Classification of Emotional States Inparkinson's Disease Patients Using Time,Frequency and Time-Frequency Analysis

Rejith K.N (rejithwireless@gmail.com)
Karpagam Academy of Higher Education: Karpagam University

Kamalraj Subramaniam
Karpagam Academy of Higher Education: Karpagam University

Ayyem Pillai Vasudevan Pillai
Gokaraju Rangaraju Institute of Engineering and Technology

Roshini T V
Vimal Jyothi Engineering College

Renjith V. Ravi
MEA Engineering College

Elamaran V
SASTRA Deemed University

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CLASSIFICATION OF EMOTIONAL STATES INPARKINSON'S DISEASE PATIENTS USING TIME,FREQUENCY AND TIME-FREQUENCY ANALYSIS

Rejith.K.N[1] Kamalraj Subramaniam[2], Ayyem Pillai Vasudevan Pillai[3], Roshini T V [4], Renjith V. Ravi [5], V. Elamaran [6]

[1]Research scholar, Karpagam academy of higher education, Coimbatore, India.(9037225424, rejith.kn@gmail.com)
[2]Associate Professor, Faculty of Engineering, Karpagam academy of higher education, Coimbatore, India. (kamalrajece@gmail.com)
[3]Professor, Department of ECE, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad (ayyempillai@yahoo.com)
[4]Professor, Department of ECE, Vimal Jyothi Engineering college, Chemperi.(roshini.tv@gmail.com)
[5]Associate Professor, Department of ECE, M.E.A Engineering college, Malappuram, Kerala (renjithravi.research@gmail.com)
[6]V. Elamaran, Assistant professor, Department of ECE, SASTRA Deemed University, Thanjavur (elamaran@ece.sastra.edu)

ABSTRACT

In this work, PD patients and healthy individuals were categorized with machine-learning algorithms. EEG signals associated with six different emotions, (Happiness(E1), Sadness(E2), Fear(E3), Anger(E4), Surprise,(E5) and disgust(E6)) were used for the study. EEG data were collected from 20 PD patients and 20 normal controls using multimodal stimuli. Different features were used to categorize emotional data. Emotional recognition in Parkinson's disease (PD) has been investigated in three domains namely, time, frequency and time frequency using Entropy, Energy-Entropy and Teager Energy-Entropy features. Three classifiers namely, K-Nearest Neighbor Algorithm, Support Vector Machine and Probabilistic Neural Network were used to observethe classification results. Emotional EEG stimuli such as anger, surprise, happiness, sadness, fear, and disgust were used to categorize PD patients and healthy controls (HC). For each EEG signal, frequency features corresponding to alpha, beta and gamma bands were obtained for nine feature extraction methods (Entropy, Energy Entropy, Teager Energy Entropy, Spectral Entropy, Spectral Energy-Entropy, Spectral Teager Energy-Entropy, STFT Entropy, STFT Energy-Entropy and STFT Teager Energy-Entropy). From the analysis, it is observed that the entropy feature in frequency domain performs evenly well (above 80 %) for all six emotions with KNN. Classification results shows that using the selected energy entropy combination feature in frequency domain provides highest accuracy for all emotions except E1 and E2 for KNN and SVM classifier, whereas other features give accuracy values of above 60% for most emotions.It is also observed that emotion E1 gives above 90 % classification accuracy for all classifiers in time domain.In frequency domain also, emotion E1 gives above 90% classification accuracy using PNN classifier.

Keywords:

Electroencephalogram, Emotions, Multimodal stimulus, Non-linear methods, Parkinson's disease, Spreadfactor, Teager Energy Entropy,Short time fourier transform.

1. INTRODUCTION

Parkinson's disease (PD) is a neurodegenerative disease caused from the decrease in the transmission of dopamine neurotransmitter with in the basal ganglia and substantianigra[1]. Idiopathic PD (reason unknown) is the reason for most of the cases of Parkinsonism and the remaining from genetic causes and others including drugs and neurodegenerative disorders. The disease mostly affects the population above 60 years of age and the volume of patients having Parkinson's disease has increased all the year's record. The deficiency of dopamine in the basal ganglia results in motor clinical symptoms and non-motor symptoms. Motor symptoms of PD exhibit resting tremor, firmness and postural imbalance while non-motor symptoms include cognitive dysfunction which appears in the initial stage of PD. Non-motor indications which include interruptions in the processing of emotional data are found in newly diagnosed PD patients and may happen in any course of disease advancement. It is found that cognitive impairments have been found before the onset of motor disorders in PD[2].

Clinical symptoms of PD cannot be detected in the early stage due to the lack of definite motor features and evident cognitive disorders.Categorization of Parkinson's disease from the view of neuroscience offers a different method to study and measure the activities of the brain and increase diagnostic certainty. Since brain signals (EEG) reflect the inherent activity of central nervous system (CNS), it can be considered as a tool to identify the actual emotion of an individual. The brain signals are usually used to analysebrain death, sleep disorders, depth of anaesthesia, encephalopathy, and epilepsy,and also for detecting tumours, stroke and other brain diseases as primary means. In general, EEG signals are used to

learn brain actions affecting the emotional responses [3].

In this work, PD patients and healthy individuals were categorized with machine-learning algorithms. EEG signals associated with six different emotions, (Happiness (E1), Sadness (E2), Fear (E3), Anger (E4), Surprise (E5) and disgust(E6)) were used for the study. EEG data were collected from 20 PD patients and 20 normal controls using multimodal stimuli[4]. Different features were used to categorize emotional data. Recognition of emotions in PD patients has been investigated in three domains namely, time, frequency and time frequency using various Entropy features. Three classifiers namely, K-Nearest Neighbor Algorithm, Support Vector Machine and Probabilistic Neural Network were used to obtain the classification results. Emotional EEG stimuli corresponding to happiness, sadness, fear, anger, surprise and disgust were used to classify PD patients and healthy controls (HC). For each EEG signal,three frequency bands- alpha, beta and gamma were used to extract nine features namely, Entropy, Energy Entropy, Teager Energy Entropy, Spectral Entropy, Spectral Energy-Entropy, Spectral Teager Energy-Entropy, STFT Entropy, STFT Energy-Entropy and STFT Teager Energy-Entropy. The rest of the paper is organized as follows: Section II describes the materials and methods. Section III describes results and discussion. Section IV describes the conclusion.

2. MATERIALS AND METHODS

2.1 INTRODUCTION

Quantitative analysis of EEG involves mathematical analysis of EEG data to acquire vital information [5,6,7].The extracted information are subsequently processed or compared with other kinds of data. QEEG provides derivative parameters which are generated from 'raw data' using computational methods.Figure-1 shows the plot of raw data of emotion E1.

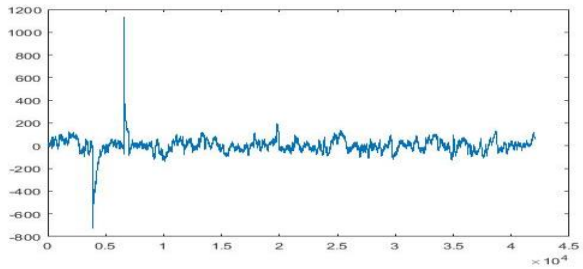
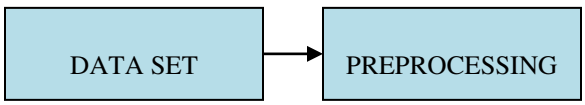


Figure-1: Raw data of emotion E1

QEEG includes mainly two steps-

- Preprocessing
- Mathematical processing

Figure-2 shows the block diagram representation of methodology for classifying the Parkinson's disease patients from healthy controls.



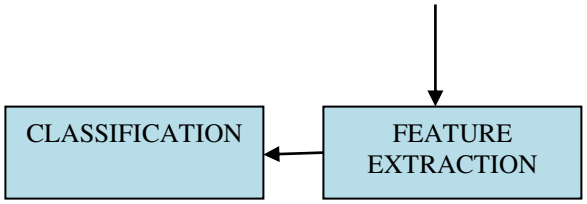


Figure-2: Block diagram representation of methodology

2.1.1 Pre-Processing

Before feature extraction, the following pre-processing methods were adopted.

2.1.1.1 Segmentation and Overlapping

Each channel of emotional EEG data is divided in to 10s length epochs with an overlapping using timewindows[8].Data is segmented in to frames of 1280 samples corresponding to 10 second data since sampling frequency is 128 Hz. Frames are overlapped with 75%.Fgure-3 shows the plot of one frame of a segment.

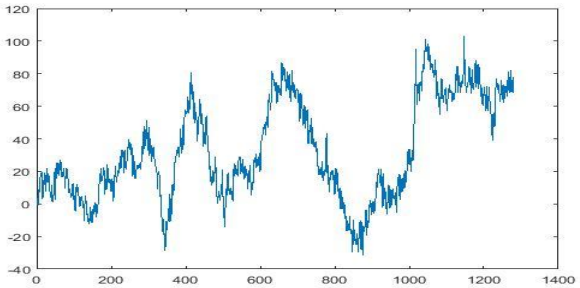


Figure-3: Plot of one frame of a segment.

2.1.1.2 Filtering

Elliptic band pass filter is used.EEG signal is filtered into respective spectral range namely alpha (8 to 13 Hz), beta (13 to 20 Hz) and gamma (20 to 34 Hz).Figure-4 shows the output of a band pass filter corresponding to one frame.

