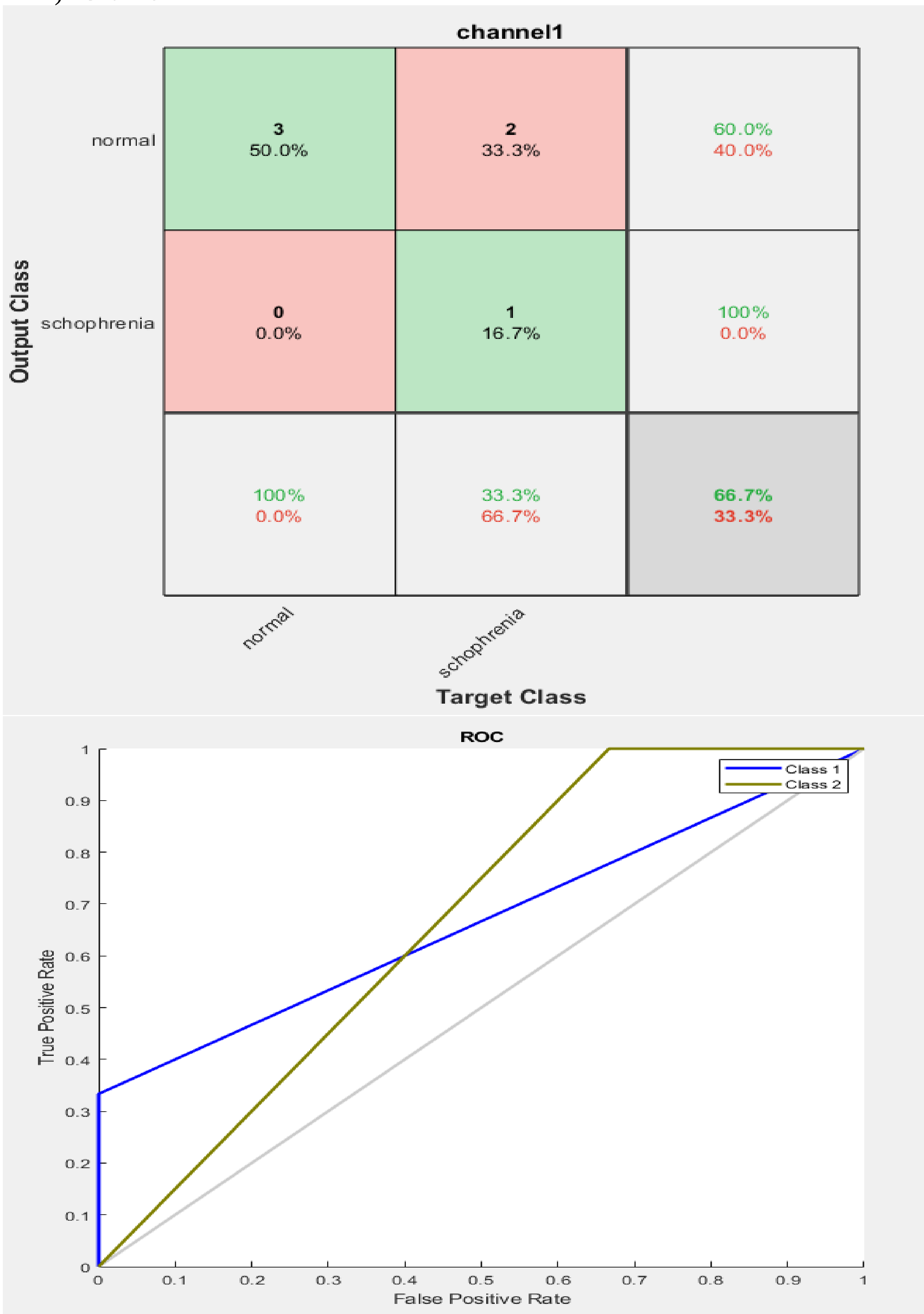
Chapter 4

Results and discussion

In this chapter we are going to discuss results of our proposed method, ROC plots, confusion plot matrices, about classification accuracy, sensitivity, specificity and many other important points. In this part of thesis we have shown ROC curve, confusion plots which are showing efficiency of our proposed. We have compared our results with previous results in term of accuracy, specificity and sensitivity.

After getting TF matrix for all the channels of complete data set it possessed through Resnet50 CNN network. This neural extracts features from this dataset and differentiate between two classes (ie normal and schizophrenia), this network extracted training features, testing features and then assembled features of these extracted features. Assembled feature shows excellent classification accuracy. We have also shown ROC plot and confusion plot for all the channels which are shown in Fig. 4.1:

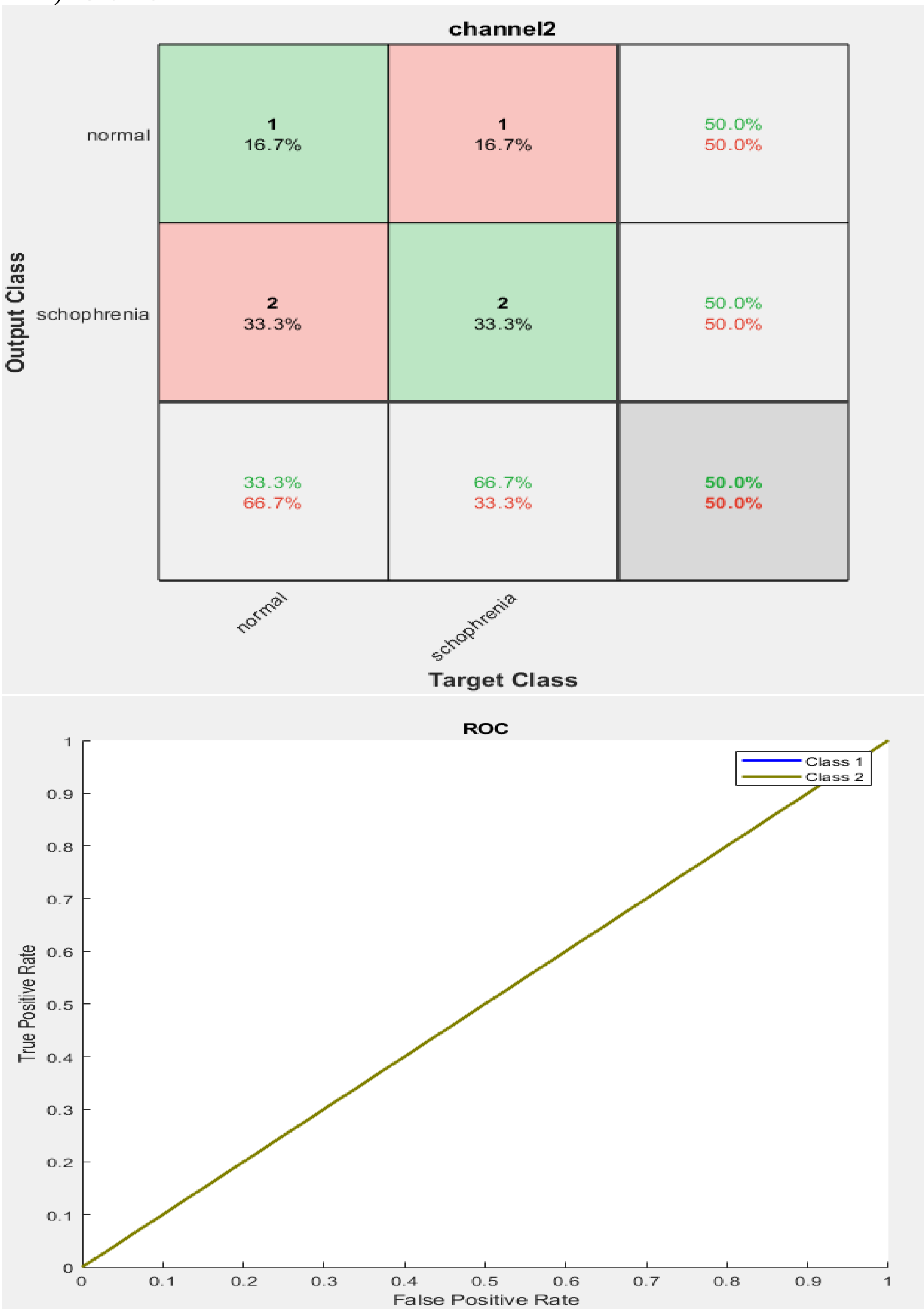
1) Channel 1



channel1
normal
schophrenia
Output Class
3
50.0%
2
33.3%
60.0%
40.0%
0
0.0%
1
16.7%
100%
0.0%
100%
0.0%
33.3%
66.7%
66.7%
33.3%
normal
schophrenia
Target Class
ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

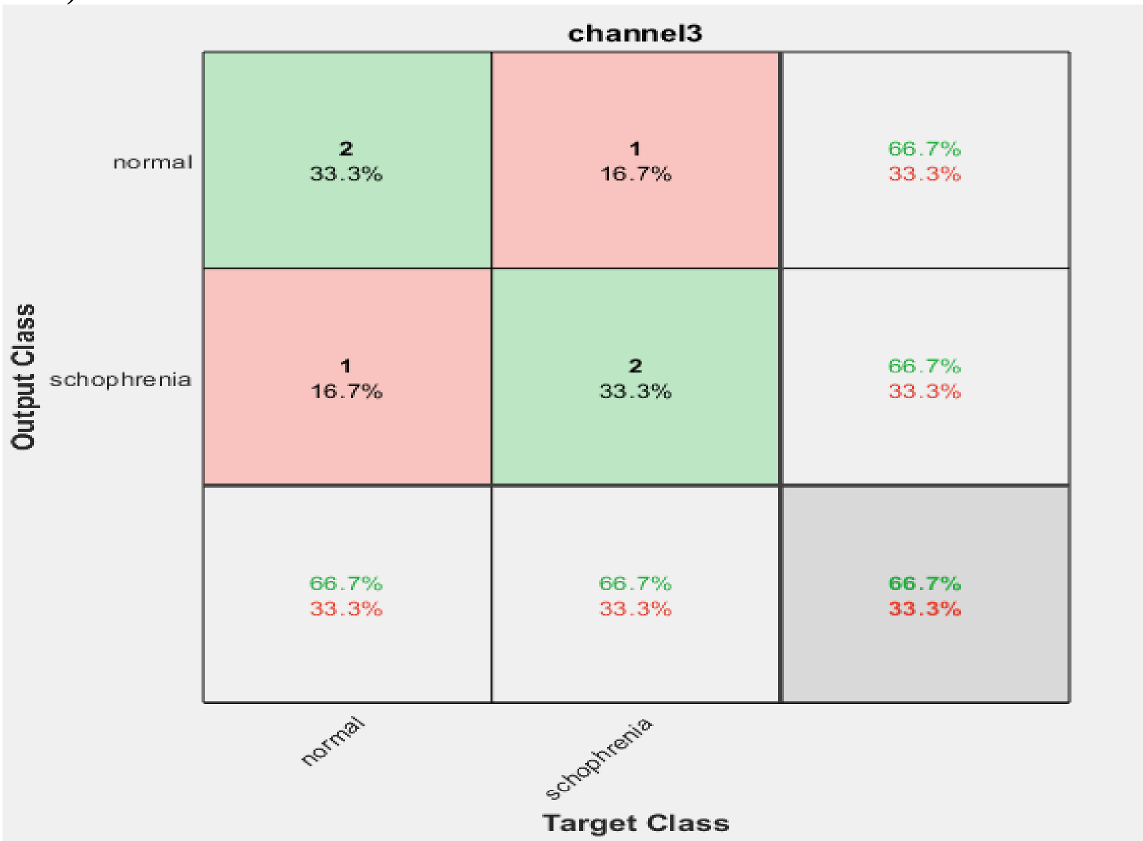
(a)

