International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I5P107

Volume 74 Issue 5, 89-103, May 2026

Original Article

Analyzing Brain Waves and Mapping Musically Stimulated EEG Signals for Emotion and Depressive Disorder Classification

Varsha K. Harpale[1*], Amit K. Bairagi[2], Sharad T. Jadhav[3], Archana R. Date[4], Mrinai Dhanvijay[5]

[1]*E&TC, Pimpri Chinchwad College of Engineering, Pune, India*
[2]*(MUHS), Sumatibhai Shah Ayurved College and Hospital, Hadapsar, Pune, India,*
[3]*E&TC, Tatyasaheb Kore Institute of Engineering and Technology, Warananagar, Kolhapur, India*
[4]*HSBPVT'S Faculty of Engineering, Department of Electronics and Computer Engineering. Ahilyanagar, India.*
[5]*MES, Wadia College of Engineering, Pune, India.*

[1]*Corresponding Author : varsha.harpale@pccoepune.org*

Received: 02 May 2025 Revised: 18 February 2026 Accepted: 28 February 2026 Published: 30 May 2026

***Abstract** - Neurological disorders have been highly prevalent problems observed in humans in recent eras. Majorly, the youth of India and the world are suffering from anxiety, stress, and depression. A significant mental imbalance observed is due to current lifestyle and economic competition; thus, maintaining good mental health is a challenge for human beings. Besides, youth cannot handle this stress, which invokes suicidal thoughts and has an impact on their behavior. Emotion Artificial Intelligence is a model for analyzing emotion. The proposed work uses emotion artificial intelligence to label an emotion as a detection of depression. In the proposed work, the classification of emotions and depression analysis, Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and Fuzzy Inference System (FIS) classification models have been discussed and implemented. The results are discussed here by comparing the classification model, performance matrix, and accuracy. The classification accuracy observed using the ANFIS model is better than that of the ANN and FIS models.*

***Keywords** - Feature Extraction and Selection, Depressive Disorder Detection, ANFIS Classification, and EEG Analysis.*

1. Introduction

Depression is a neurological disorder that has a significant impact on human life [1]. As per primary symptoms defined by the clinical approach, most of the time in a week, people experience depressed feelings, no interest in activities, self-destruction, feelings of uselessness, and a lousy ability to think and concentrate.

Electroencephalography (EEG) is a simple method of recording the complex electrical activity of the brain. The Scalp EEG (sEEG) is a non-invasive method used for regular monitoring of brain activity, and the invasive method (iEEG) is preferred in brain surgery [2]. EEG signal is statistically different for mental states such as sleep and wakefulness, and is also characterized differently as per diseases such as epilepsy, dementia, depression, and many more. The brain wave signal is non-stationary and irregular; thus, no specific pattern is observed in the EEG like ECG signals. The multi-frequency behavior of EEG signals can be filtered in five EEG sub-bands named gamma, theta, alpha, beta, and gamma brain waves, which describe various behavioral states of human beings.

The brain generates effective electrical signals to invoke the activities and control of different related organs, and hence, the EEG signal is an effective tool for analyzing brain behavior [3]. Due to complex signal behavior, advanced digital signal processing techniques are required to extract brain-captured information from a human subject. EEG signals represent the brain's electrical activity by capturing the voltage variations measured during internal neuron activity. They are called Event-Related Potential (ERP) or Evoked Potential (EP). The human emotion analysis analyzes the temporal emotional state of the human subject. The specific emotion persists for a short time. However, a few emotions exist for an hour, such as mood or temper. The emotional information is extracted using defined signal processing steps such as data measurement and pre-processing, feature extraction and optimization, labeling training set, and classification or interpretation. Recent research uses various multi-model inputs: Physiological sensors, speech signals, real-time video, and many more [4].

An extensive literature review was carried out to finalize the proposed work, as shown in Table 1.