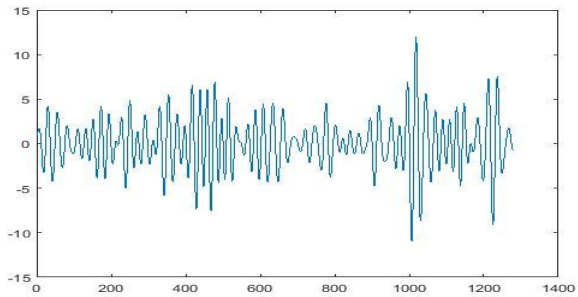


Figure-4:Bandpass filter output

2.1.2 MATHEMATICAL PROCESSING

It includes two processing operations-

- Feature Extraction
- Feature Classification

2.1.2.1 Feature Extraction

Feature extraction is performed in three domains namely, time, frequency and time-frequency domain and the following features namely Entropy, Energy-Entropy, Teager Energy-Entropy, Spectral Entropy, Spectral Energy-Entropy, Spectral Teager Energy-Entropy, STFT Entropy, STFT Energy-Entropy and STFT Teager Energy-Entropy[9] were extracted..

2.1.2.1.1 Time domain features

(a) ENTROPY (EN)

Entropy value is calculated using the Shannon entropy [10]. The entropy feature is extracted using the Equation (1),

where N is the size of the sample.

$$H_{ij}^{k} = -\sum_{q=1}^{N}[x_{ij}^{k}(q)\ln(x_{ij}^{k}(q))] \quad (1)$$

(b) ENERGY ENTROPY (EEN)

The power values of Shannon entropy [11] is used to evaluate Energy-Entropy. The EEN feature is extracted using the Equation (2),

Where N is the size of the sample.

$$S_{ij}^{k} = -\sum_{q=1}^{N}[(x_{ij}^{k}(q))^{2}\ln(x_{ij}^{k}(q))^{2}] \quad (2)$$

(c) TEAGER ENERGY ENTROPY (TEEN)

Teager Energy is a powerful nonlinear operator proposed by Kaiser[12]. The continuous form of the Teager Energy is given as

$$\varphi_c[y(t)] = (\frac{d}{dt}y(t))^{2} - y(t)\frac{d^{2}}{dt^{2}}y(t)$$

TheTeager Energy-Entropy (TEEN) is extracted using Equation (3)

$$H_{ij}^{k} = -\sum_{q=1}^{N}[\varphi y_{ij}^{k}(q)\ln(\varphi y_{ij}^{k}(q))] \quad (3)$$

Where N is the size of the sample.

2.1.2.1.2 Frequency domain features

(a) Spectral Entropy (SEN)-

The filtered data, x(q) were first frequency converted to Y(m) using the Equation(4),

$$Y_{ij}^{k} = \sum_{q=1}^{N} x_{ij}^{k}(q)\ w_{n}^{(q-1)(l-1)} \quad (4)$$

Where $w_n = e^{(-2\pi i)/N}$ is the complex exponential and N represents the number of data in the filtered signal.

From Y(m), the Spectral Entropy is found using Equation (5)

$$H_{ij}^{k} = -\sum_{m=1}^{N} Y_{ij}^{k}(m)\ln(Y_{ij}^{k}(m))] \quad (5)$$

where N = 128, is the number of samples.

(b) SPECTRAL ENERGY- ENTROPY (SEEN)

The power values of Spectral entropy is used to find SEEN value.The SEEN feature is extracted using the Equation (6)
,

$$S_{ij}^{k} = -\sum_{m=1}^{N}[(Y_{ij}^{k}(m))^{2}\ln(Y_{ij}^{k}(m))^{2}] \quad (6)$$

where N is the size of the sample.

(c) SPECTRAL TEAGER ENERGY ENTROPY (STEEN)

The continuous form of the Teager Energy is given as

$$\varphi_c[y(t)] = (\frac{d}{dt}y(t))^{2} - y(t)\frac{d^{2}}{dt^{2}}y(t)$$

STEEN is calculated from the transformed signal Y(m), using Equation (7),

$$H_{ij}^{k} = -\sum_{q=1}^{N}[\varphi Y_{ij}^{k}(m)\ln(\varphi Y_{ij}^{k}(m))] \quad (7)$$

where N is the size of the sample.

2.1.2.1.3 Time-Frequency Analysis

(a) STFT Entropy (STFTEN)

The filtered values, x(q) were first Short Time Fourier transformed to Y(m) using the Equation (8),

$$STFT(t',u) = \int[f(t)*W(t-t')]*e^{-j2\Pi ut}dt \quad (8)$$

From the Short time Fourier transformed signal Y(m), the STFTEN value is found using Equation (9),

$$H_{ij}^{k} = -\sum_{m=1}^{N} Y_{ij}^{k}(m)\ln(Y_{ij}^{k}(m))] \quad (9)$$

(b) STFT Energy- Entropy (STFTEEN)

The power values of STFT entropy is used to derive STFTEEN value. The STFTEEN feature is extracted using the Equation (10),

$$S_{ij}^{k} = -\sum_{m=1}^{N} [(Y_{ij}^{k}(m))^{2} \ln(Y_{ij}^{k}(m))^{2}] \quad (10)$$

where N is the size of the sample.

(c) STFT Teager Energy Entropy feature (STFTTEEN)

The continuous form of the Teager Energy is given as

$$\varphi_c[y(t)] = (\frac{d}{dt}y(t))^{2} - y(t)\frac{d^{2}}{dt^{2}}y(t)$$

STFTTEEN value is calculated using Equation (11),

$$H_{ij}^{k} = -\sum_{q=1}^{N} [\varphi Y_{ij}^{k}(m)\ln(\varphi Y_{ij}^{k}(m))] \quad (11)$$

where N is the size of the sample.

2.1.2.2 FEATURE CLASSIFICATION

Feature classification is done using three classification algorithms namely Probabilistic Neural Networks, k-Nearest Neighbor, and Support Vector Machine. Out of the three, Support Vector Machine is a non-linear classifier while the other two are linear.

2.1.2.2.1 K-Nearest Neighbor Algorithm

K nearest neighbor (KNN) is a classification algorithm that keeps all classes and categorizes new class based on the degree of resemblance [13].KNN is a non-parametric classification method. In KNN classification, the output is a member of a class. An object is allocated to a class based on the maximum vote of the members close to it. An item is allocated to the class that is common among its k nearest neighbors. If k = 1, then the object is assigned to the class of the neighbor very near to it. In this model, 42 extracted values corresponding to 3 frequencies(one in each band) in 14 channels were given and the accuracy results of all emotions were found. Smoothing parameter k is varied from 1 to 10.

K-Nearest Neighbors (KNN) is one of the simplest algorithms used in Machine Learning for regression and classification problem. KNN algorithms use data and classify new data points based on similarity measures (e.g. distance function). Classification is done by a majority vote to its neighbors. KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).The Nearest Neighbor rule (NN) is the simplest form of KNN when K = 1.

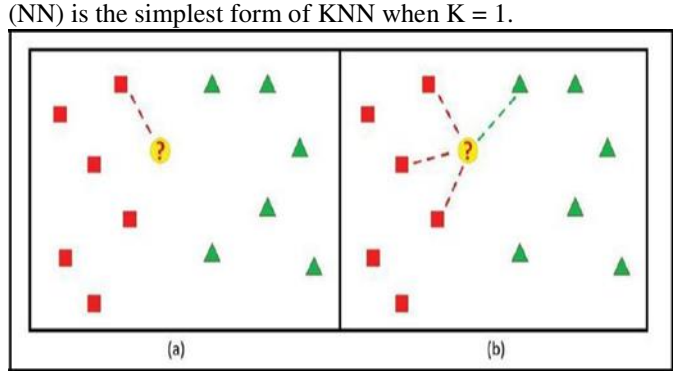


Figure-5:

Figure 5 shows the KNN decision rule for K= 1 and K= 4 for a set of samples divided into 2 classes. In Figure 5(a), an unknown sample is classified by using only one known sample; In Figure 5(b) more than one known sample is used. In the last case, the parameter K is set to 4, so that the closest four samples is considered for classifying the unknown one. Three of them belong to the same class, whereas only one belongs to the other class. In both cases, the unknown sample is classified as belonging to the class on the left.

2.1.2.2.2 Probabilistic Neural Network

PNN has been appliedto differentiate PD and HC for six different emotions. PNN is a feed forward algorithm, commonly employed in classification operations. In the PNN algorithm,a Parzen window is used to approximate the parent probability distribution function (PDF) of each class. The likelihood of incoming data is measured using PDF of each class and by applying Bayes' rule, highest posterior probability is allocated to new input data. It is found that the error probability is greatly reduced.

The operations of PNN are structured into a multi-layered feed forward network using four layers. PNN is a supervised neural network proposed by Donald F. Specht and it is a type of radial basis network appropriate for classification problems [14].The classification accuracy of PNN depends on the value selected for smoothing factor/spread factor. The network structure of PNN is almost same as back propagation. It differs in the use of exponential activation function rather than sigmoid activation function and also the training time is less compared to multi-layer feed forward network trained by back propagation algorithm.

A probabilistic neural network (PNN) has 3 layers of nodes. Figure 6 shows the architecture for a PNN that recognizes K =

2 classes, but it can be extended to any number K of classes. The input layer (on the left) contains N nodes: one for each of the N input features of a feature vector. These are fan-out nodes that branch at each feature input node to all nodes in the hidden (or middle) layer so that each hidden node receives the complete input feature vector x. The hidden nodes are collected into groups: one group for each of the K classes.