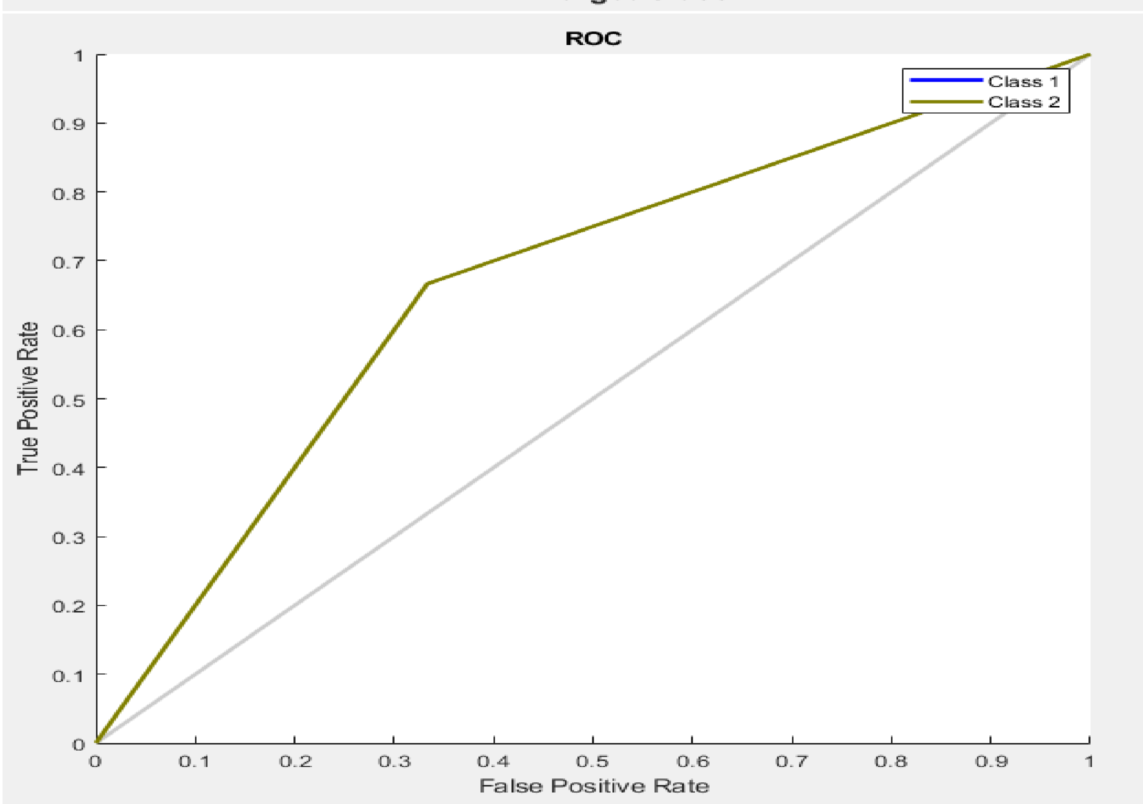
2) Channel 2


channel2
Output Class
normal
schophrenia
1
16.7%
1
16.7%
50.0%
50.0%
2
33.3%
2
33.3%
50.0%
50.0%
33.3%
66.7%
66.7%
33.3%
50.0%
50.0%
normal
schophrenia
Target Class
ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(b)

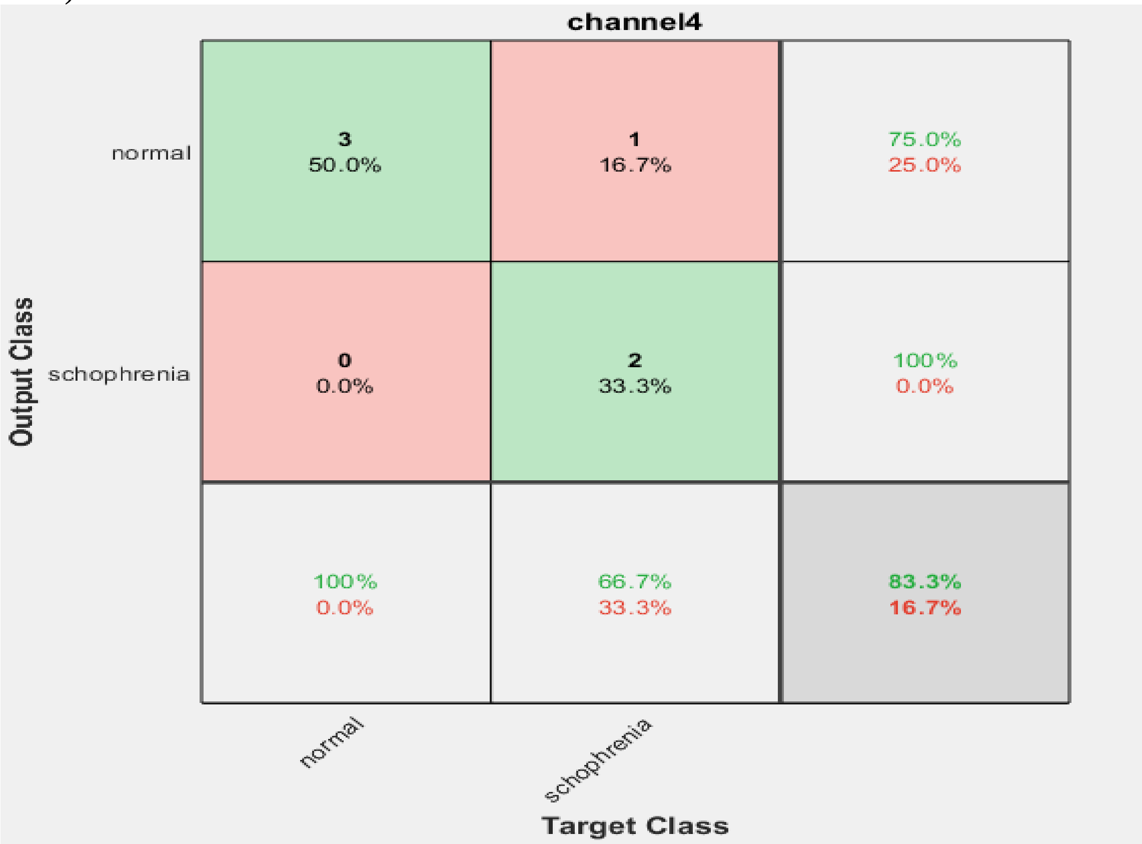
3) Channel 3

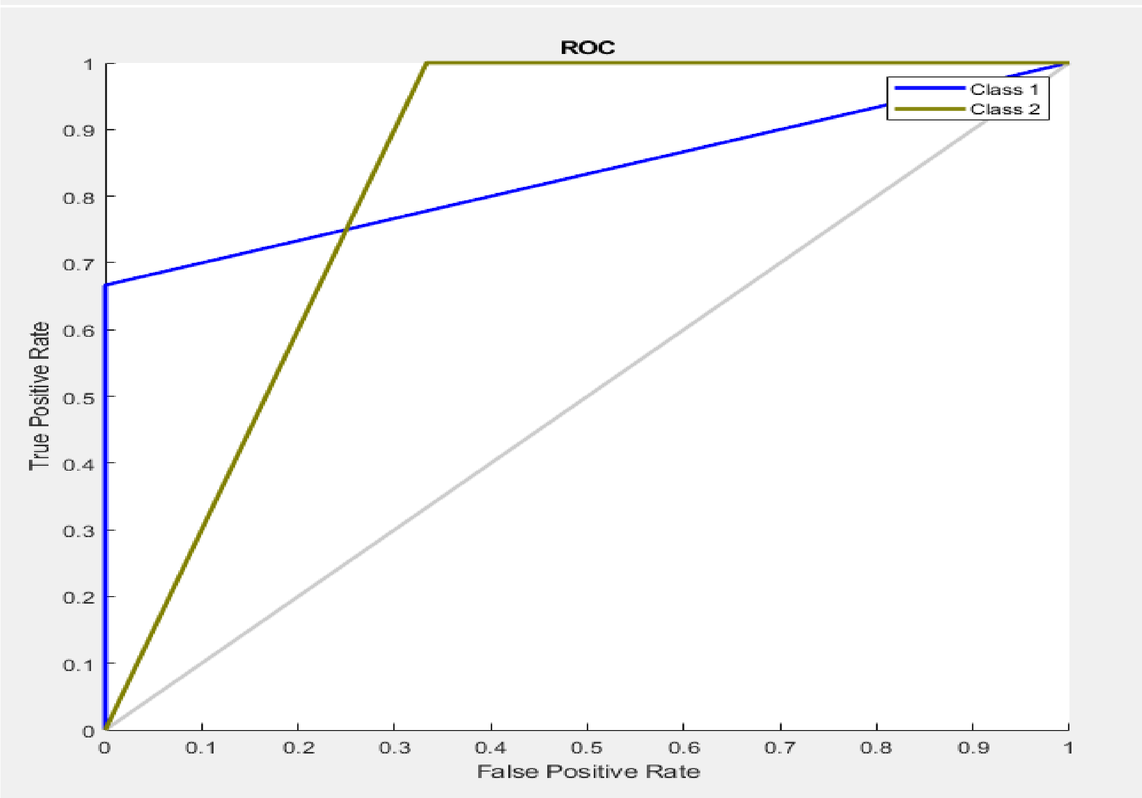

channel3
normal
schophrenia
Output Class
2
33.3%
1
16.7%
66.7%
33.3%
1
16.7%
2
33.3%
66.7%
33.3%
66.7%
33.3%
66.7%
33.3%
66.7%
33.3%
normal
schophrenia
Target Class


ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(c)

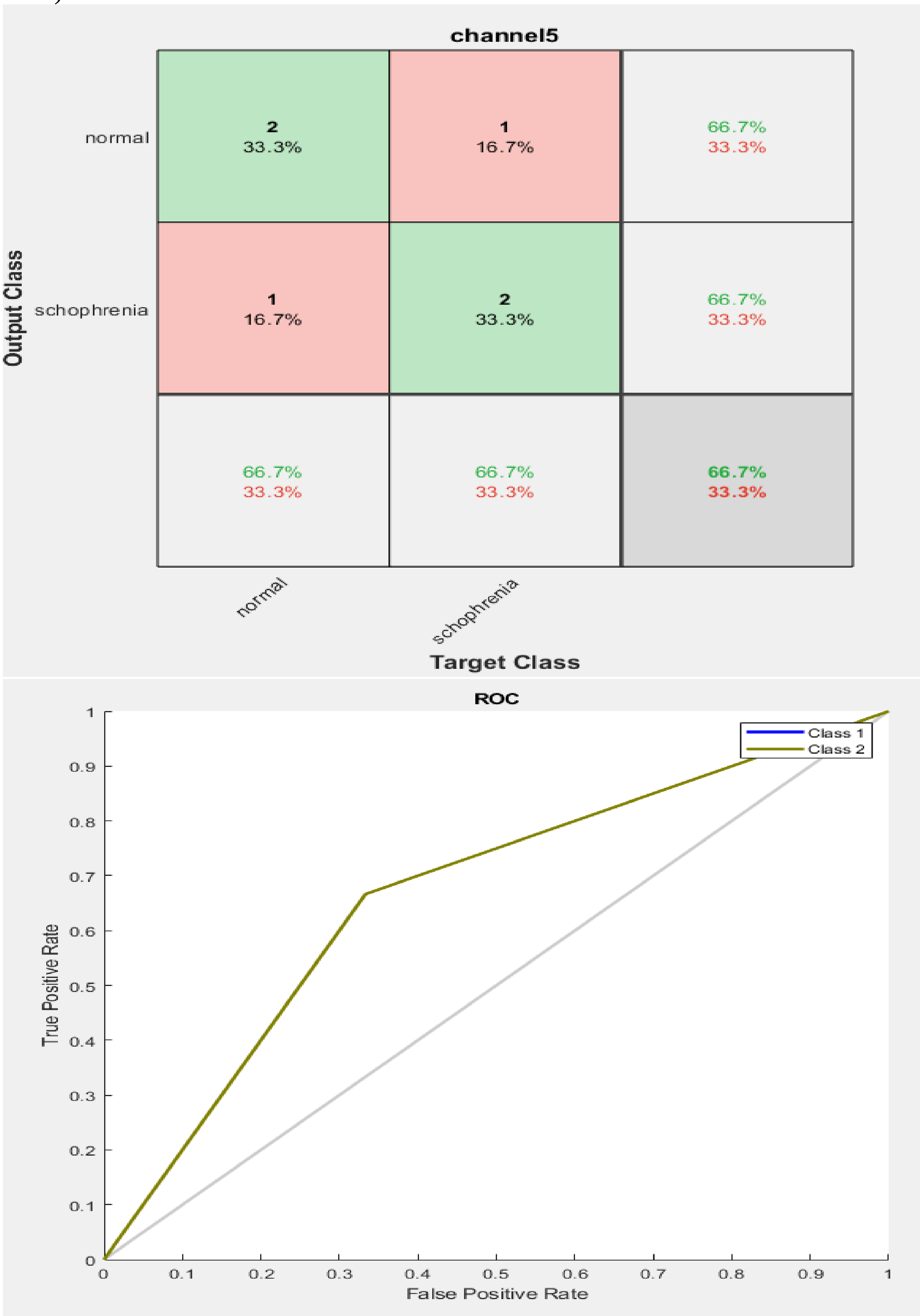
4) Channel 4


channel4
normal
schophrenia
Output Class
3
50.0%
1
16.7%
75.0%
25.0%
0
0.0%
2
33.3%
100%
0.0%
100%
0.0%
66.7%
33.3%
83.3%
16.7%
normal
schophrenia
Target Class


ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(d)

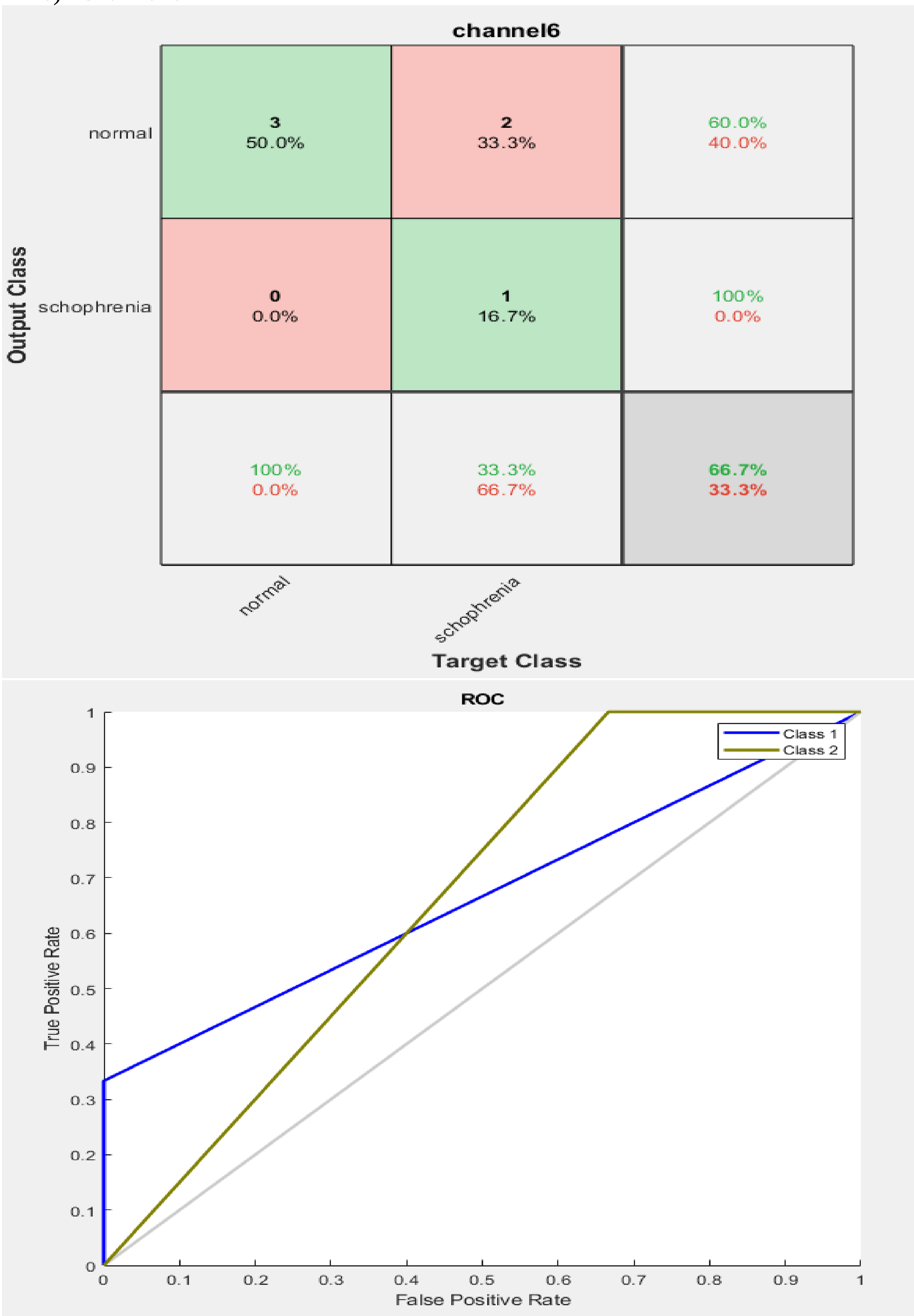
5) Channel 5



channel5
normal
schophrenia
Output Class
2
33.3%
1
16.7%
66.7%
33.3%
1
16.7%
2
33.3%
66.7%
33.3%
66.7%
33.3%
66.7%
33.3%
66.7%
33.3%
normal
schophrenia
Target Class
ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

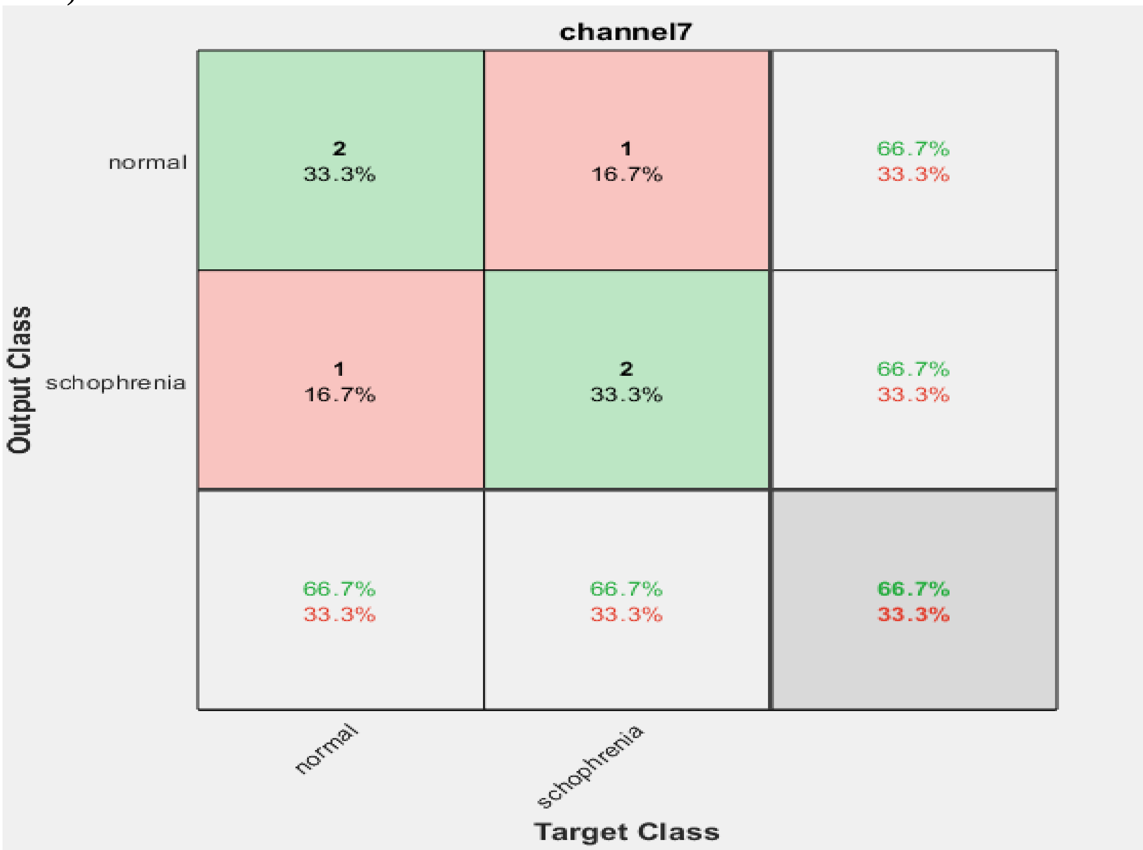
(e)

6) Channel 6

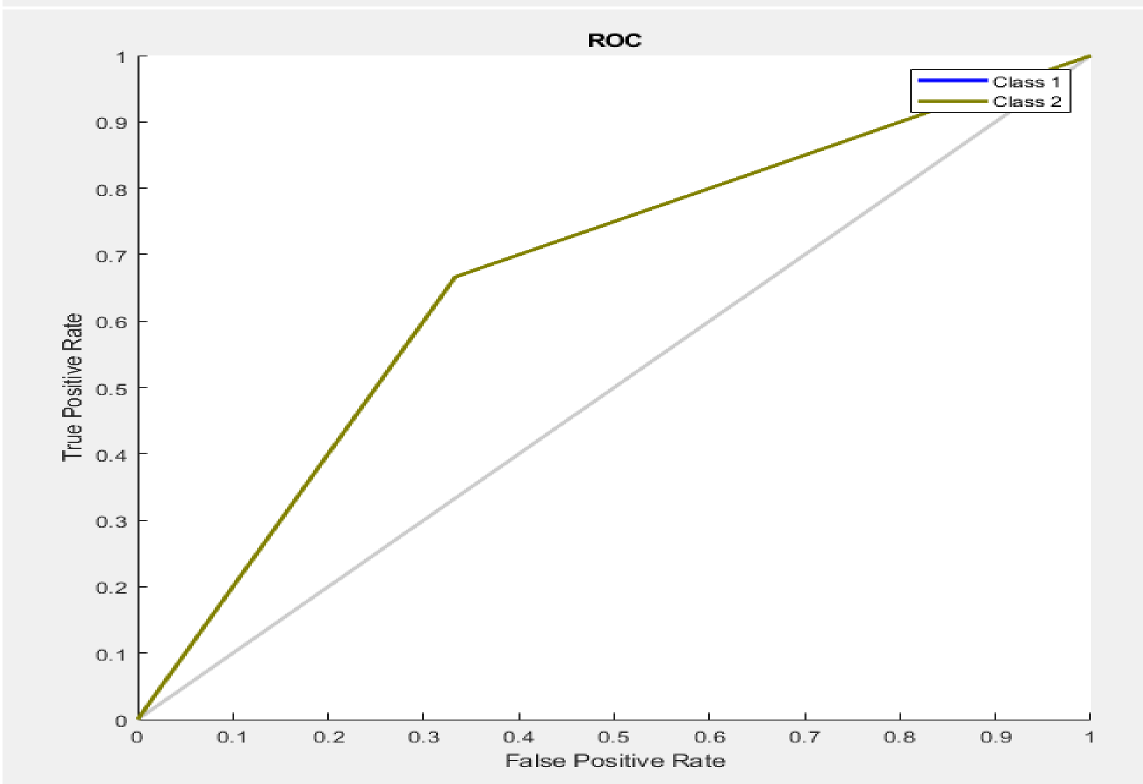

channel6
normal
schophrenia
Output Class
3
50.0%
2
33.3%
60.0%
40.0%
0
0.0%
1
16.7%
100%
0.0%
100%
0.0%
33.3%
66.7%
66.7%
33.3%
normal
schophrenia
Target Class
ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(f)