Table 1. Recent study in the area of depression analysis

Topic	Method used	Performance
EEG clinical foundation modeling [1]	Self-Supervised Transformer Learning + spectral tokenization	AUROC = 0.926, , AUPRC = 0.97, Sensitivity = 0.909
Emotion Classification using EEG [2]	PCA and Singular Value decomposition	Improve dimensionality reduction and classification faster
Depression detections using EEG [3]	ML classifier Random Forest, Naive Bayes, SVM, CNN	Accuracy > 95%
EEG-based depression detection [4]	Split learning + Transformer + Random Forest	96.23% accuracy
Depression detection using emotions AI [5]	ANN emotion modeling	Effective for automated mental health predictions
Depression prediction in the Diabetic patient [6]	Supervised ML classifiers	High clinical prediction accuracy
Music emotions classifications [7]	ANN using vocal and Instrumental timbre	Accurate music emotions categorization
FPGA implementation of neural network [8]	Feed-forward ANN implemented in VHDL/FPGA	Low power and real-time ANN processing
Epilepsy risk levels classification [9]	EEG statistical features + SVM classifiers	High prediction accuracy and risk classifications
End-to-end depression detection [10]	EEGNet (Deep Learning CNN)	Accuracy > 95%.
Resource identification via classifier [11]	ANFIS (Neuro-Fuzzy Logic)	High generalization and classification accuracy
BCI EEG classification [12]	Time domain features + ANN	Good BCI control accuracy
Motor imagery EEG analysis [13]	Wavelet packet decomposition	Improved motor imagery separability
Autism EEG analysis [14]	FFT + Short-time Fourier transform	Distinguishable EEG biomarkers for autism
Mental task classification [15]	Linear vs. Nonlinear Classifiers	Non-linear models provided the best accuracy
Multimodal emotion recognition [16]	EEG + physiological fusion (Deep Learning)	Accuracy > 90% multimodal input
Depression detection [17]	Graph Convolution Network + attention	Accuracy 92.87%
mental disorder dataset [18]	EEG + clinical + multimodal dataset	Benchmark dataset used for future ML
Robust MDD diagnosis from EEG[19]	3D-CNN + Capsule Network using temporal spatial frequency fusion	Improved generalization and accuracy over prior DL approaches
EEG-based Depression Detection [20]	PCA+ANFIS	Accuracy 99.5% for Two Classes: Positive and Negative
Depression detection across brain regions [21]	EEG feature fusion + ML classifiers	High clinical detection accuracy

It shows that the maximum accuracy 99.5% [20], with the Kaggle dataset, for positive and negative emotions. The work proposed has the contribution as the work experimented for ANN, FIS, and ANFIS to get good membership optimization and interpretability with multiple classes, and the experimentation achieves depression detection accuracy 92.4% for a four-class model and 89.55% for a two-class model.

The proposed research paper elaborates on the work. The information about the dataset used, pre-processing techniques, features used, and feature selection is presented in the second part. Further, the methodology of the research is discussed. Experimentation and results are highlighted in the third part. The comparative analysis with state-of-the-art work in the area is explained in the next part. The final section describes a conclusion and summarizes the results.

2. Materials and Methods

2.1. Datasets

The SEED-IV database is used for experimentation. This includes information about 15 subjects recorded with a 200Hz Sampling rate with 24 trials in 3 sessions [17]. The noise is removed with a bandpass filter of 1Hz and 75Hz. DWT is applied to extract the statistical features, Power Spectral Density (PSD), Differential Entropy (DiE), and other relevant features. The experimentations were performed on eeg_raw_data (Mat Files) for four emotions. The MODMA Dataset is a musically stimulated EEG signals dataset. It is used in experimentation to train the system, which contains Depressive EEG Data for Event-Related Potential recorded with 128 channels of 54 subjects (24 subjects with Depressive Disorder and 29 Normal subjects) [18]. The .raw files are read using EEGLAB Toolbox, pre-processed, and saved as .mat files for feature extractions. Thus, the work is aligned with musically stimulated EEG for depression detection.

2.2. Proposed Methodology

The methodology adopted in experimentation is modular and performed on the EEG Raw Data. A flow process of emotion and depression analysis of the EEG signal classification is presented in Figure 1. The method presented here is applied to the SEED IV dataset for happy, Sad, Fear, and neutral, and the MODMA dataset for depression. The workflow starts with the pre-processing of datasets with a filtering action. Two filters were used for a pre-processing step: an Low-Pass Filter (LPF) and a Notch Filter.

After this action, wavelet decomposition features were extracted in five bands of the EEG signal. After extracting features, relevant features were given to PCA for optimized feature selection. The training and testing models are applied to the output of PCA to classify emotions and detect depression.

2.2.1. Pre-Processing

To remove power line noise and unwanted artifacts, pre-processing of the EEG signal was performed using filters and ICA, which is implemented through the EEGLAB Toolbox of MATLAB.

1) Artifacts Removal: The unwanted information observed in the EEG signal is artifacts, which are mainly observed due to bad electrode position or placements, scalp surface impurity, electrode characteristics such as impedance, etc. There are a few physiological artifacts, like heart and muscular activity, blinking of the eye, and eyeball movement.
2) Power Line Noise: Due to the instrumentation used in recording EEG signals, power noise of 50 or 60 Hz frequency interference from wires is often observed.

The following steps were used for preprocessing and to remove artifacts such as muscular movements, eye movements, etc., and unwanted noise from the system. A Low-Pass Filter (LPF) is used to smooth the signal and remove a few artifacts from the signal. A notch filter rejects the 60 Hz or 50 Hz power line noise. It also removes a small frequency band with the selected central frequency. Independent Component Analysis (ICA) with EGLAB Toolbox is used to remove eye blink and Muscle movement-related artifacts [19].