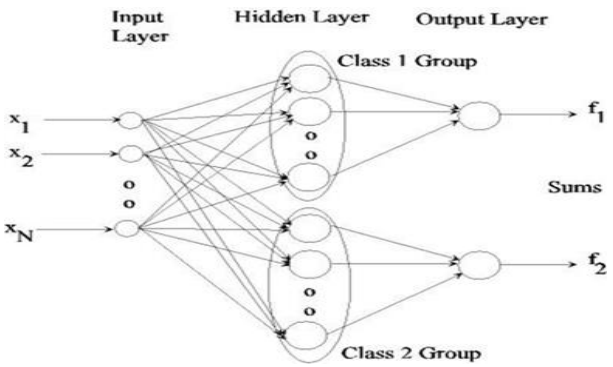


Figure-6:

Each hidden node in the group for Class k corresponds to a Gaussian function centered on its associated feature vector in the kth class (there is a Gaussian for each exemplar feature vector). All of the Gaussians in a class group feed their functional values to the same output layer node for that class, so there are K output nodes.

In this paper, PNN classification is implemented and analyzed using MATLAB software. This problem requires 42 input neurons. The classification accuracy and the best smoothing parameter (K) ranges were found for all the six emotions.

2.1.2.2.3 Support Vector Machine

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression [15]. They belong to a family of generalized linear classifiers. In another terms, Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data [16]. Support Vector machines can be defined as systems which use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. SVM becomes famous when, using pixel maps as input; it gives accuracy comparable to sophisticated neural networks with elaborated features in a handwriting recognition task. It is also being used for many applications, such as hand writing analysis, face analysis and so forth, especially for pattern classification and regression based applications [17]. The foundations of Support Vector Machines (SVM) have been developed by Vapnik and gained popularity due to many promising features such as better empirical performance. The formulation uses the Structural Risk Minimization (SRM) principle [18], which has been shown to be superior to traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks. SRM minimizes an upper bound on the expected risk, whereas ERM minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize, which is the goal in statistical learning. SVMs were developed to solve the classification problem, but recently they have been extended to solve regression problems.

3. RESULTS AND DISCUSSION

Three classifiers namely KNN, PNN and SVM models were used to investigate theemotional states of PD and HC using nine features. The overall classification accuracies of nine features for each emotion using three models were tabulated. TEEN with SVM gives maximum accuracy of 99.59% for emotion E1 and EEN with SVM gives second highest accuracy of 99.39%. For emotion E2, SEN with KNN gives maximum accuracy of 90.2% and SEEN with KNN gives second highest accuracy of 75.2%. For emotion E3, maximum accuracy of 95.07% is obtained using SEEN with KNN and second highest accuracy of 94.93% using SEEN with SVM. For emotion E4,SEEN with SVM gives maximum accuracy of 91.42% and SEEN with KNN gives second highest accuracy. For E5, SEEN with KNN gives maximum accuracy of 94.53% and SEN with KNN gives second highest accuracy of 88.04. For E6, SEEN with SVM gives maximum accuracy of 88.18% and SEN with KNN gives second highest accuracy of 86.42%.

3.1 Time Domain Analysis

Three features namely entropy, energy entropy and teager energy entropy were used to performtime domain analysis on the EEG data. Classification accuracy is determined using three classification algorithms namely K-nearest neighbor, probabilistic neural networks and support vector machines. Results in charts are shown.

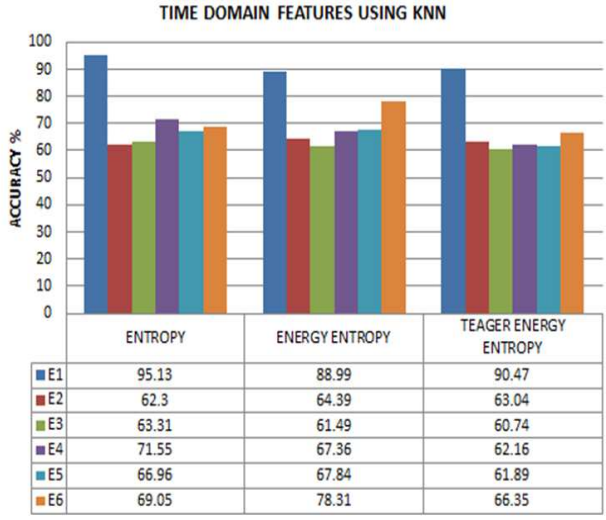


Figure-8: Time Domain Features Using KNN

From Figure-8, it can be seen that the highest classification accuracy of 95.13 % is obtained for emotion E1(Happiness) using Entropy feature. Second highest accuracy is also

obtained for emotion E1(88.99 %) for Energy Entropy feature. All time domain features gives above 60 % classificationaccuracy. It can be concluded that the happiness emotion has elicited maximum response for all time domain features using KNN.

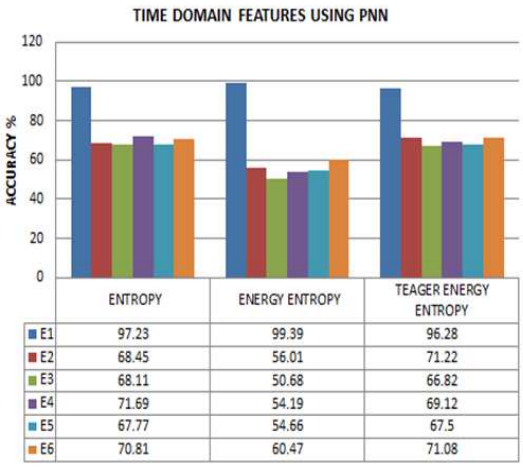


Figure-9: Time Domain Features Using PNN

From figure 9,it can be seen that highest classification accuracy of 99.39 % is obtained for emotion E1 (Happiness) using Energy Entropy feature. Second highest accuracy is also obtained for emotion E1 (97.23 %) for Entropyfeature. All time domain features gives above 90 % classification accuracy for emotion E1.It can be concluded that the happiness emotion has elicited maximum response for all time domain features using PNN.

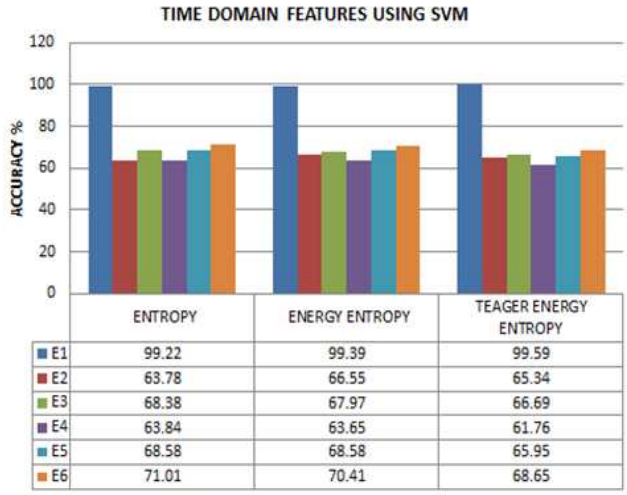


Figure-10: Time Domain Features Using SVM

From the Figure-10,it can be seen that highest classification accuracy of 99.59 % is obtained for emotion E1(Happiness) using Teager Energy Entropy feature. Second highest accuracy is also obtained for emotion E1(99.39 %) for Energy Entropy feature. All time domain features gives above 90 % classification accuracy for emotion E1.It can be concluded that the happiness emotion has elicited maximum response for all time domain features using SVM classifier.

3.2 Frequency Domain Analysis

Frequency domain analysis is performed on EEG data using three features namely spectral entropy, spectral energy entropy and spectral teager energy entropy. Classification accuracy is determined using three classification algorithms namely K-nearest neighbor, probabilistic neural networks and support vector machines. Results in charts are shown.

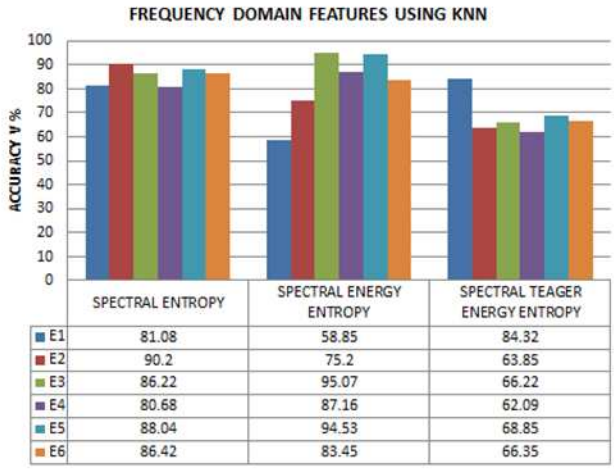


Figure-11: Frequency Domain Features Using KNN

From the Figure11,it can be seen that Spectral Energy Entropy feature gives highest classification accuracy of 95.07 % for emotion E3(Fear). Spectral Energy Entropy feature gives second highest accuracy for emotion E5(94.53 %).All frequency domain features gives above 60 % classification accuracy.It can be concluded that Spectral Energy Entropy feature gives good classification efficiency except for emotions E1 and E2 for KNN classifier.