7) Channel 7



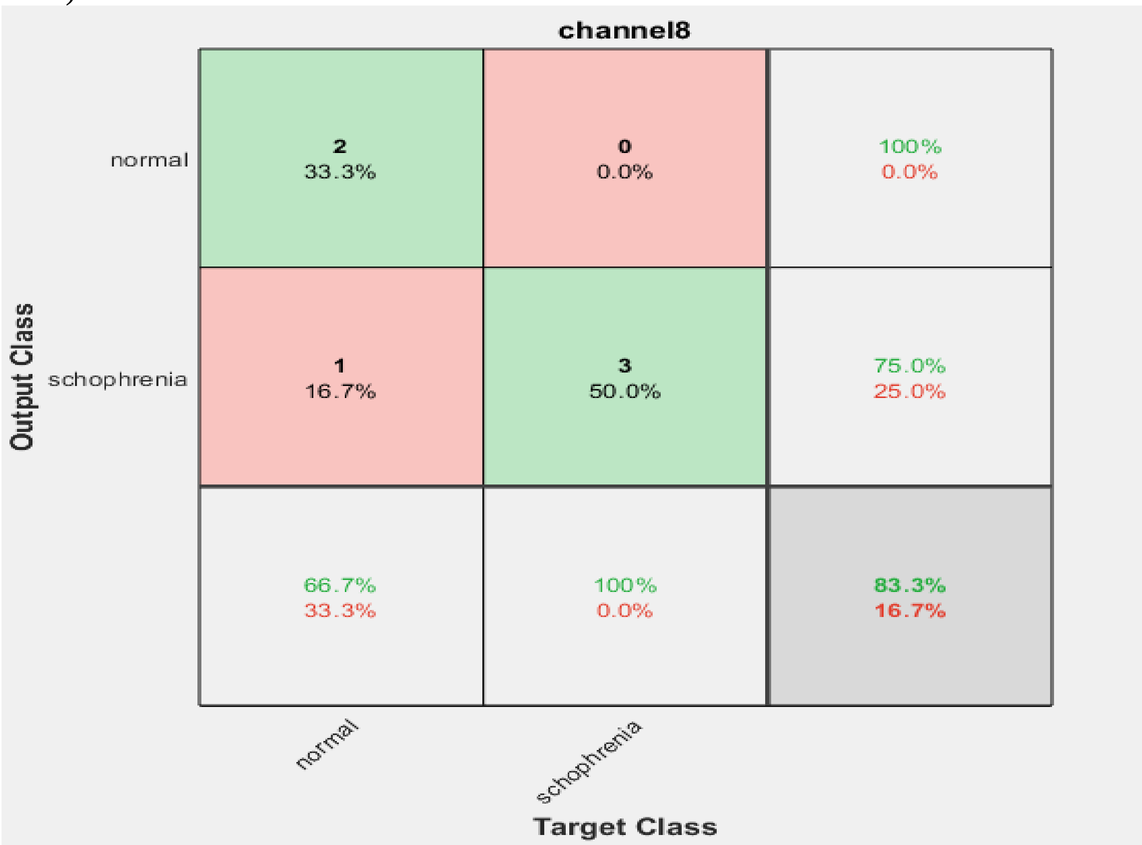
channel7
normal
schophrenia
Output Class
2
33.3%
1
16.7%
66.7%
33.3%
1
16.7%
2
33.3%
66.7%
33.3%
66.7%
33.3%
66.7%
33.3%
66.7%
33.3%
normal
schophrenia
Target Class

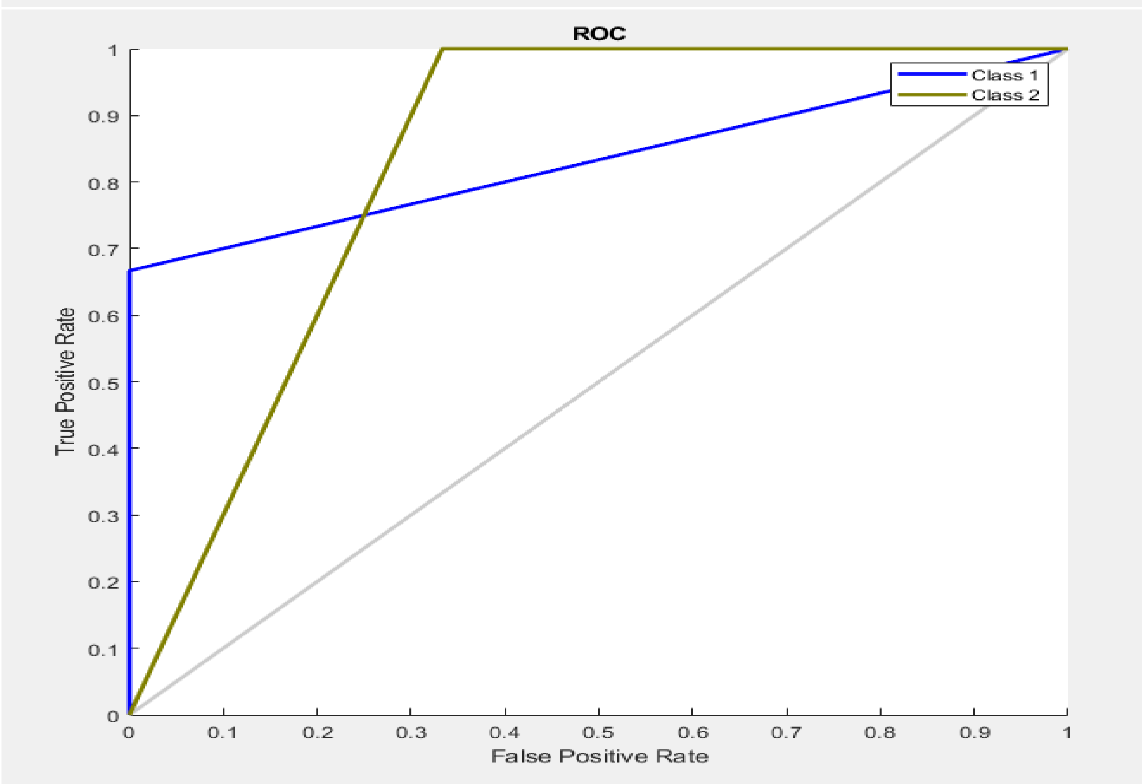


ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(g)

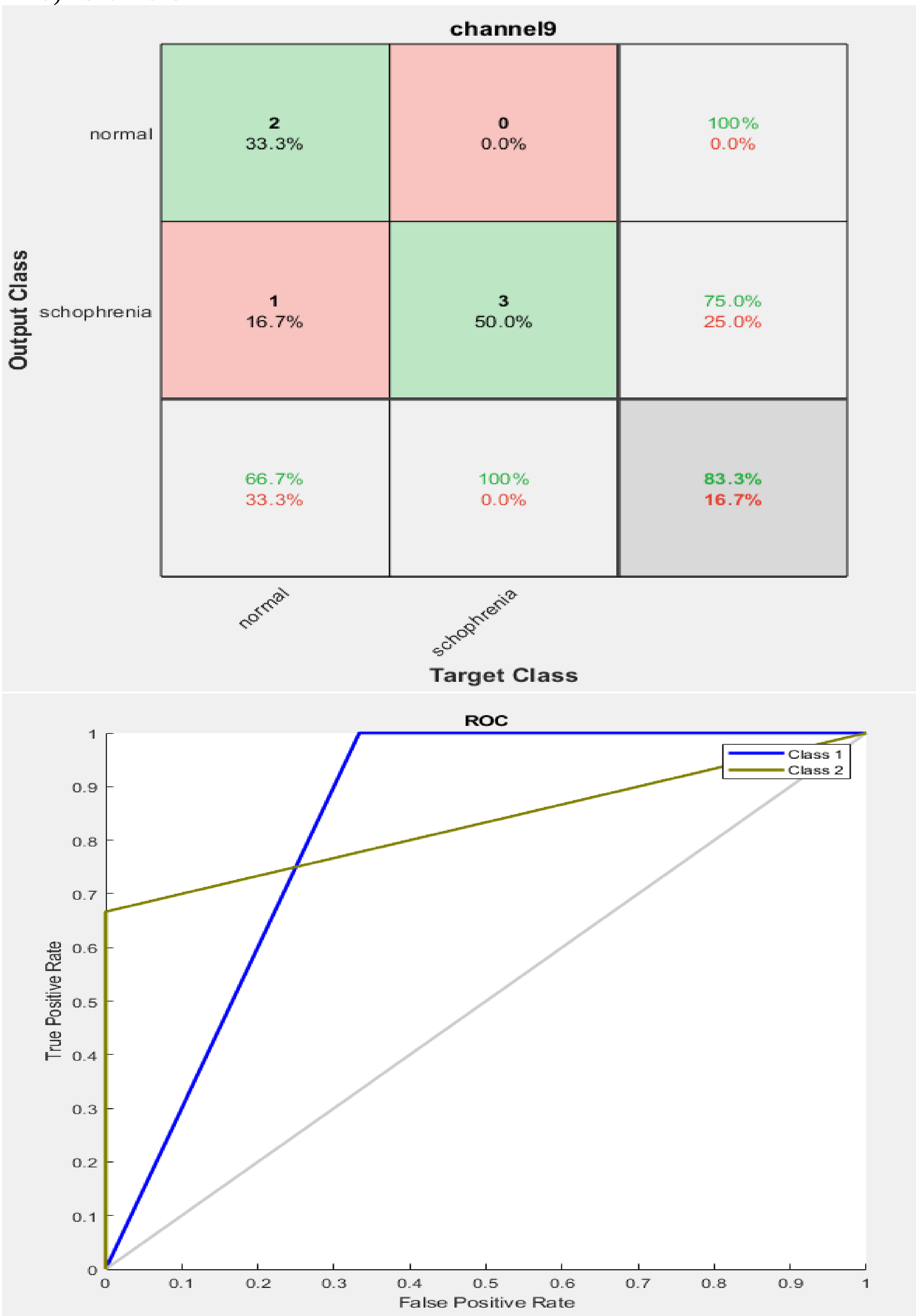
8) Channel 8


channel8
Output Class
normal
schophrenia
2
33.3%
0
0.0%
100%
0.0%
1
16.7%
3
50.0%
75.0%
25.0%
66.7%
33.3%
100%
0.0%
83.3%
16.7%
normal
schophrenia
Target Class


ROC
True Positive Rate
False Positive Rate
Class 1
Class 2
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(h)