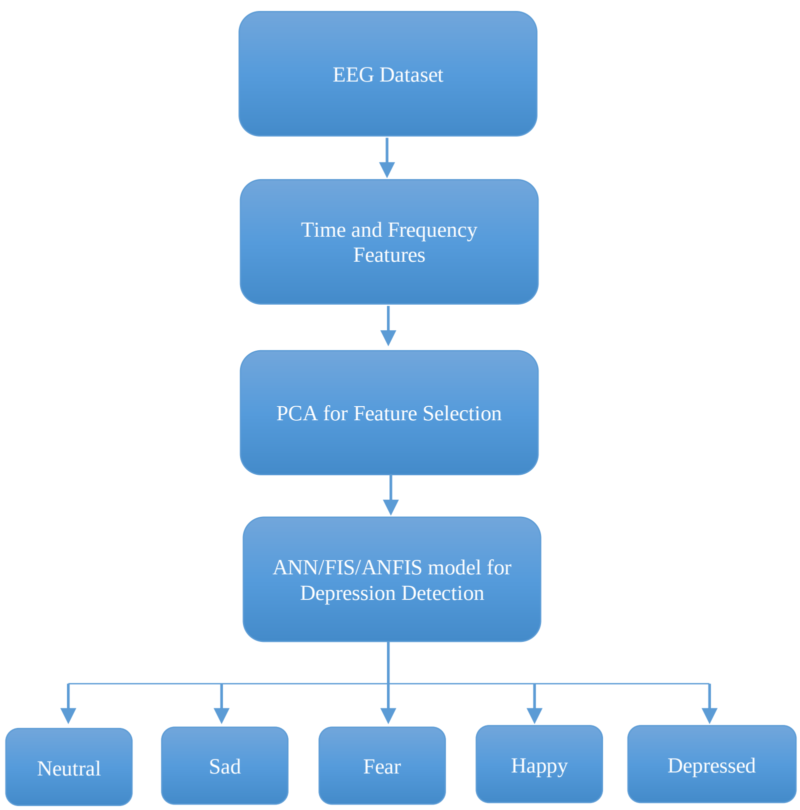


Fig. 1 Depression detection methodology

2.2.2. Feature Extraction

Feature extraction is a significant preprocessing step in extracting relevant features from raw data for decision-making. The raw EEG signal is complex due to instances created in each sample.

It has energy distribution in a scattered form over the time interval. The EEG Signal is considered to be a function of time and frequency. The frequency-specific features extracted from EEG signals represent important information about human brain states [5].

Time and Frequency Feature parameters

The time and frequency parameters are extracted from the raw EEG and mathematically represented below.

a) Integrated EEG: Integrated EEG (IEEG) is an onset detection parameter used in clinical analysis [6, 7].

$$\text{IEEG} = \sum_{i=1}^{N} |x_i| \quad (1)$$

Where, xi = EEG signal,
i = 1 to N,
N = Length of x.

b) Mean Absolute Value (MAV) is a basic parameter of EEG signal analysis.

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \quad (2)$$

c) MAV features are extended as Modified MAV (MAV1).

$$MAV1 = \frac{1}{N}\sum_{i=1}^{N} w_i |x_i|$$
$$w_i = \begin{cases} 1, & if \ \ 0.25N \le i \le 0.75N \\ 0.5, & else \ if \end{cases} \quad (3)$$

Where i=1,2,3,….N

d) Simple Square Integral (SSI) represents energy by the integral square of the one-dimensional EEG.

$$SSI = \sum_{i=1}^{N} x_i^2 \quad (4)$$

e) Variance of EEG (VAR) is calculated by finding the square value of the deviation of the value from its mean and averaging it.

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})^2 \quad (5)$$

f) Waveform Length (WL) is a complexity value defined by the collective length of the EEG signal over the time samples.

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (6)$$

g) The Difference Absolute Standard Deviation Value (DASDV) is as

$$DASV = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (x_{i+1} + x_i)^2} \quad (7)$$

h) Autoregressive (AR) is a concept of modeling univariate time series

$$y_t = \sum_{i=1}^{N} a_i y_{t-1} + \varepsilon_t \quad (8)$$

i) Hjorth mobility represents the relation between standard deviation and the power spectrum.

$$Hjorth_2 = \frac{\sigma_{\dot{x}}}{\sigma_x} \quad (9)$$

j) Hjorth complexity is the complexity observed in the change in frequency.

$$Hjorth_2 = \frac{\frac{\sigma_{\ddot{x}}}{\sigma_{\dot{x}}}}{\frac{\sigma_{\ddot{x}}}{\sigma_x}} \quad (10)$$

k) Power Spectral Density (PSD) is calculated for frequency coefficients x over a sample window of s.

$$PSD(w) = \log_{s\to\infty} |X(w)|^2 \quad (11)$$

l) Differential Entropy (DiE) is a measure of randomness calculated by the average of the random variable to the probability distribution of the function.

Discrete Wavelet Transform (DWT) Features

The DWT features are extracted to analyze the frequency-based features. The signal is decomposed into approximation coefficients and detailed coefficients.