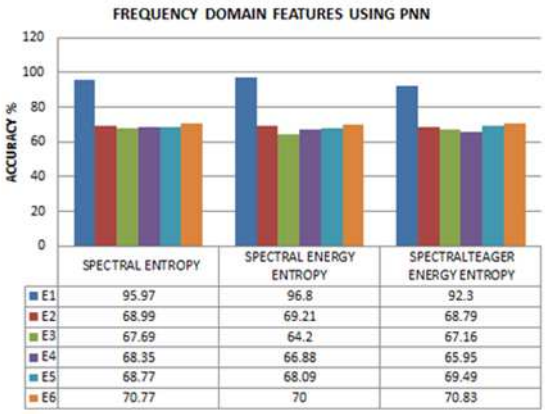


Figure-12: Frequency Domain Features Using PNN

From the Figure-12, it can be seen that highest classification accuracy of 96.8 % is obtained for emotion E1(Happiness) using Spectral EnergyEntropy feature.Second highest accuracy is also obtained for emotion E1(95.97 %) for Spectral Entropy feature.All frequency domain features gives above 60 % classification accuracy.It can be concluded that the happiness emotion(E1) has elicited maximum response for all frequency domain features using PNN.

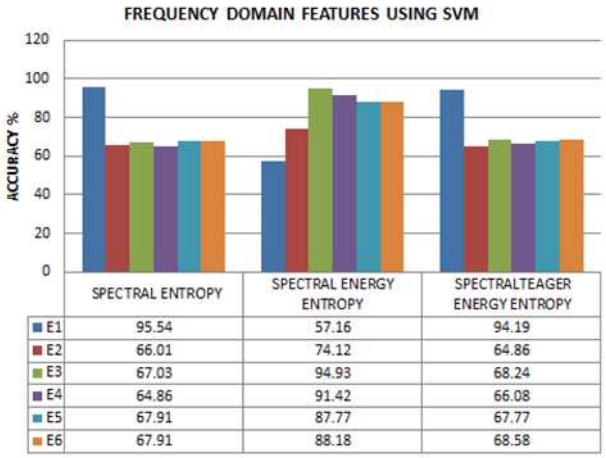


Figure-13: Frequency Domain Features Using SVM

From the Figure-13, it can be seen that highest classification accuracy of 95.54 % is obtained for emotion E1(Happiness) using Spectral Entropy feature. Second highest accuracy is obtained for emotion E3 (94.93 %) for Spectral Energy Entropy feature. Spectral Energy Entropy gives highest accuracy for emotions E3, E4, E5and E6.All frequency domain features gives nearly 60 % classificationaccuracy. It can be concluded that Spectral Energy Entropy feature gives good classification efficiency except for emotions E1 and E2 for SVM classifier.

3.3 Time-Frequency domain analysis

Time-Frequency domain analysis is performed on the EEG data using three features namely STFT entropy, STFT energy entropy and STFTteager energy entropy. Classification accuracy is determined using three classification algorithms namely K-nearest neighbor, probabilistic neural networks and support vector machines. Results in charts are shown.

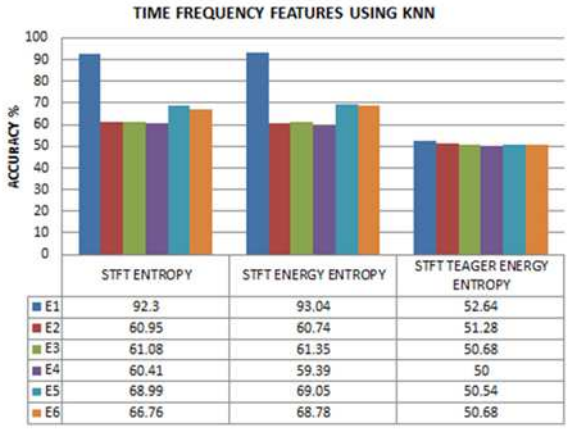


Figure-14: Time Frequency features Using KNN

From the Figure-14,it can be seen that highest classification accuracy of 93.04 % is obtained for emotion E1(Happiness) using STFT Energy Entropy feature.Second highest accuracy is also obtained for emotion E1(92.3 %) for STFT Entropy feature.STFT Entropy and STFT Energy Entropy gives accuracy of above 90 % for emotion E1. It can be concluded that only emotion E1 has elicited good response for KNN classifier.

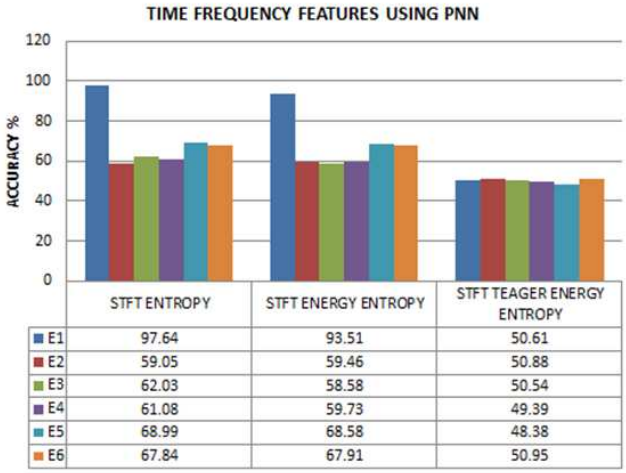


Figure-15: Time Frequency features Using PNN

From the Figure-15,it can be seen that highest classification accuracy of 97.64 % is obtained for emotion E1(Happiness) using STFT Entropy feature. Second highest accuracy is also obtained for emotion E1(93.51 %) for STFT Energy Entropy feature.STFT Entropy and STFT Energy Entropy gives accuracy of above 90% for emotions E1, It can be concluded that only emotion E1 has elicited good response for PNN classifier.

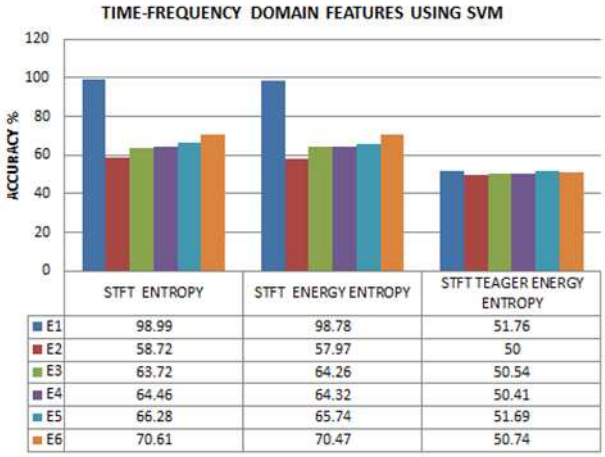


Figure-16: Time Frequency features Using SVM

From the Figure-16,it can be seen that highest classification accuracy of 98.99 % is obtained for emotion E1(Happiness) using STFT Entropy feature.Second highest accuracy is also

obtained for emotion E1(98.78 %) for STFT Energy Entropy feature.STFT Entropy and STFT Energy Entropy gives accuracy of above 90 % for emotion E1. It can be concluded that only emotion E1 has elicited good response for SVM classifier.

4. CONCLUSION

Deficits in the capability to process emotions are the characteristics of several neuropsychiatric disorders and there is a need for evaluating emotions other than clinical diagnosis. The emotional state of a person can be determined using bio signals from autonomous nervous system such as ECG, galvanic skin response, EMG, , body temperature, respiration rate etc. Also signals taken from the Central nervous system can be used to provide informative characteristics associated with emotional states namely electroencephalogram, magneto encephalogram, positron-emission tomography and functional magnetic resonance imaging.Out of these bio signals, EEG is supposed to be less invasive and has best time resolution than the other three (MEG, PET, and fMRI).

The first objective of the research was to collect sufficient data set of PD patients and healthy controls. The data set used in the research (Yuvaraj et al.,) consist of EEG recordings of twenty PD patients and twenty healthy controls taken from fourteen scalp locations using a 14 channel wireless recording head set. Both of the groups were shown audio video stimulus pertaining to six emotions. All of the patients were diagnosed with idiopathic PD by a neurologist.

The next objective was to develop suitable feature extraction methods in any domain that can efficiently discriminate PD patients from healthy controls.In my research, three time domain featuresnamely Entropy, Energy Entropy and Teager Energy Entropy are used to differentiate PD patients from healthy controls. Three frequency domain featuresnamely Spectral Entropy, Spectral Energy Entropy and Spectral Teager Energy Entropy are used to differentiate PD patients from healthy controls. Three time frequency domain featuresnamely STFT Entropy, STFT Energy Entropy and STFT Teager Energy Entropy are used to differentiate PD patients from healthy controls.

The final objective was to develop classification algorithms that maximize the accuracy in differentiating PD from healthy controls based on six emotional data. In this work, classification is done using three classifiers namely k-nearest neighbour, Probabilistic neural network and support vector machine.

The features corresponding to each emotion were extracted and the models were applied to categorize the PD and HC individuals. The results were tabulated and compared. In this paper, the time domain features EN, EEN & TEEN, the frequency domain features SEN, SEEN &STEEN and time-frequency domain features STFTEN, STFTEEN &STFTTEEN were extracted from the PD and HC EEG signals and the results were analyzed. From the analysis, it is observed that, for emotion E1, TEEN feature gives highest accuracy forSVM classifier (99.59 %) among the other features. For emotion E2, SEN feature gives highest accuracy for KNN classifier (90.2 %) among the other features.For emotion E3, SEEN feature gives highest accuracy for KNN classifier(95.07 %) among the other features. For emotion E4, SEEN feature gives highest accuracy for KNN classifier (91.42 %) among the other features. For emotion E5, SEEN feature gives highest accuracy for KNN classifier (94.53 %) among the other features. For emotion E6, SEEN feature gives highest accuracy for SVM classifier (88.18 %) among the other features.