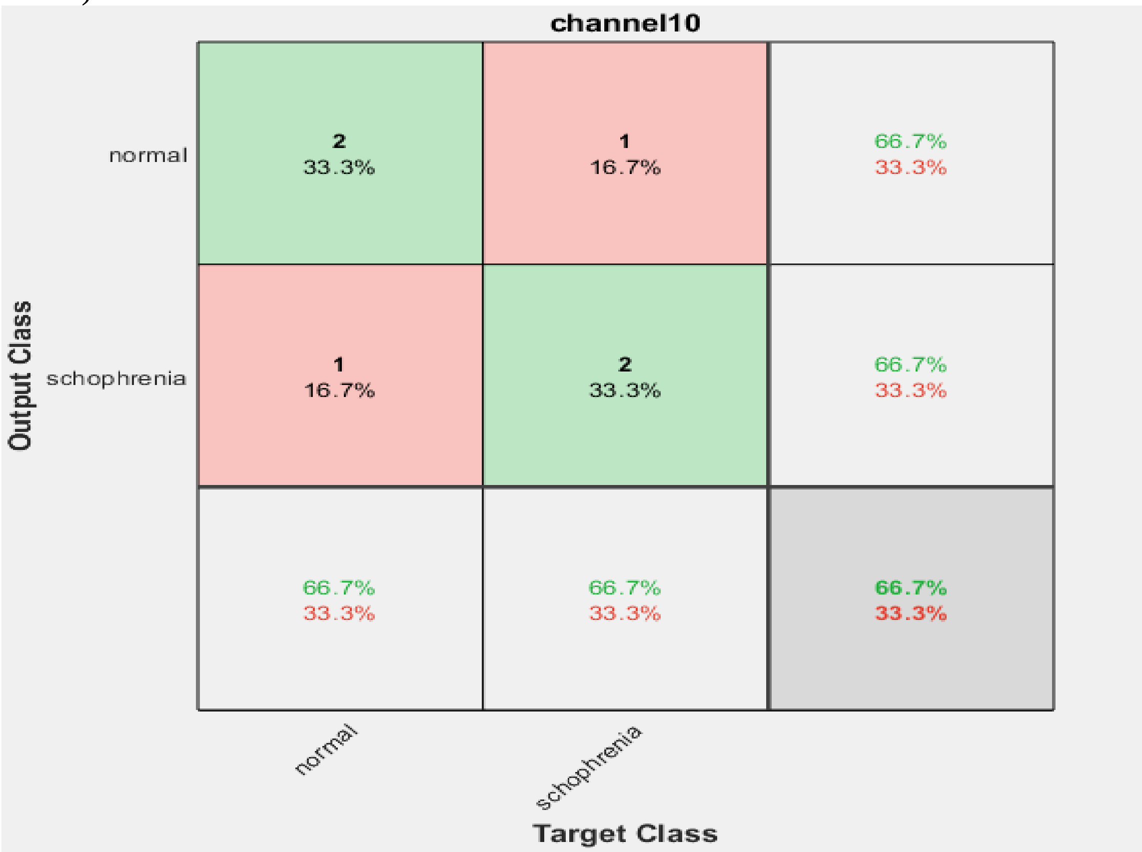
9) Channel 9

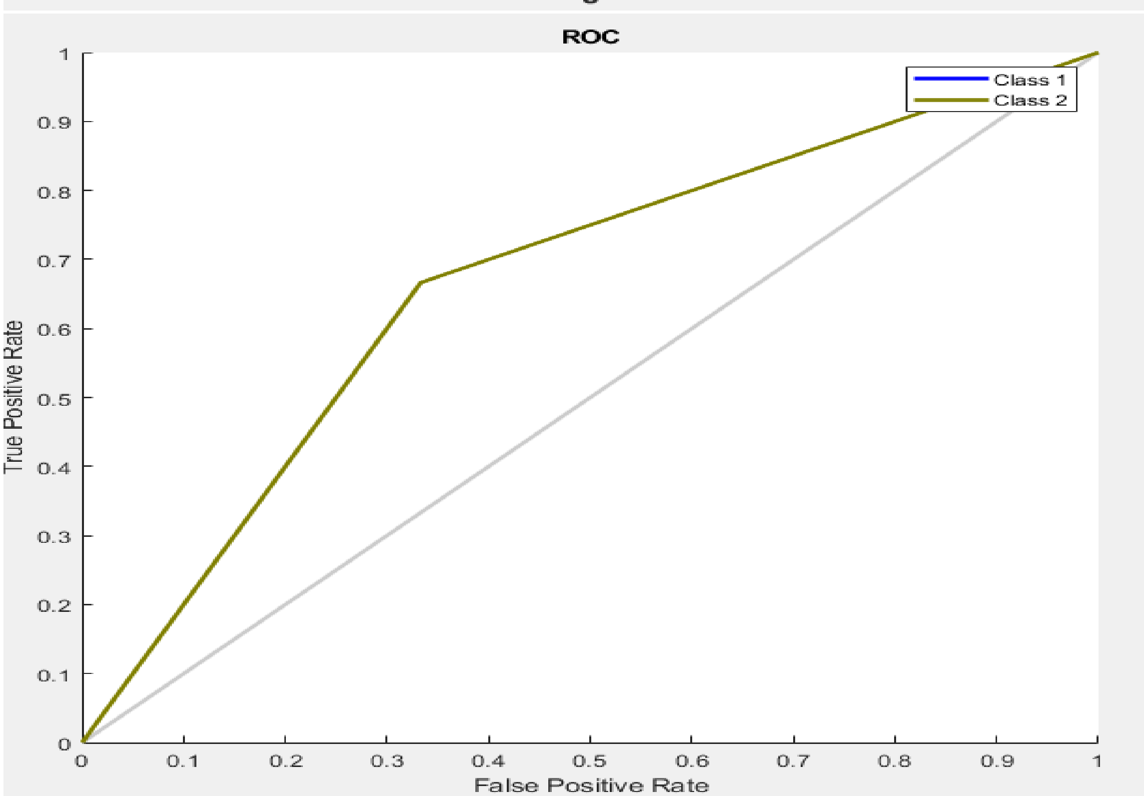


channel9
Output Class
normal
schophrenia
2
33.3%
0
0.0%
100%
0.0%
1
16.7%
3
50.0%
75.0%
25.0%
66.7%
33.3%
100%
0.0%
83.3%
16.7%
normal
schophrenia
Target Class
ROC
Class 1
Class 2
True Positive Rate
False Positive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

(i)

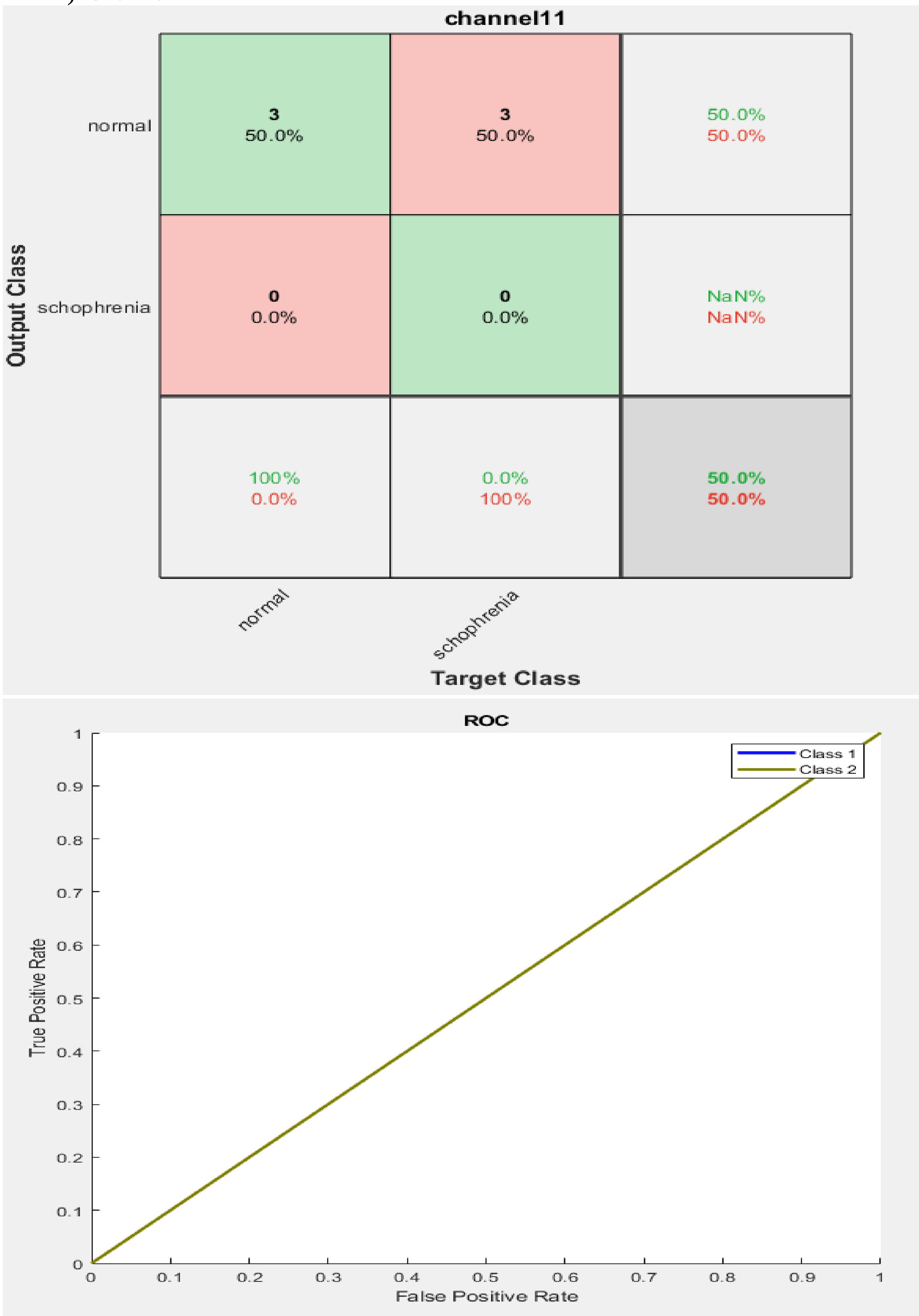
10) Channel 10





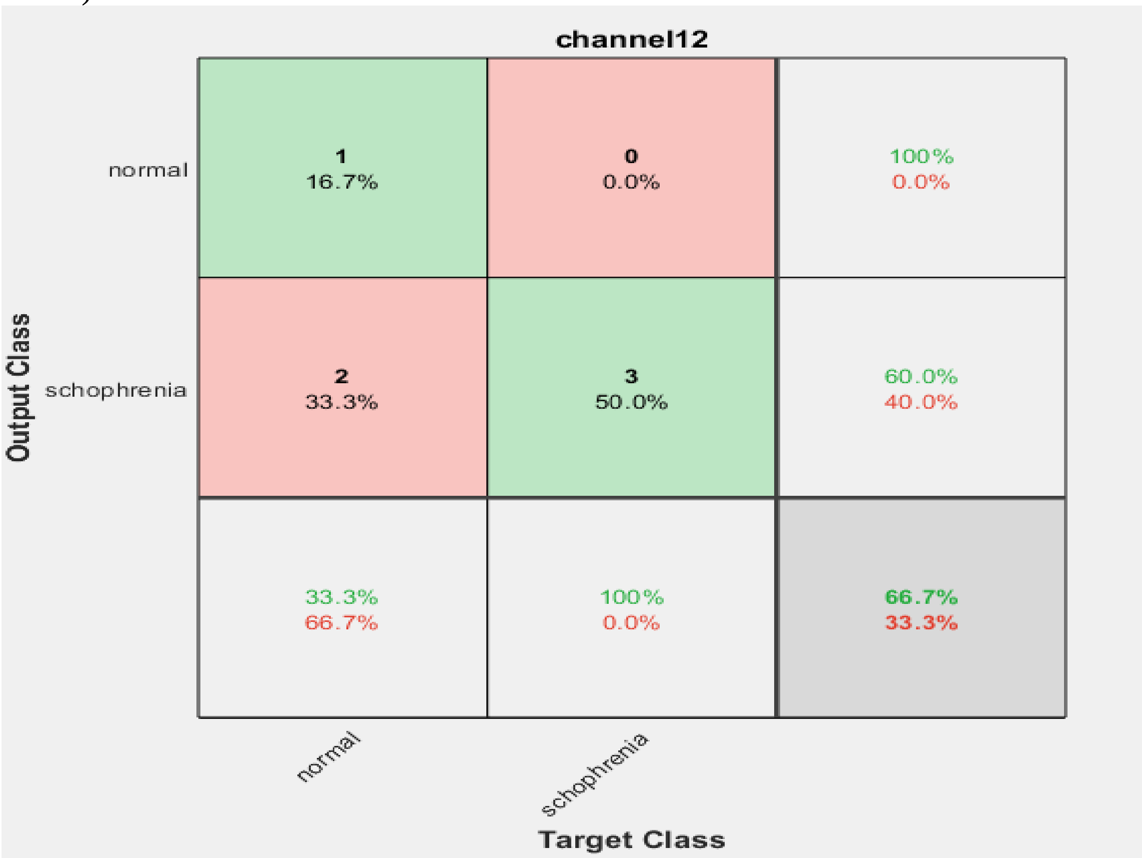
(j)