The detailed approximation, D1, is the outcome of the down-sampled High-Pass Filter (HPF) and Low-Pass Filter (LPF) approximation A1[10]. Figure 2 shows the decomposition of the signal x[n] into HPF coefficients g[n] and LPF coefficients h[n].

Figure 4 describes the EEG Gamma band variation for Sad, Happy, Fear, and Neutral classes. The frequency decomposition is experimented with DB8 for four levels.

As discussed in Table 2, the detailed and approximation coefficients are extracted for Happy, Sad, Fear, Normal, and Depressed.

The windowed sample of generated coefficients is used to extract features f_a to f_l-baseline features calculated as Equations (12) and (13), analyzed for the classes. Then, ANOVA is applied, and a new feature vector is constructed.

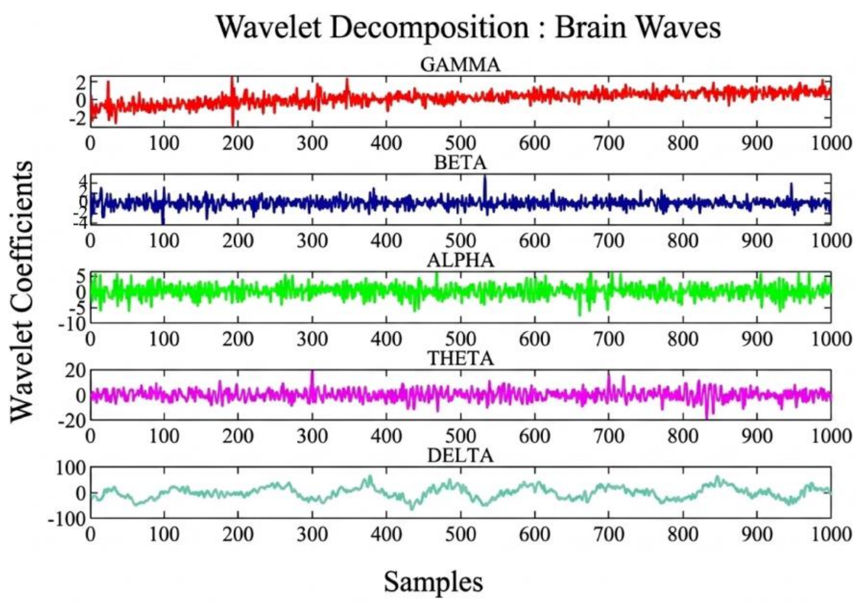


Fig. 2 Wavelet decomposition of EEG signals

$$FV_b = [IEEG, MAV, MAV1, MAV2, SSI, VEEG, RMS, MEDIAN(wl), MEDIAN(dastd), MAX, HA, HM, HC] \quad (12)$$

$$FV_w = [DiE_g, DiE_b, DiE_a, DiE_t, DiE_d, PSD_g, PSD_b, PSD_a, PSD_t, PSD_D] \quad (13)$$

The final feature vector calculated is on the basis of ANOVA feature selection [20].

Table 2. EEG frequency bands by wavelet decomposition

Wavelet Decomposition Levels	Frequency Ranges (Hz)	Frequency Band
A4	0.1 to 4	Delta
D4	4 to 8	Theta
D3	8 to 14	Alpha
D2	14 to 30	Beta
D1	30 to 63	Gamma

Figure 3 shows that the EEG clearly distinguishes between the EEG signals for neutral and depression. Thus, EEG is a technical tool to identify differences.

Feature selection using PCA

The features or attributes are calculated from the Time and Frequency characteristics (f_a, f_b …f_l) and DWT coefficient PSD and DiE features (f_k and f_l). The ANOVA statistical technique is applied to select frequency bands and relevant features. It is observed that the features PSD and DiE (F_k and F_l) in the Gamma Band significantly contribute to classification. Considering the significance of the feature space in dimensionality reduction, the features are analyzed using Principal Component Analysis (PCA) for different classes. The principal components are orthogonal, and 1st principal component retains the maximum variation. The PCS summarizes the features and generates an optimized feature vector with scaled features per relevance [11, 12].