From the analysis, it can be concluded that the proposed spectral energy-entropy feature in frequency domain gives better performance for all emotions except E1 and E2, but for different classifiers. It is also observed that the spectral entropy feature in frequency domain performs evenly well (above 80 %) for all six emotions with KNN classifier. The classifier KNN works well for spectral entropy feature for all the six emotions.

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CONFLICT OF INTEREST:

There is no conflict of interest.

AVAILABILITY OF DATA AND MATERIAL:

There is no availability of data and material.

CODE AVAILABILITY:

There is no code availability.

AUTHOR'S CONTRIBUTION:

There is no author's contribution.

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Rejith.K.N received his B.Tech degree in Electronics and Communication Engineering from LBS College of Engineering, Kasaragod in 1998 and M.Tech degree from MIT,Manipal in 2004. He is currently working as Associate Professor in MES College of Engineering,Kuttippuram.His research interest include Biomedical signal Processing, Wireless sensor networks etc.

Kamalraj Subramaniam is presently working as Associate Professor& HOD in the Electronics and Communication Engineering department at Karpagam Academy of Higher Education. He has involved in developing a prototype model of a Brain Controlled Wheelchair. His Research Interests are Bio Signal Processing, Medical Image Analysis, Mathematical Modeling and Algorithms, Artificial Neural Networks He has published more than 70 Scopus indexed Journals and 20 SCI Journals. He has guided 8 Phd Scholars.

Dr Ayyem Pillai Vasudevan Pillai joined the Indian Air Force (IAF) on 11 July 1988. After having a three years long guided-missile system training (electronics stream), he worked in Surface-to-Air VIII missile system's Radar guidance and simulator systems up to the end of year 2000. He obtained AMIE(I) in 1998. He qualified in GATE-99 conducted by IIT Bombay. He joined Karpagam College of Engineering on 10 November 2003 in ECE department, where he worked up to 06 April 2013. He obtained his Ph D from Anna University, Chennai, India in 2014. Presently, he is working as Professor of ECE department of Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India. He has concentrated mostly in electromagnetics, communication and signal processing courses for both UG and PG programmes. His research interests are MIMO communications , Smart Antennas and Electromagnetics and signal processing. He was a member of IEEE from 2005 to 2015.

Dr.Roshini T V, Professor, Department of ECE, Vimal Jyothi Engineering college, Chemperi. Completed PhD in 2018 from Karpagam academy of Higher Education and M Tech from National Institute of Technology, Calicut. She has published more than 15 articles in national and international journals.

Renjith V. Ravi is presently employed as Associate Professor in the department of electronics and communication engineering of M.E.A Engineering college, Malappuram, Kerala, India. He has published 10 articles in various international journals and conferences and having an experience of around 10 years of in Teaching and Research. He has completed his Ph.D in Electronics and Communication Engineering in 2019, M.E. in Embedded System Technology in 2011 and B.Tech in Electronics and Communication Engineering in 2007. He is the reviewer of various reputed international journals from Elsevier, Springer, Inderscience, IGI Global

V. Elamaran received the B.E. degree in Electronics and Communication Engineering from Madurai

Kamaraj University, the M.E. degree in Systems Engineering and Operations Research from Anna University, and the Ph.D. degree in the area of VLSI Signal Processing from SASTRA Deemed University, Thanjavur, India. His main research interests are signal, image and video processing, digital VLSI design circuits, design for testability, FPGA based systems, and Computer Networks. He has published more than 100 research papers in reputed international journals and conferences. He is currently working as an Assistant Professor in the Department of ECE, School of EEE, SASTRA Deemed University, Thanjavur. He is a Life Member of the Indian Society for Technical Education (ISTE) and the Indian Society of Systems for Science and Engineering (ISSE).

Figures

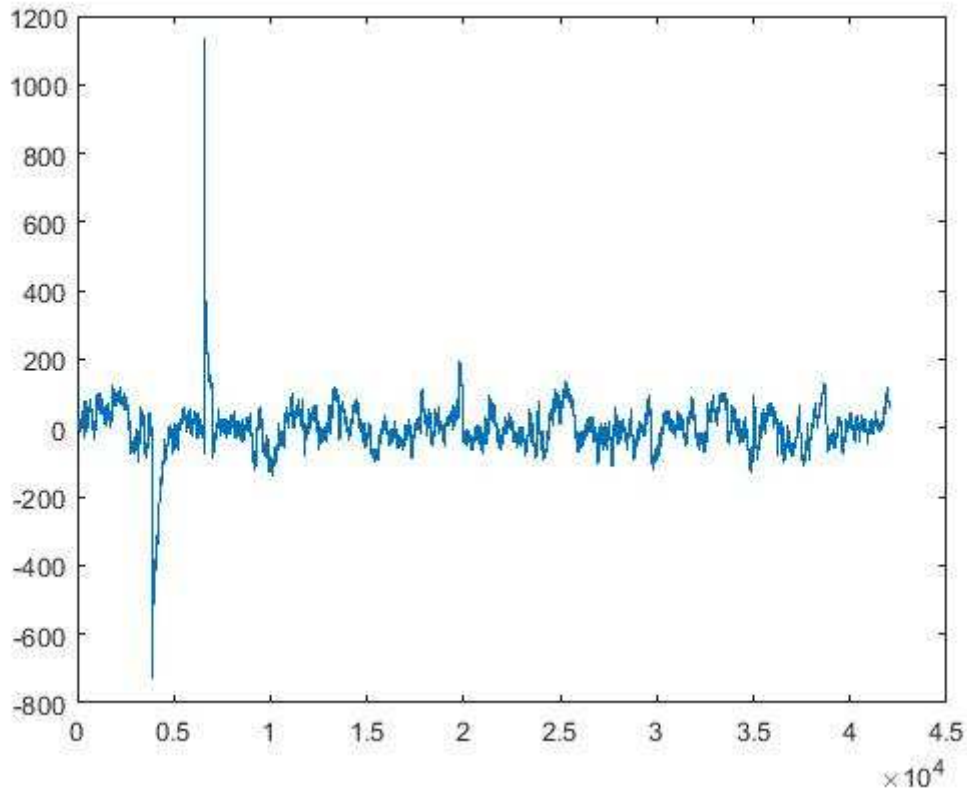


Figure 1

Raw data of emotion E1

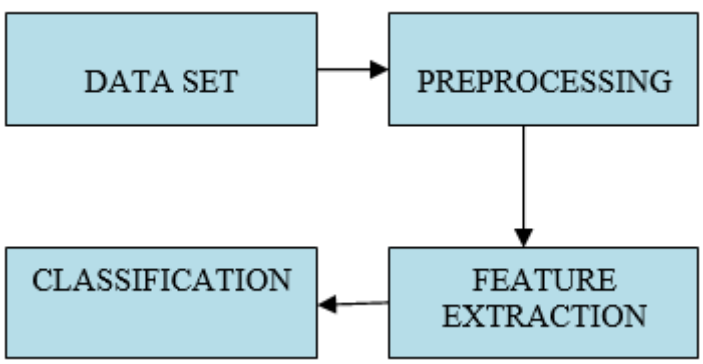


Figure 2

Block diagram representation of methodology

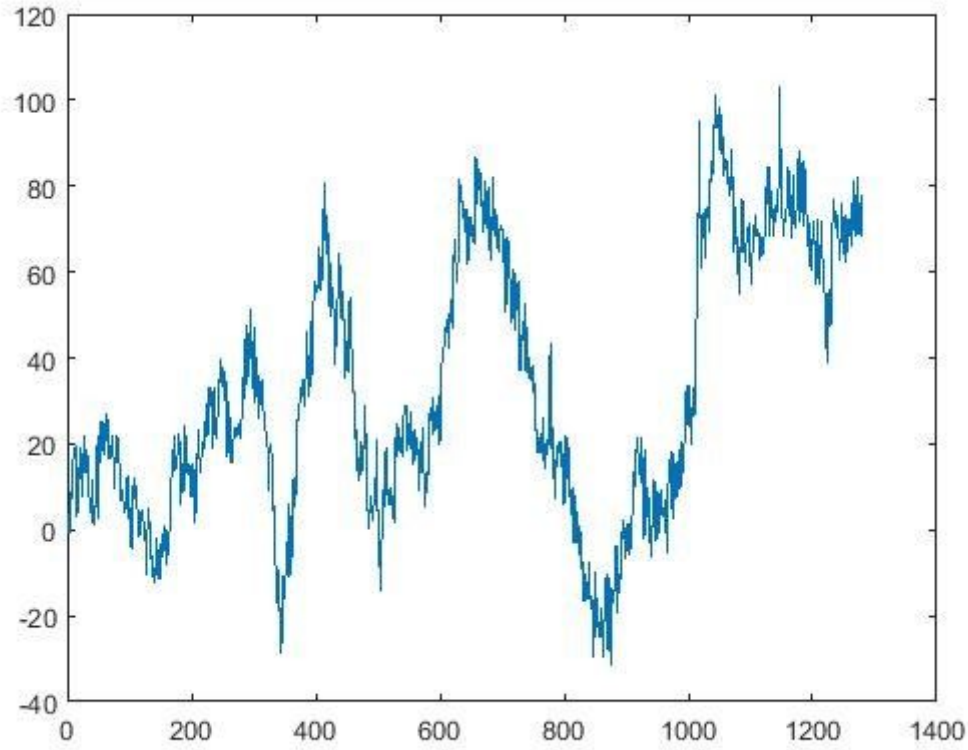


Figure 3

Plot of one frame of a segment.