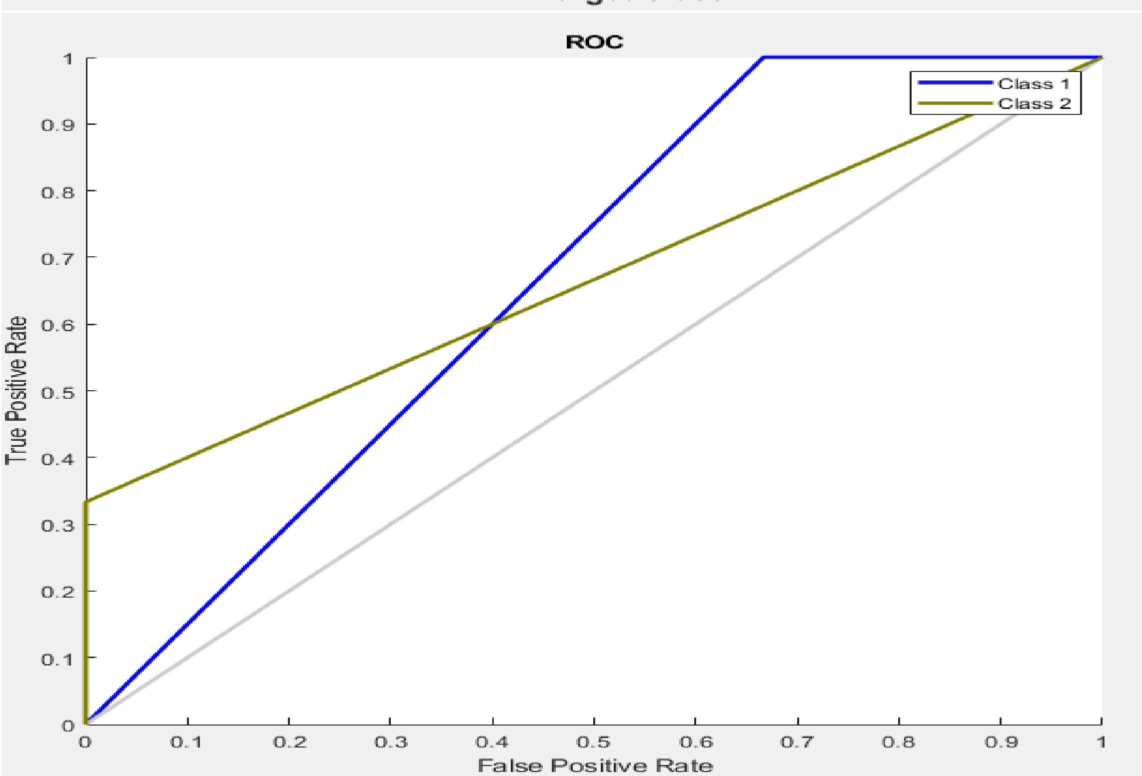
11) Channel 11



(k)

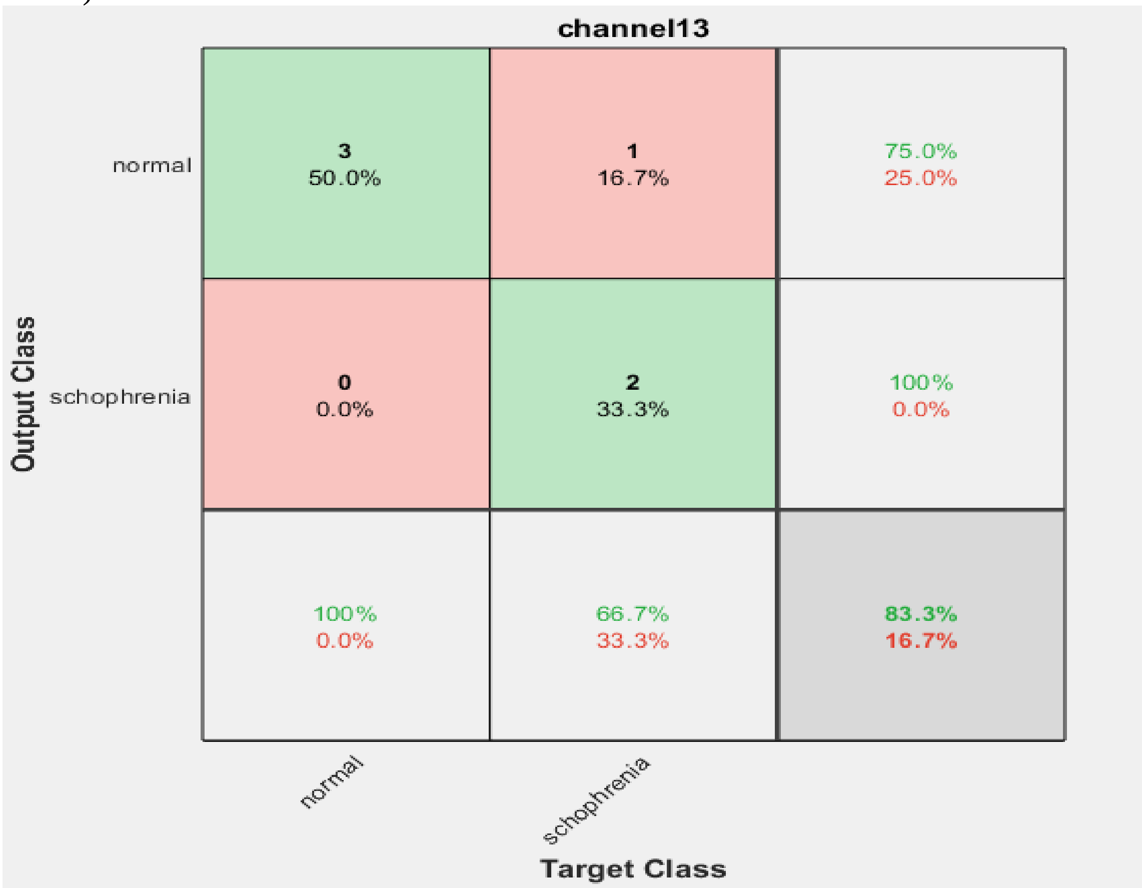
12) Channel 12

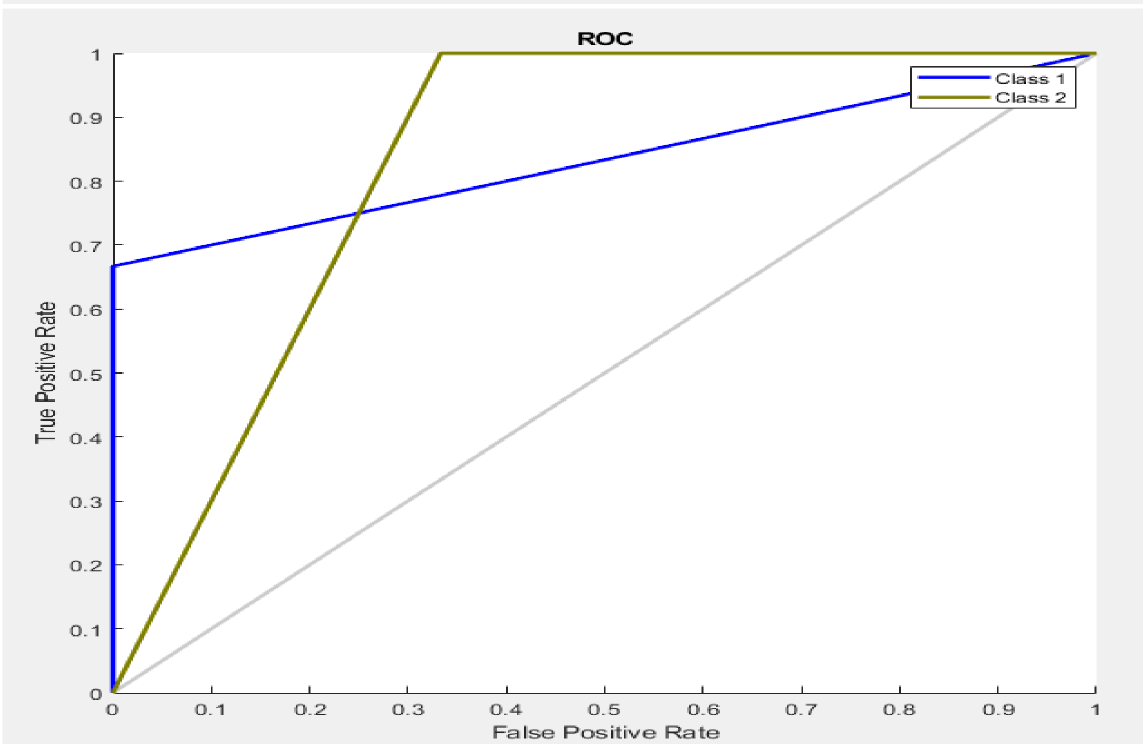




(l)