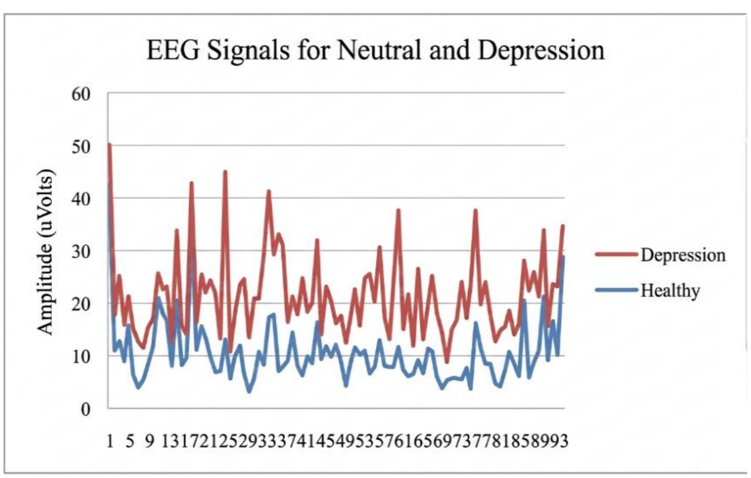


Fig. 3 EEG signal for depression

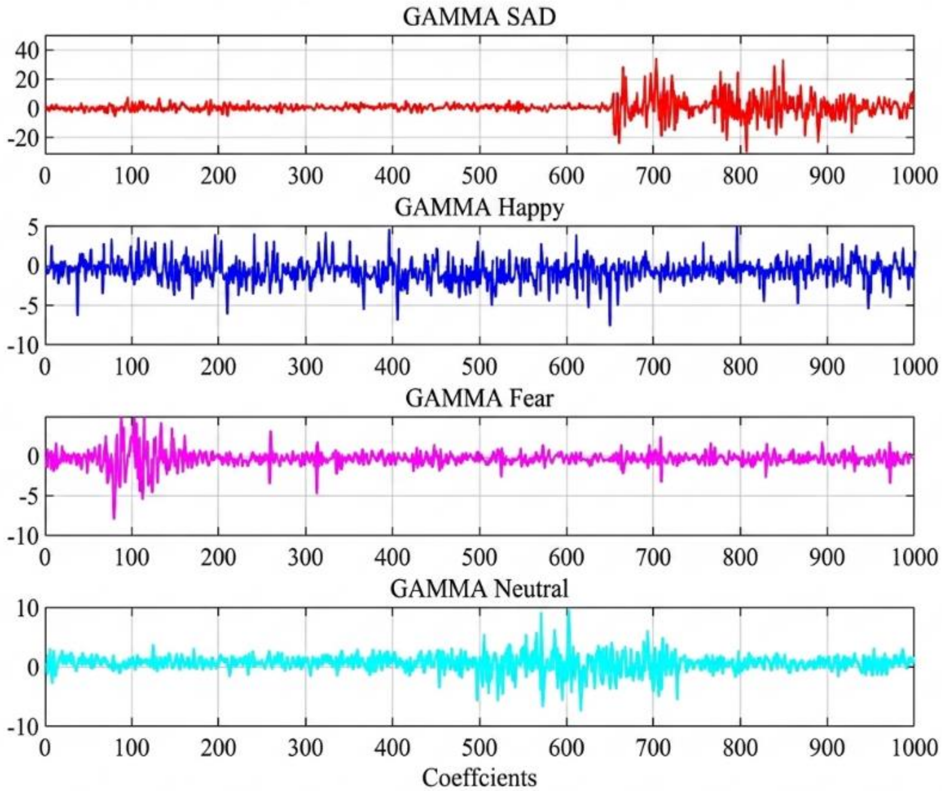


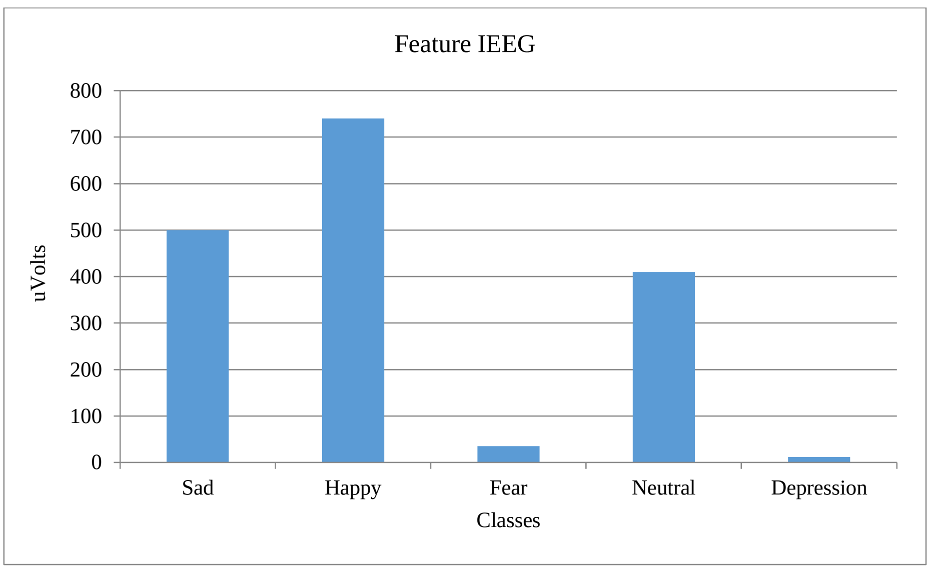
Fig. 4 Gamma band variations for different classes