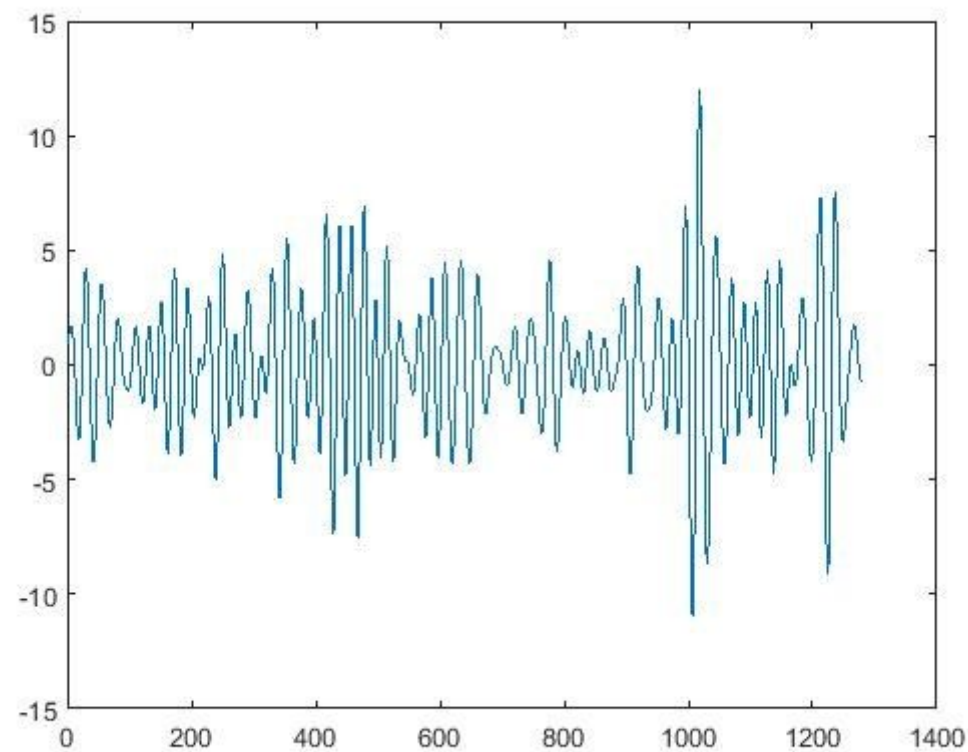


Figure 4

Bandpass filter output

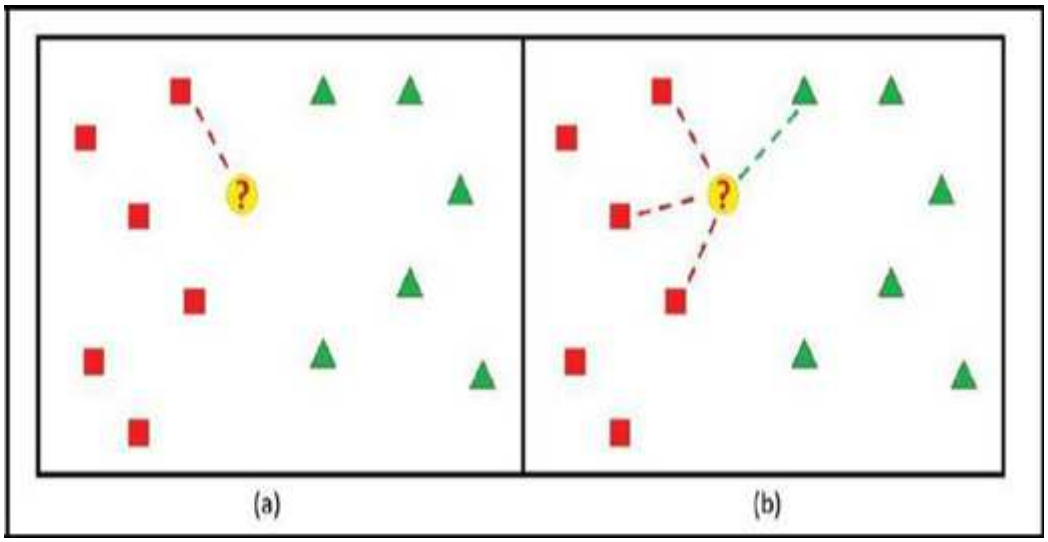


Figure 5

shows the KNN decision rule for K= 1 and K= 4 for a set of samples divided into 2 classes.

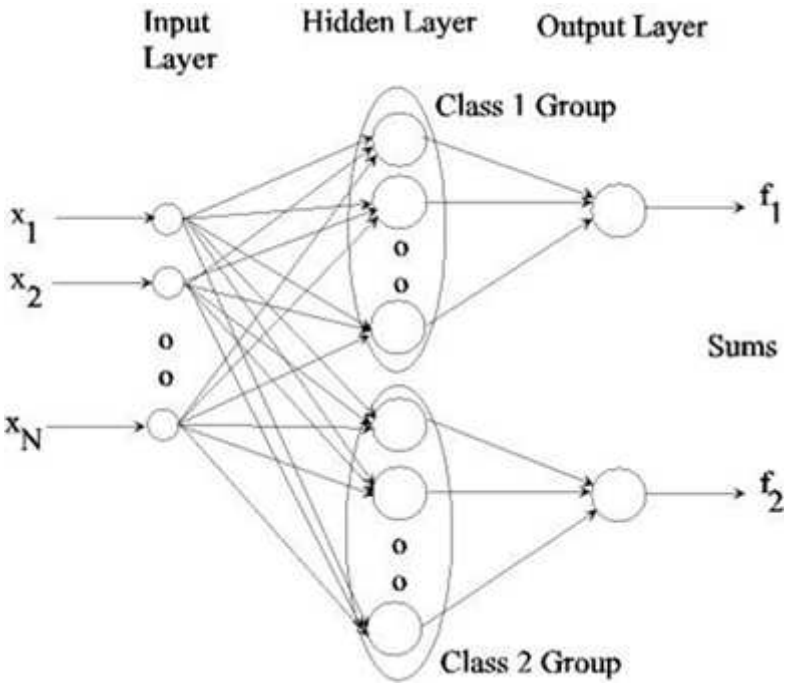


Figure 6

shows the architecture for a PNN that recognizes K = 2 classes, but it can be extended to any number K of classes. The input layer (on the left) contains N nodes: one for each of the N input features of a feature vector. These are fan-out nodes that branch at each feature input node to all nodes in the hidden (or middle) layer so that each hidden node receives the complete input feature vector x.