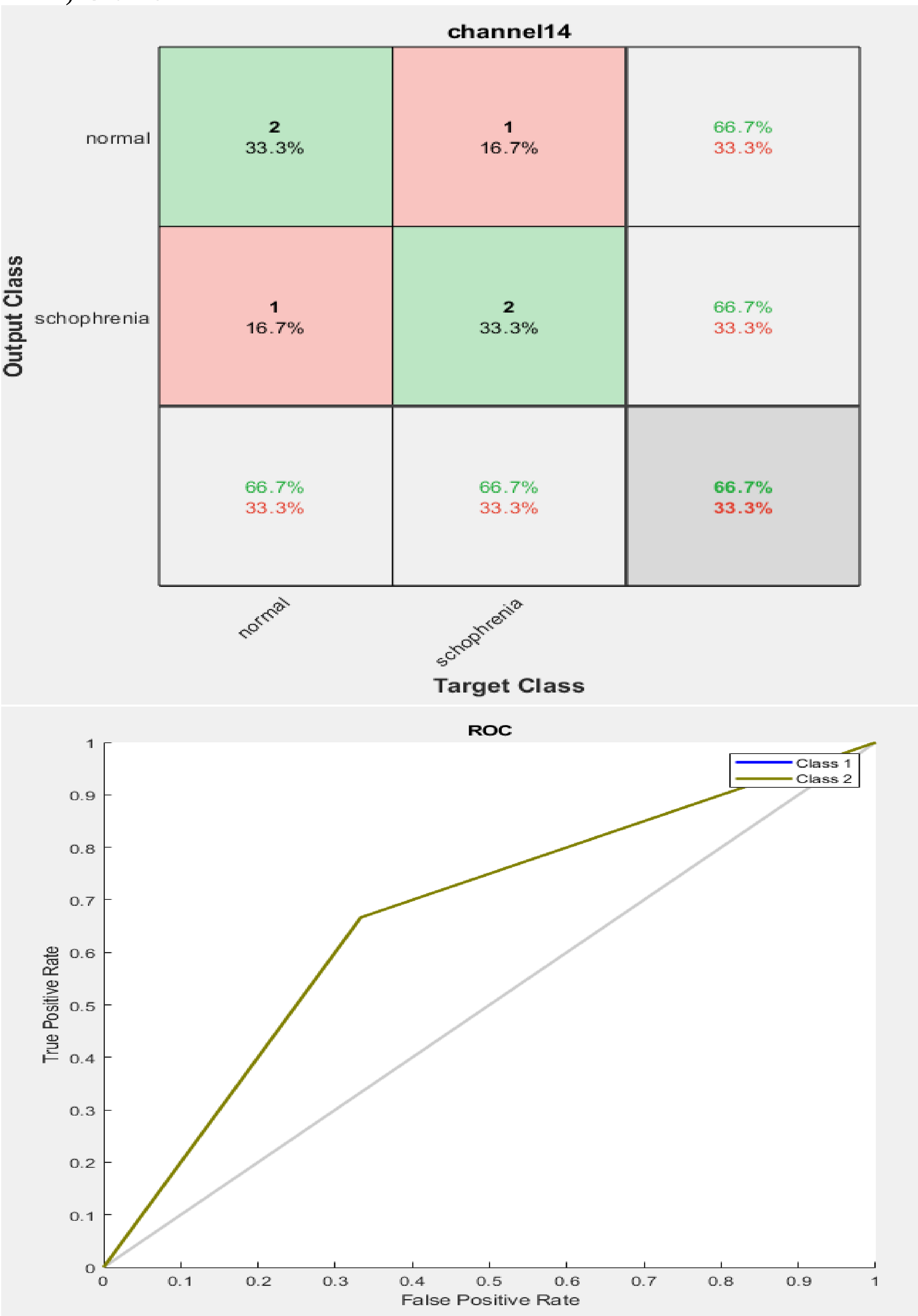
13) Channel 13





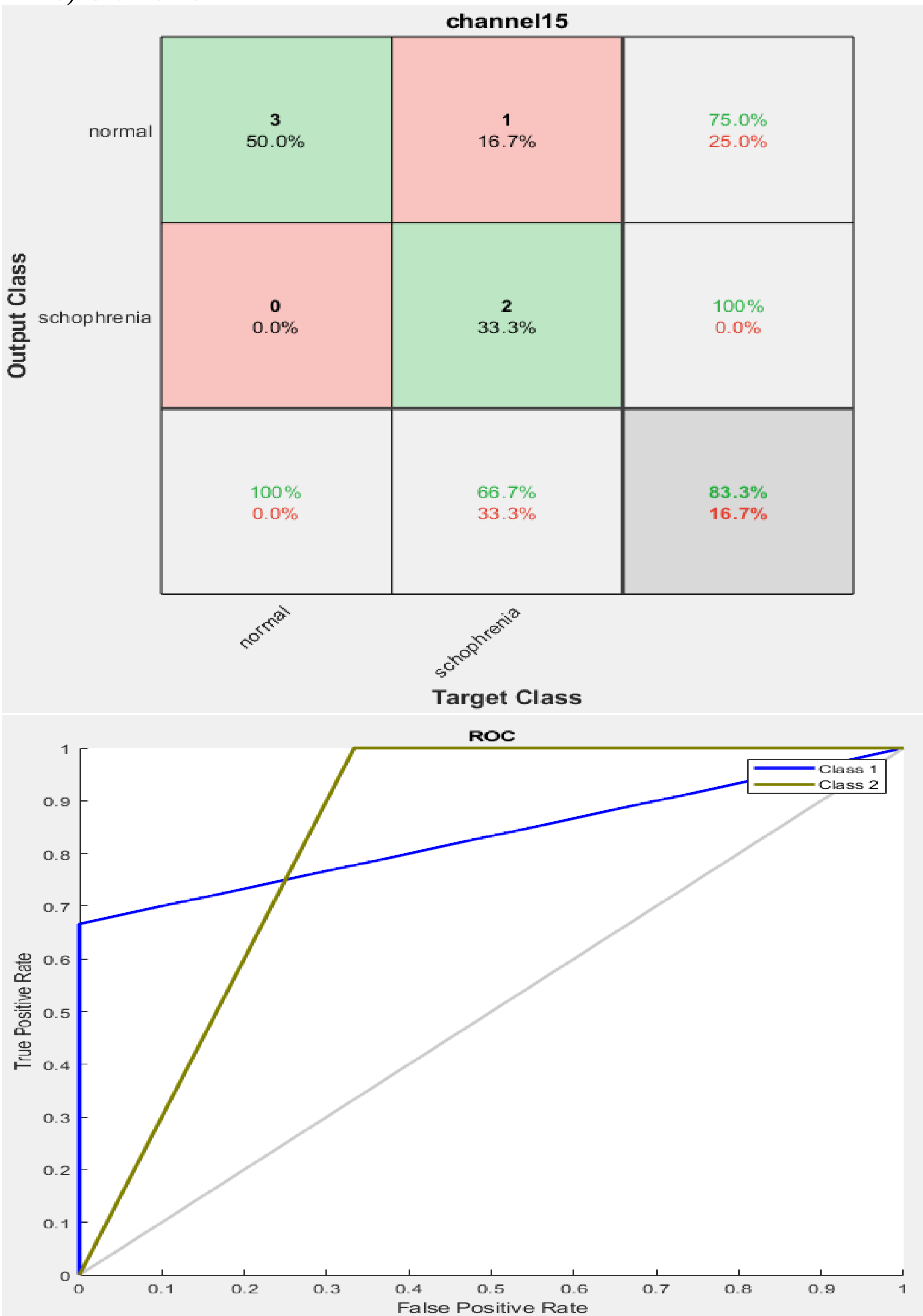
(m)

14) Channel 14



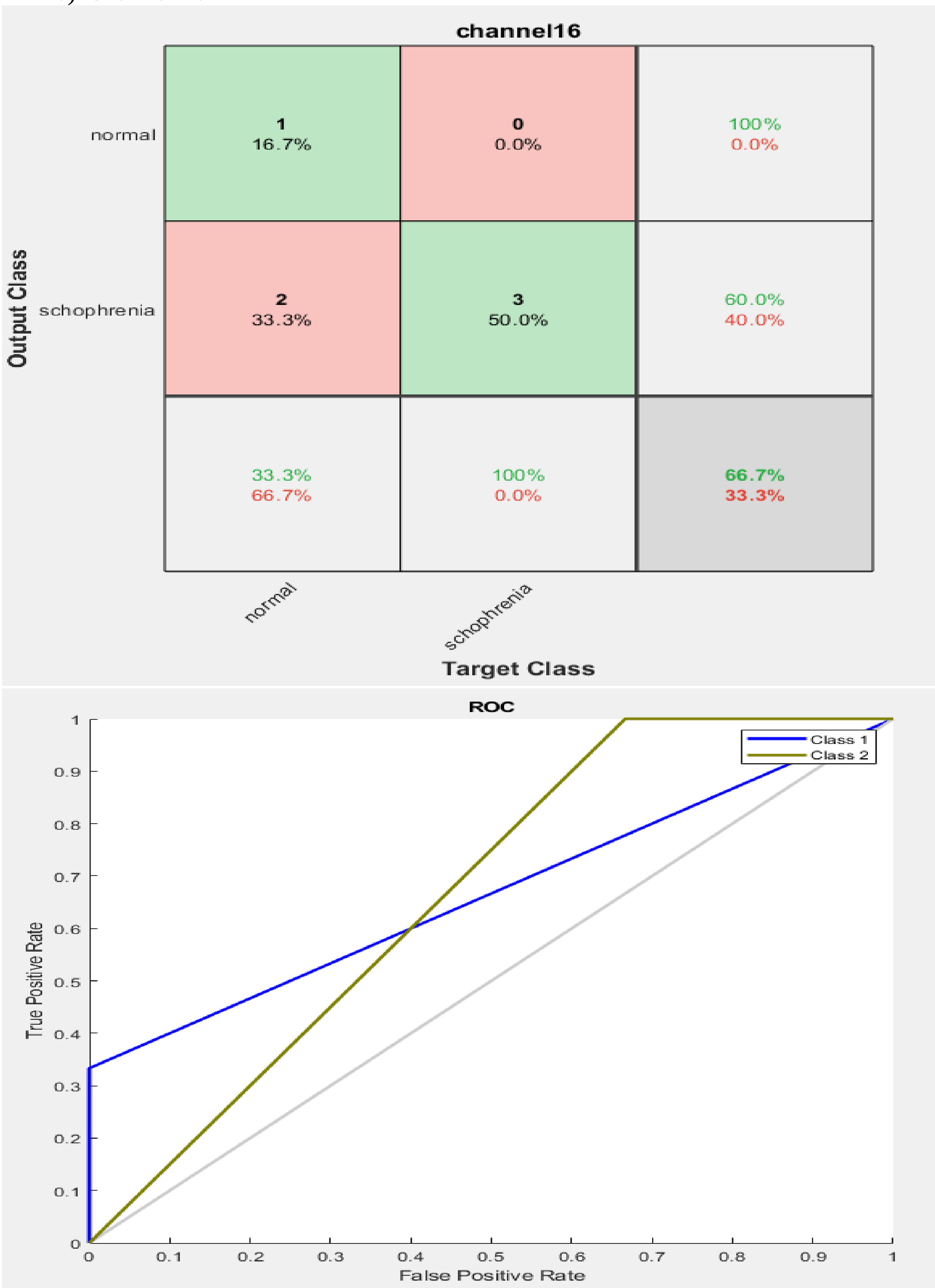
(n)

15) Channel 15



(O)

16) Channel 16



(P)

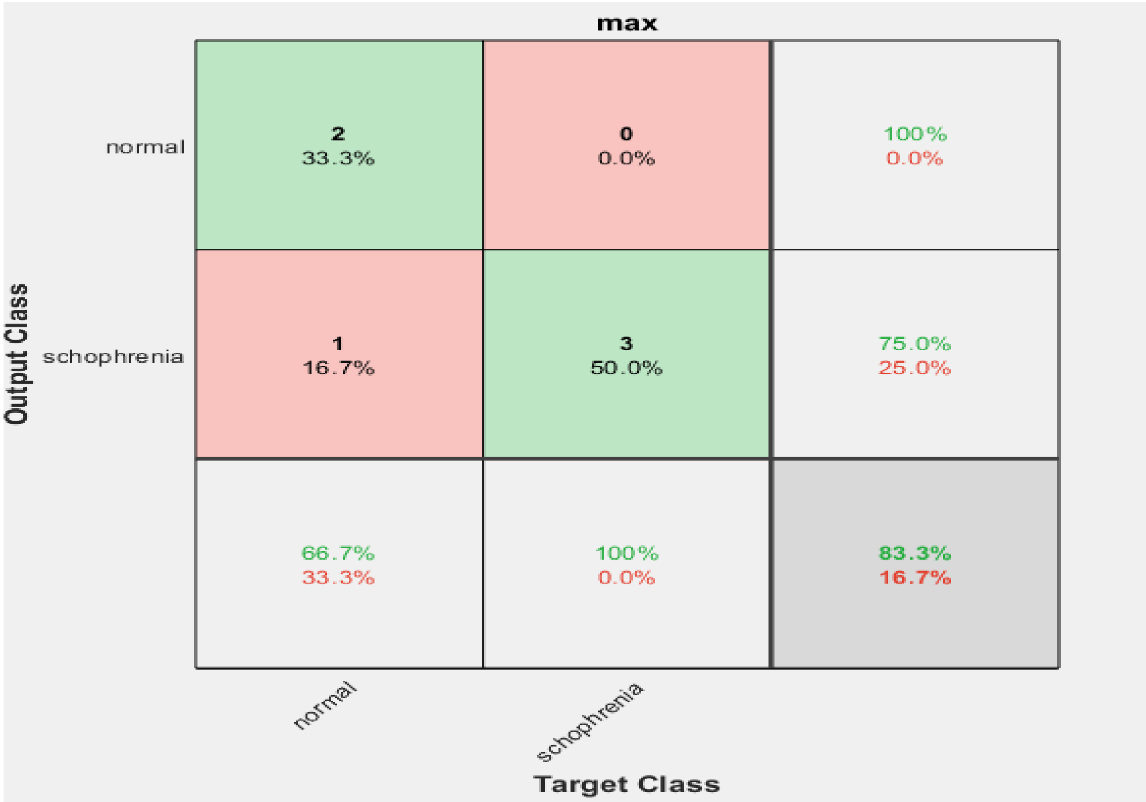
Figure 4.1 Confusion matrix and ROC of all the 16 channels

Table 4.1: Classification accuracy, sensitivity and specificity of all 16 channels using CNN classifier