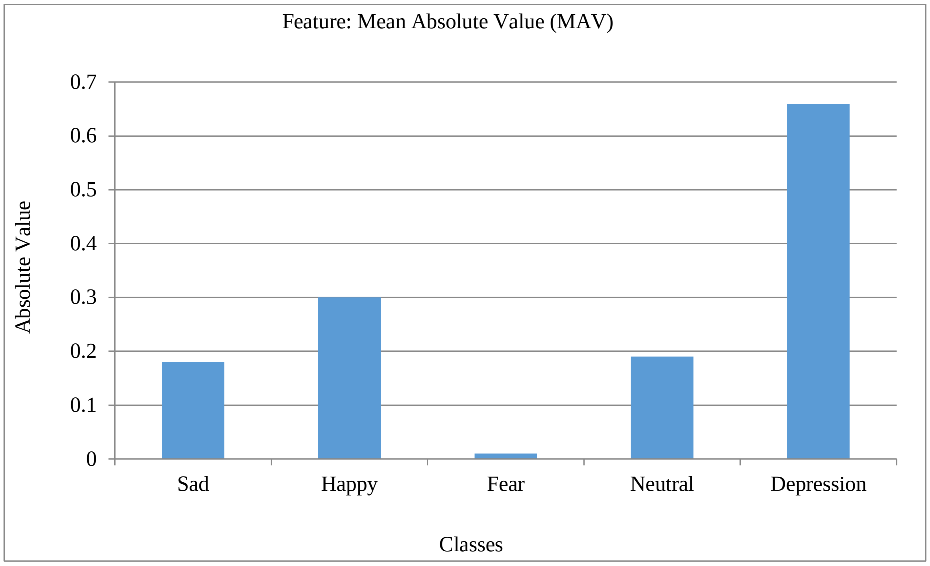
3. Result and Discussion

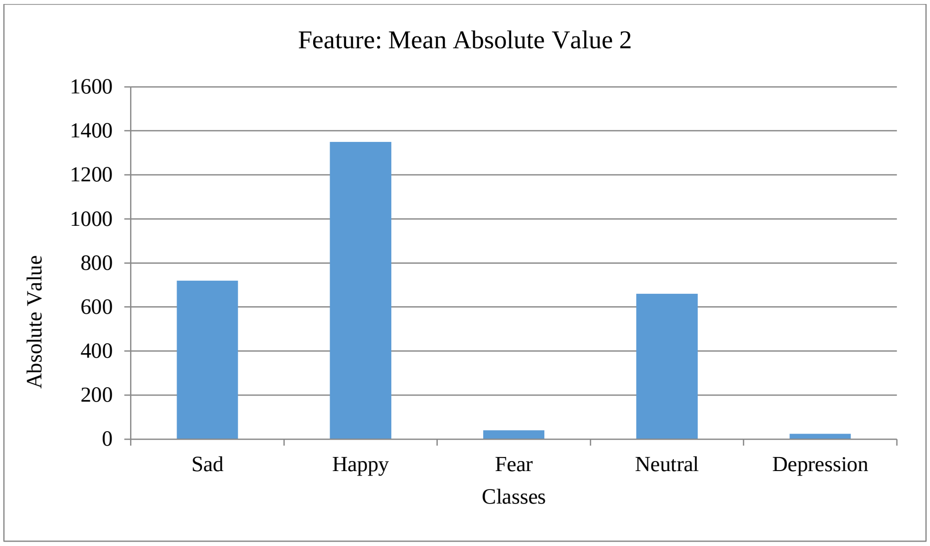
3.1. Feature Extraction by Baseline and DWT

The Time and frequency-specific baseline attributes and DWT features for the Gamma band are extracted. In order to analyze the characteristic natures of different EEG patterns, the work proposed timing and frequency-related parameters for extraction. In addition, we applied ANOVA to baseline features, and power, standard deviation, and variance were observed to be significant for classifying emotions. Figures 5(a) and 5(b) show variation in features for all brain waves; similarly, features are extracted for other emotions.

It is observed that the gamma band has distinguished feature values, so only the gamma bands are used for extraction. As per the variation observed in the feature value of the gamma band for happy, sad, fear, and depressed, it is observed that MAV2, VAR, and SSI are important features. Thus, these features are extracted for all categories of files.