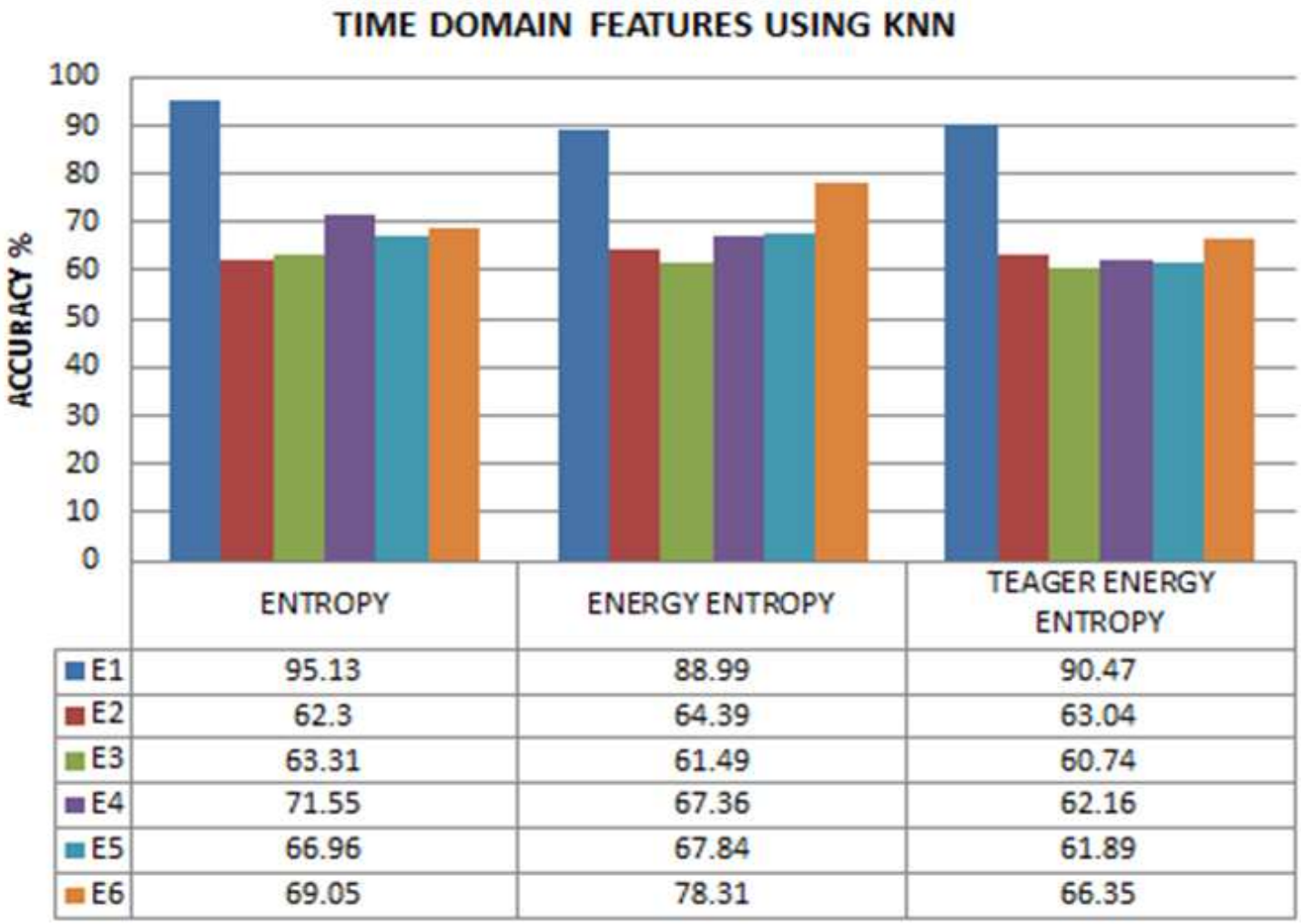


Figure 7

Time Domain Features Using KNN

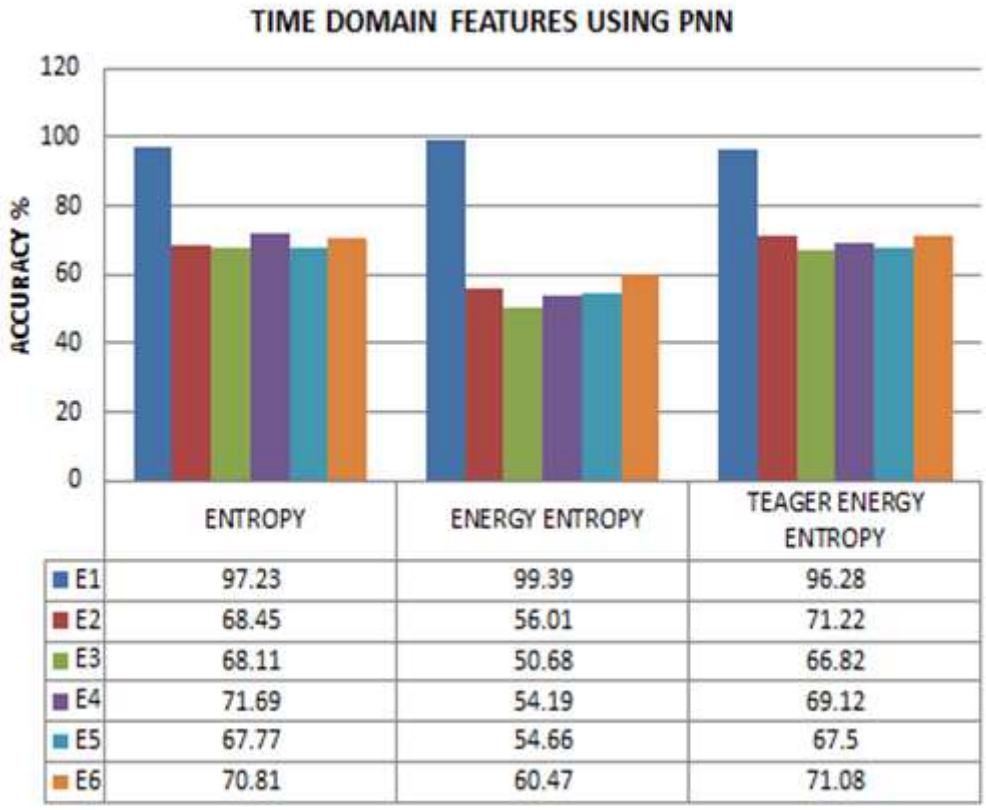


Figure 8

Time Domain Features Using PNN

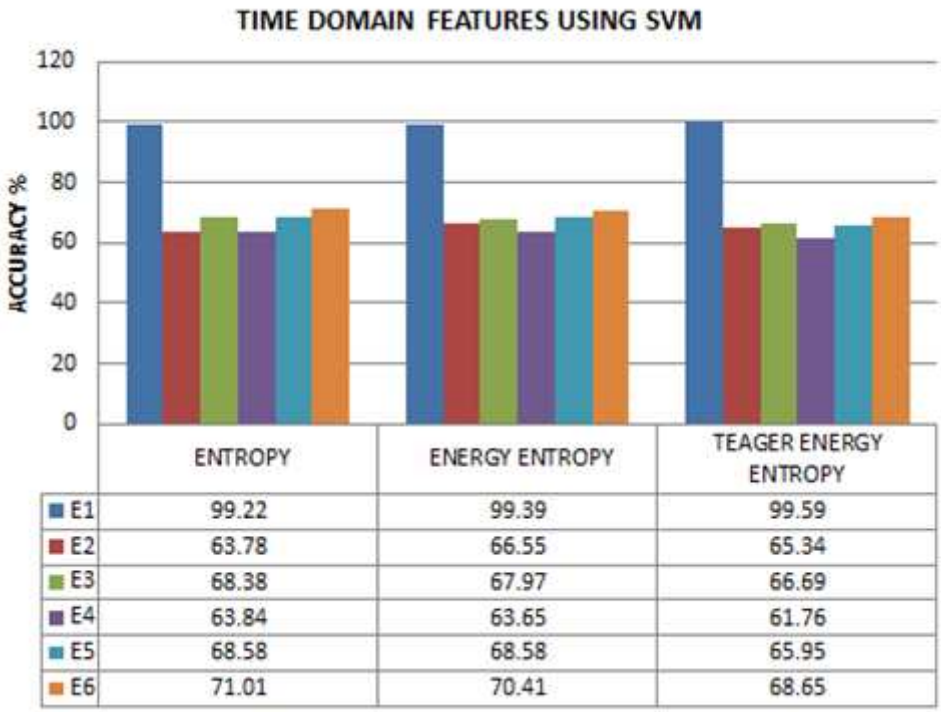
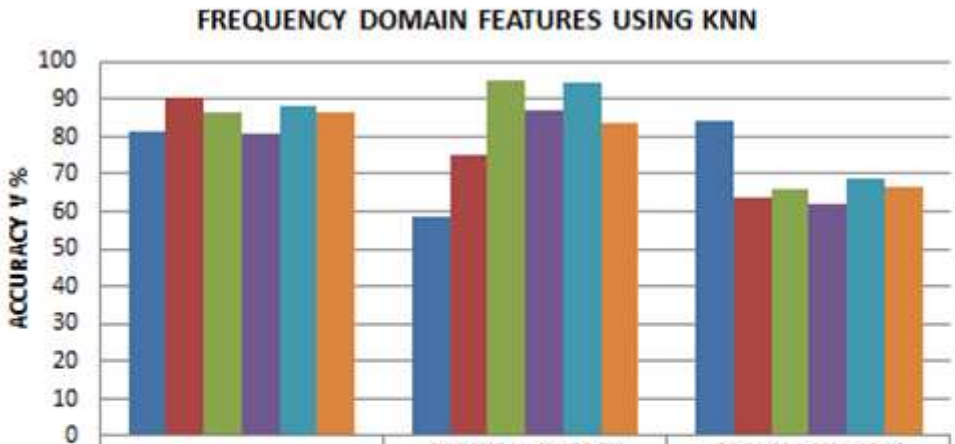


Figure 9

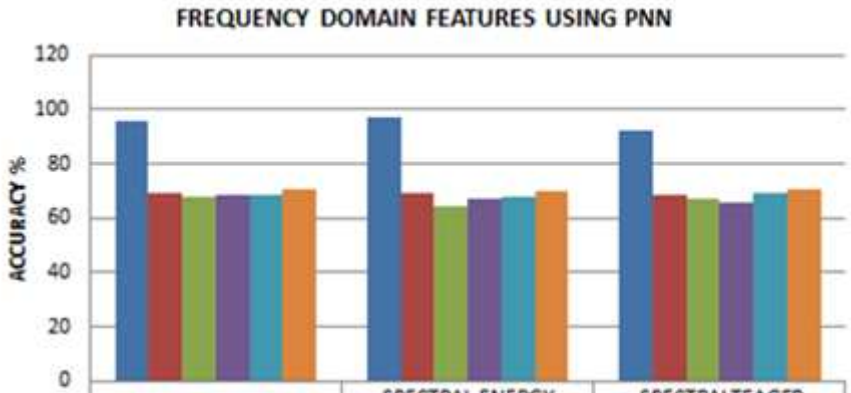
Time Domain Features Using SVM



	SPECTRAL ENTROPY	SPECTRAL ENERGY ENTROPY	SPECTRAL TEAGER ENERGY ENTROPY
E1	81.08	58.85	84.32
E2	90.2	75.2	63.85
E3	86.22	95.07	66.22
E4	80.68	87.16	62.09
E5	88.04	94.53	68.85
E6	86.42	83.45	66.35

Figure 10

Frequency Domain Features Using KNN



	SPECTRAL ENTROPY	SPECTRAL ENERGY ENTROPY	SPECTRALTEAGER ENERGY ENTROPY
E1	95.97	96.8	92.3
E2	68.99	69.21	68.79
E3	67.69	64.2	67.16
E4	68.35	66.88	65.95
E5	68.77	68.09	69.49
E6	70.77	70	70.83