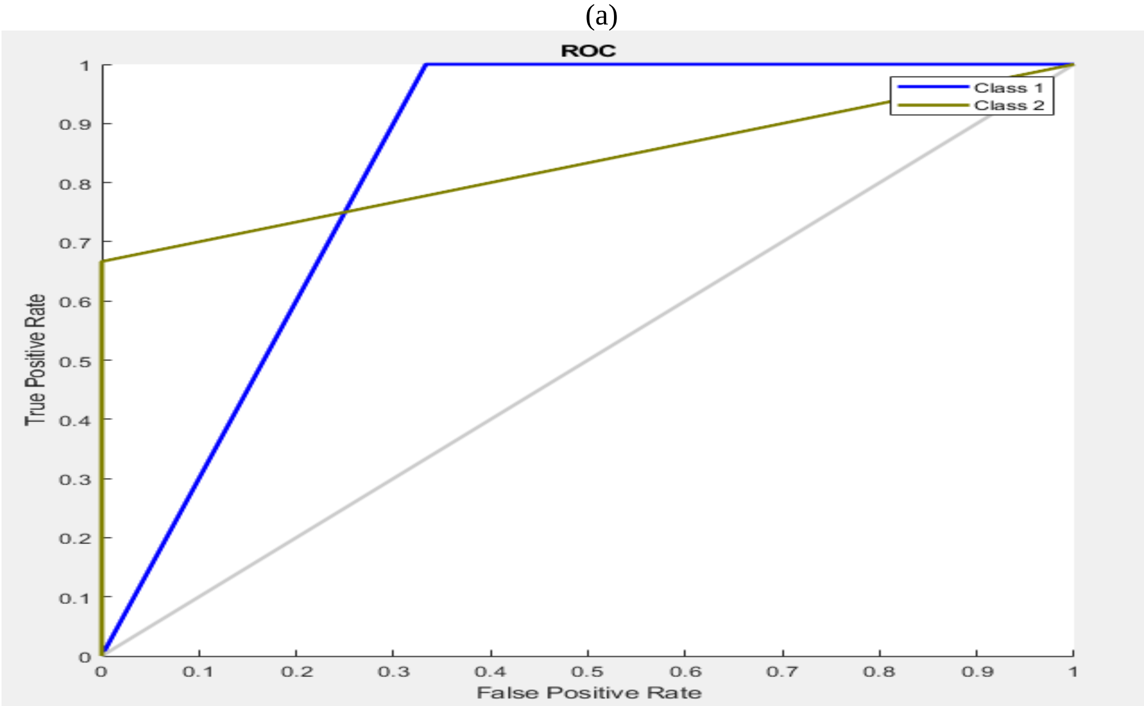
Channel number	Classification accuracy	Sensitivity	Specificity
Channel 1	66%	34%	100%
Channel 2	50%	66%	33.3%
Channel 3	66.7%	66.7%	66.7%
Channel 4	84%	67%	100%
Channel 5	66.6%	66%	66%
Channel 6	66%	33%	33%
Channel 7	66.7%	66.6%	66.6%
Channel 8	84%	100%	67%
Channel 9	83%	100%	66%
Channel 10	66%	67%	66%
Channel 11	50%	0%	100%
Channel 12	66.7%	100%	33%
Channel 13	84%	67%	100%
Channel 14	66.7%	66%	66.6%
Channel 15	83%	67%	100%
Channel 16	67%	100%	33%

From the table 4.1 we can observe that channel 4, channel 8 and channel 13 are the best for the classification purpose. Channel 2 has 84% classification accuracy, same for channel 8 and channel 13. Also channel 8 has 100% sensitivity. So we can conclude that channel 4,8,13 are having more information compare to others from classification perspective. Also we can observe that channel 11 has least information as it has 0% sensitivity, ie channel 11 is least required for this classification purpose.

We have also found two ensemble features namely max and min. these max and min features are giving excellent classification with excellent classification accuracy.

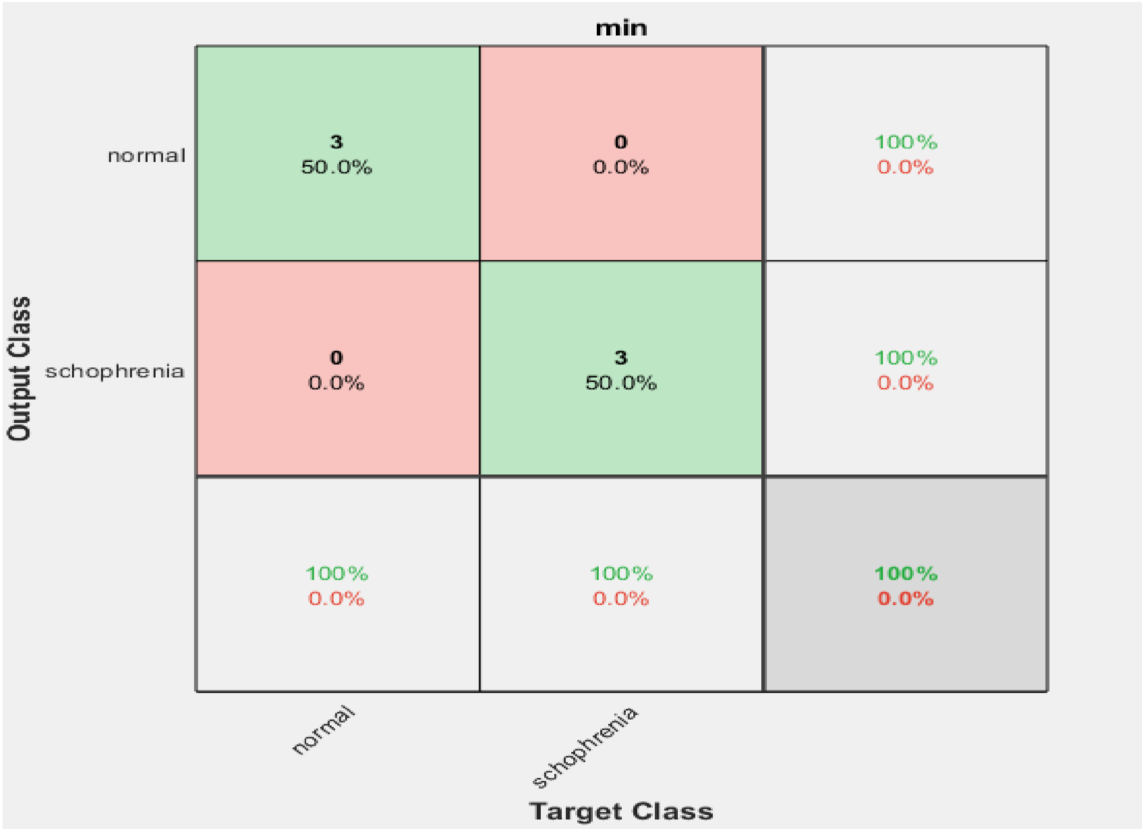


(a)

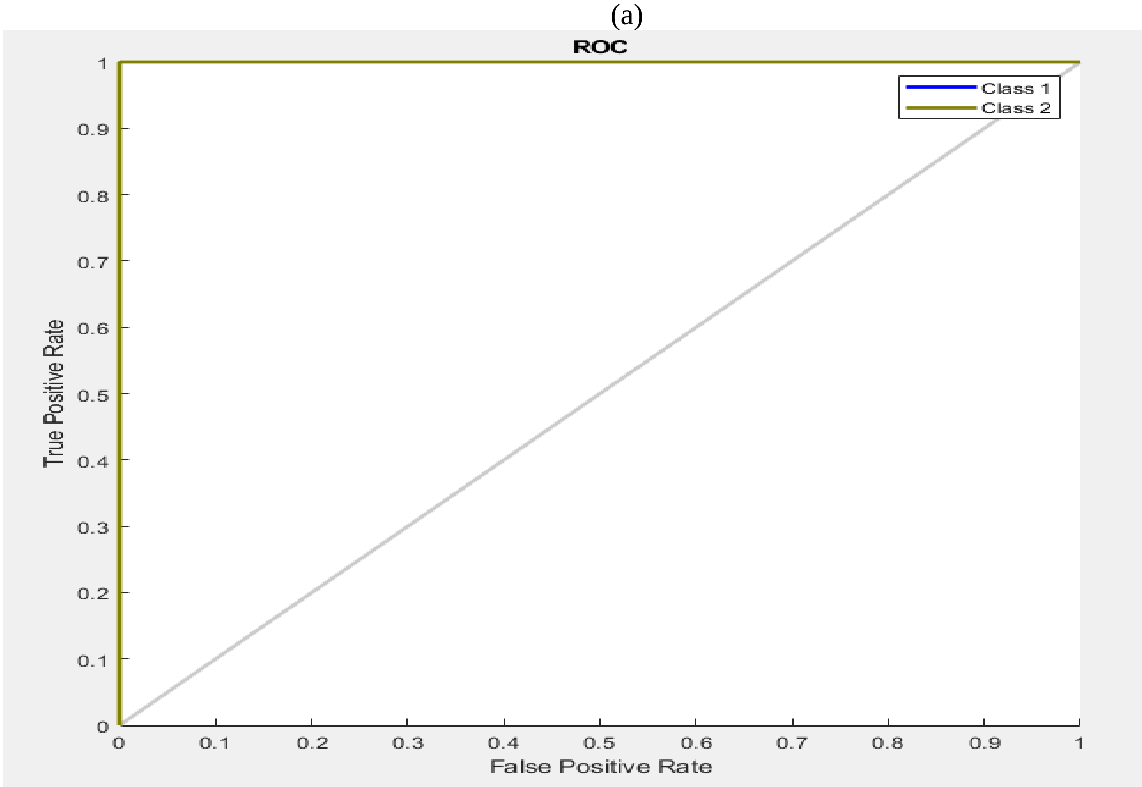


(b)

Fig 4.2 (a) confusion plot and (b) ROC plot of ensemble max features



(a)



(b)

Fig 4.3 (a) confusion plot and (b) ROC plot of ensemble min features

We have shown the confusion plots and the ROC plots for both these ensemble features. Here in confusion plots diagonal elements show the true values for the experiments while of diagonal shows the false values. In the confusion plot if output class (also called predicted class) is schizophrenia then it is positive value and if output class is healthy (normal) then it is negative value. Now if predicted output class is same as target output class then it is true value otherwise it is false value. ROC plot shows efficiency of the classifier, area under the curve in ROC plot is directly proportional to the efficiency of the classifier, more area implies more efficient classifier. Fig. 4.2 and 4.3 show the confusion plot and ROC plot of both the ensemble features.

From both the confusion plots and ROC curves we can easily observe that ensemble min feature is giving excellent Classification accuracy of 100% .

Table 4.2: Classification accuracy, sensitivity and specificity of two ensemble feature using CNN classifier

Ensemble features	Classification accuracy	Sensitivity	Specificity
Max	84%	100%	67%
Min	100%	100%	100%

The table 4.2 shows both ensemble feature’s (ie max and min) accuracy, sensitivity and specificity, which shows good performance of our proposed method.

Chapter 5

Conclusion and future work

5.1 Conclusion

In the proposed method we have used FBSE-EWT technique for decomposition of EEG signal and then by using CNN technique we have classified between schizophrenia and healthy adolescent. Many authors have been classified between two classes using various signal processing and machine learning techniques. But in this work we have used combination of FBSE and EWT (ie. FBSE-EWT method). This technique is very much suitable for analyzing non-stationary signals. EWT filter banks are deciding factors for number of sub-bands. Now days CNN is useful in many fields, based on image processing it can works as excellent classifier. So here we have used CNN for classification. Here we have taken complete data set (ie. For complete 60 seconds), due to which this process became a bit lengthier, but also due to the same reason we obtain more accurate results than the previous results.

5.2 Future work

In the thesis, we have proposed a method for classifying between these two classes namely schizophrenia and healthy. We have used complete dataset (ie. complete 60 second dataset without any filtering or reducing data points), due to which we got better classification accuracy but on the other hand this much long data required very much time only for signal decomposition also some extra time is needed for CNN processing. Hence in this process time requirement is more, if this problem will be resolve further then this method will be enhanced in terms of performance.

The proposed method can be studied for classification of other biomedical signal corresponding to normal and abnormal classes. Hardware implementation of the proposed framework can be taken as a future work.

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