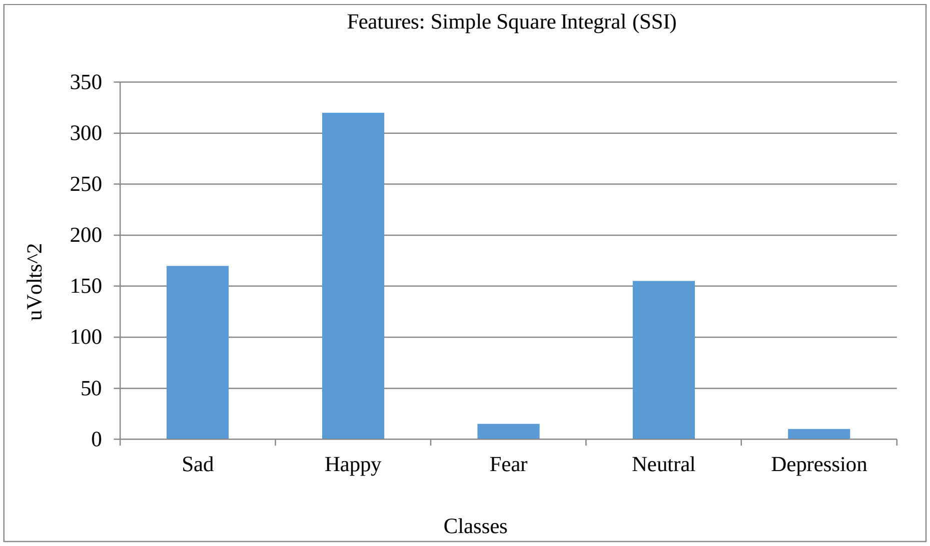
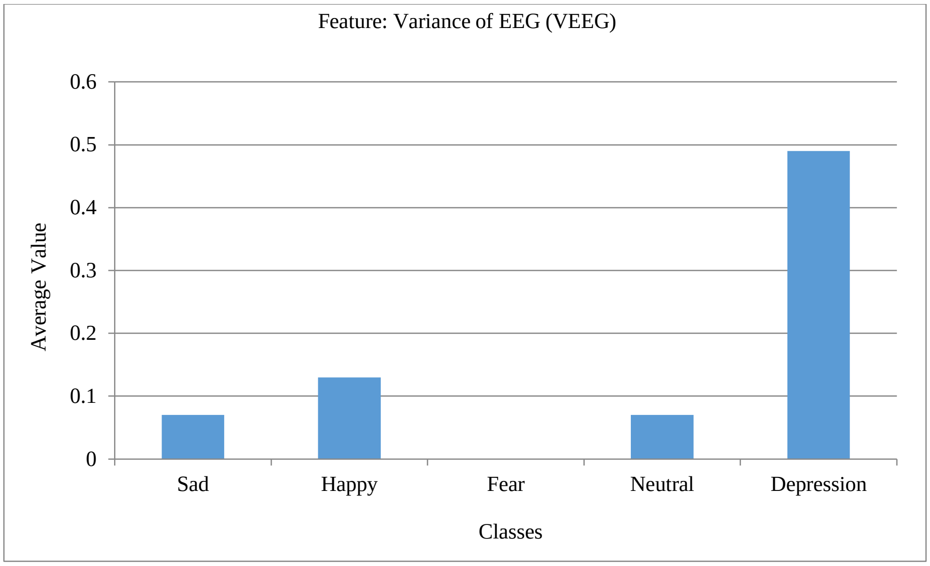
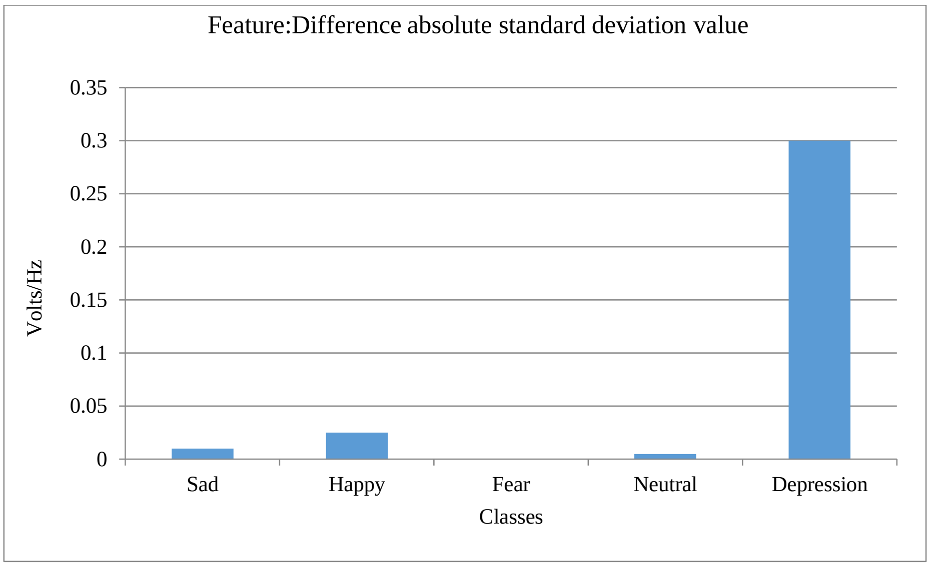
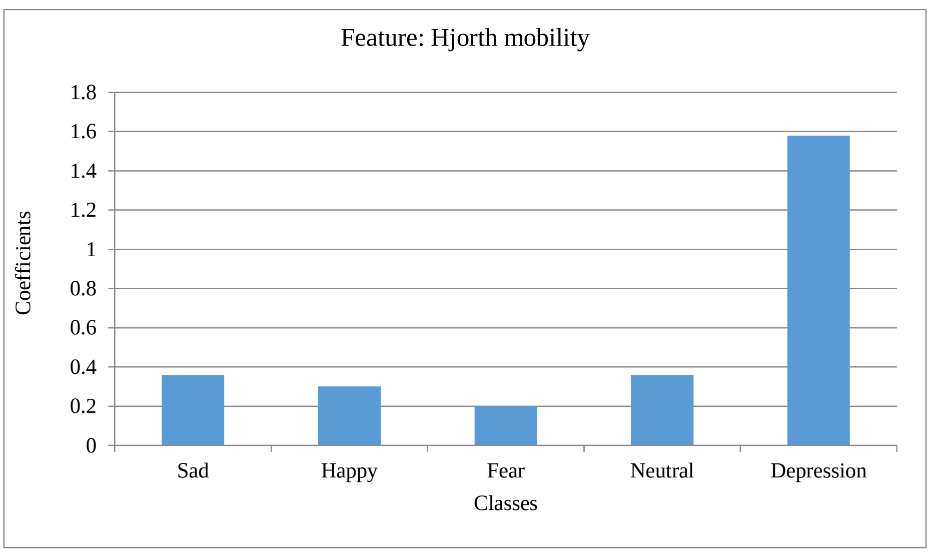