Figure 11

Frequency Domain Features Using PNN

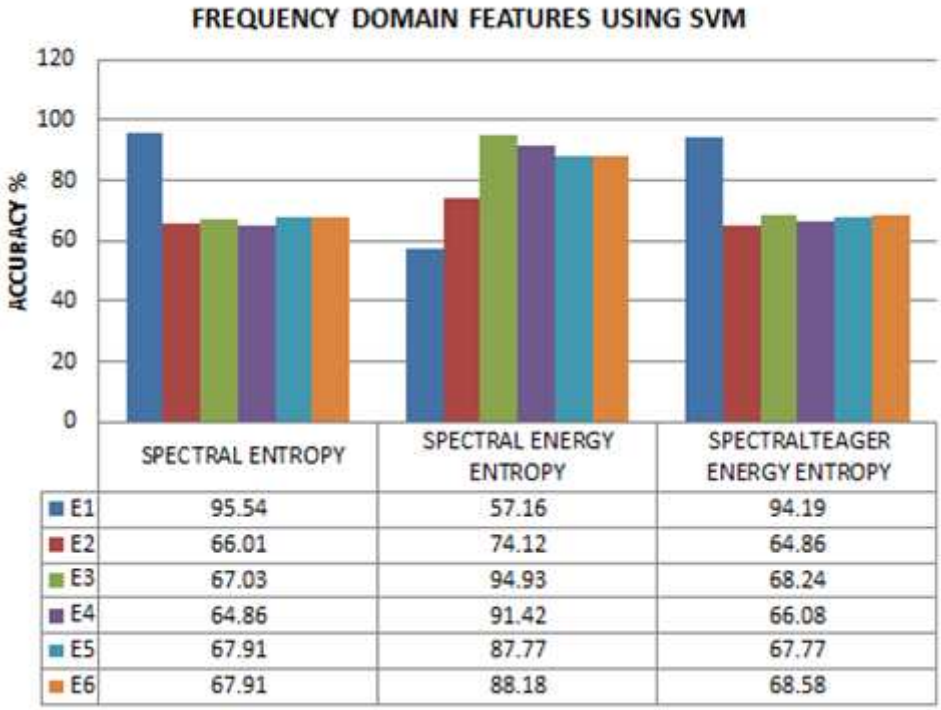


Figure 12

Frequency Domain Features Using SVM

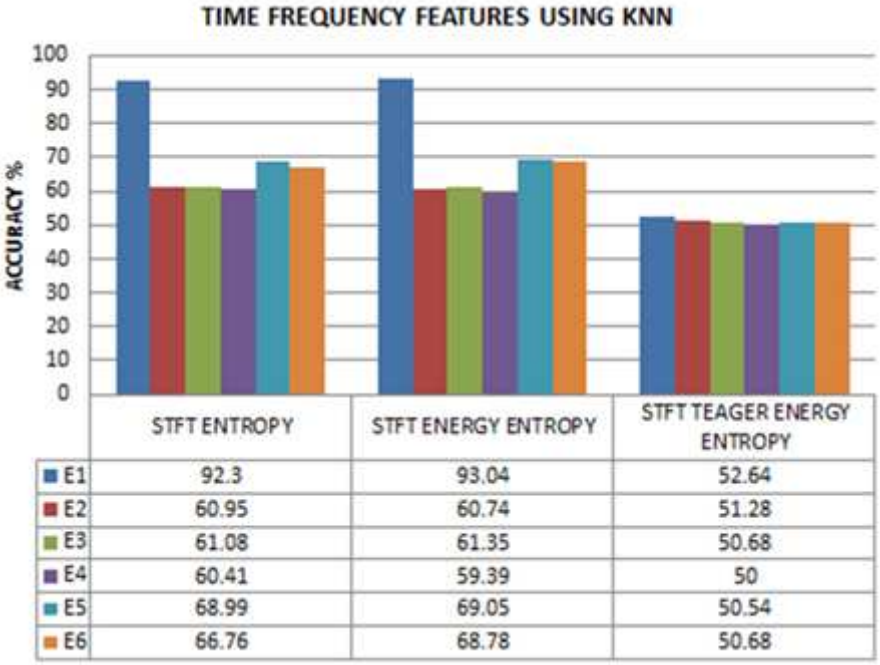


Figure 13

Time Frequency features Using KNN

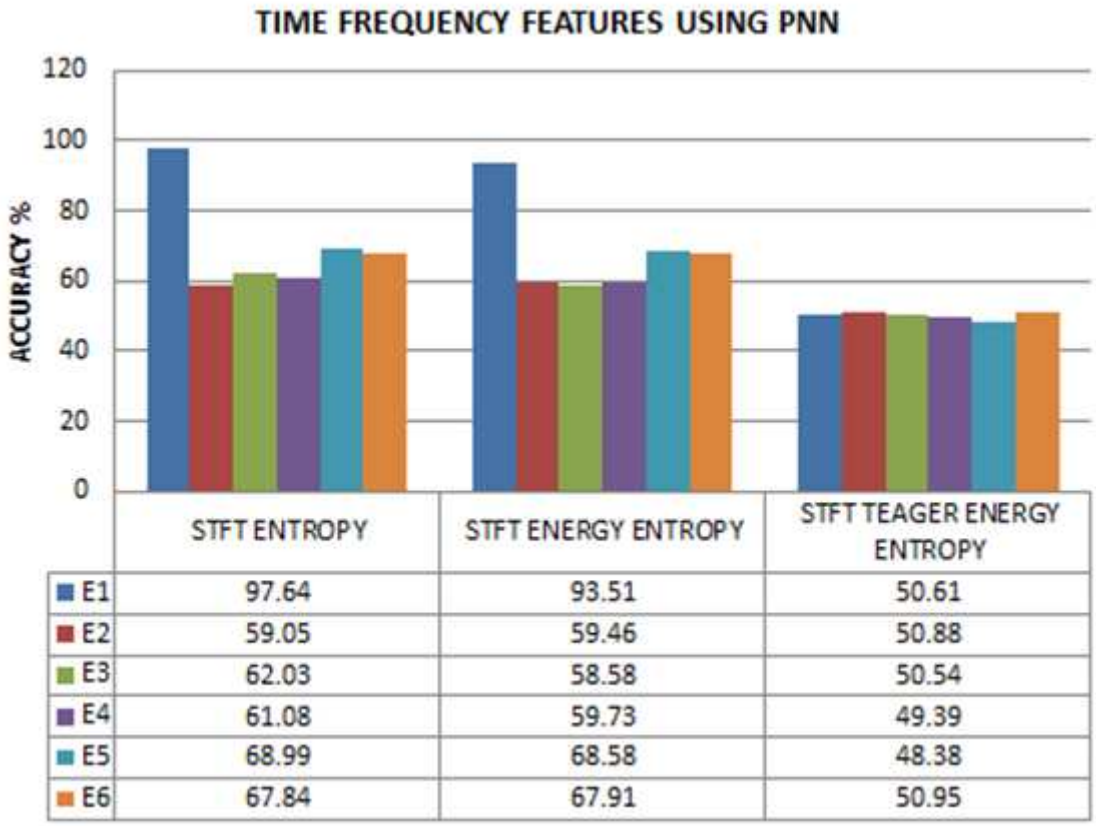


Figure 14

Time Frequency features Using PNN

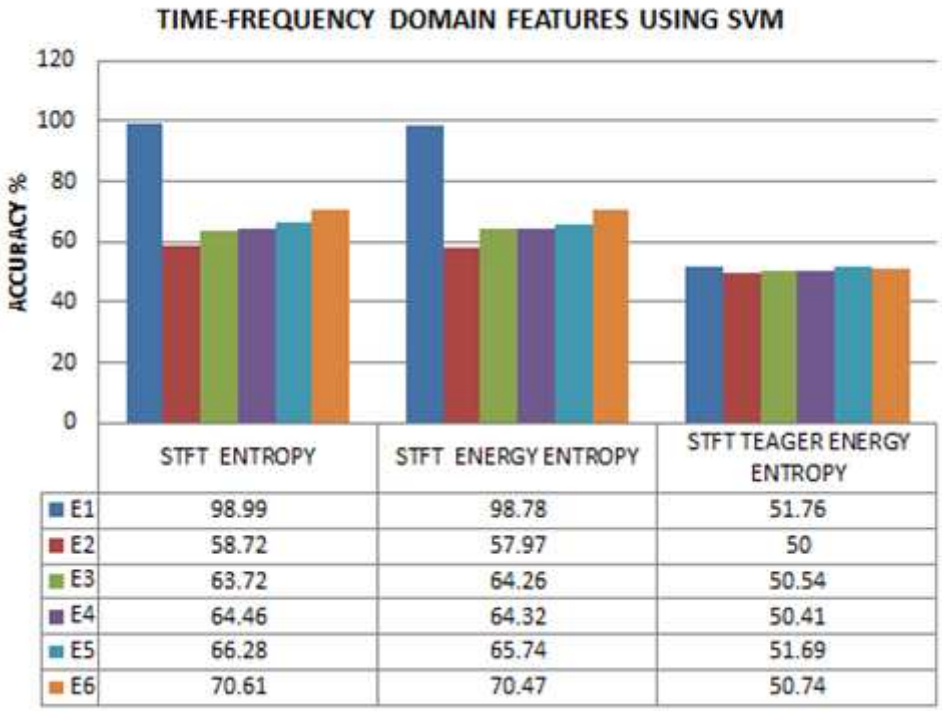


Figure 15

Time Frequency features Using PNN