Fig. 5(a) Significant baseline features group-1


Feature: Variance of EEG (VEEG)
Average Value
0.6
0.5
0.4
0.3
0.2
0.1
0
Sad
Happy
Fear
Neutral
Depression
Classes


Feature:Difference absolute standard deviation value
Volts/Hz
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Sad
Happy
Fear
Neutral
Depression
Classes


Feature: Hjorth mobility
Coefficients
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Sad
Happy
Fear
Neutral
Depression
Classes

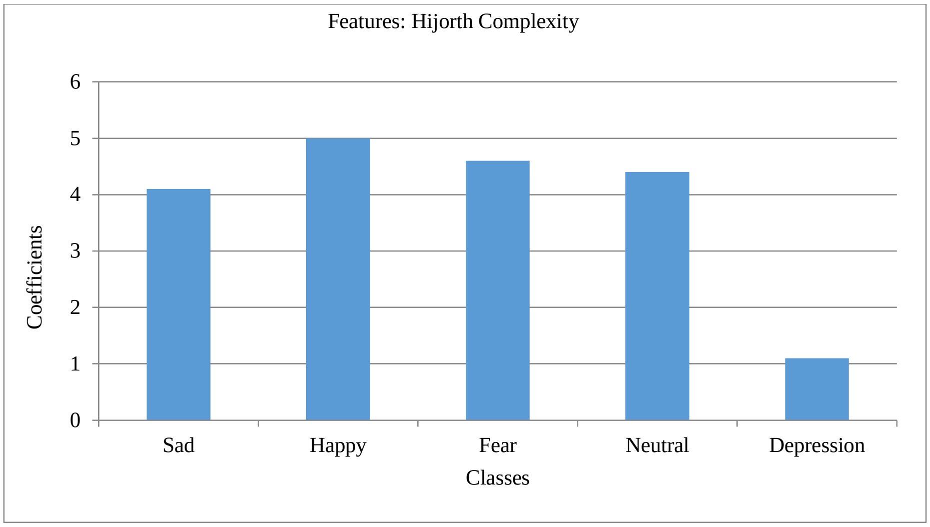


Fig. 5(b) Significant baseline features group-2

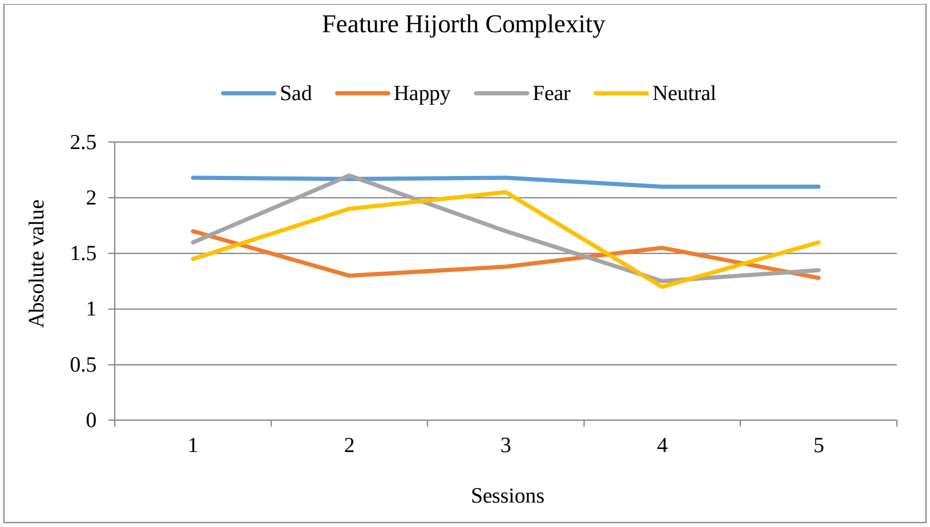


Fig. 6(a) Hijorth complexity

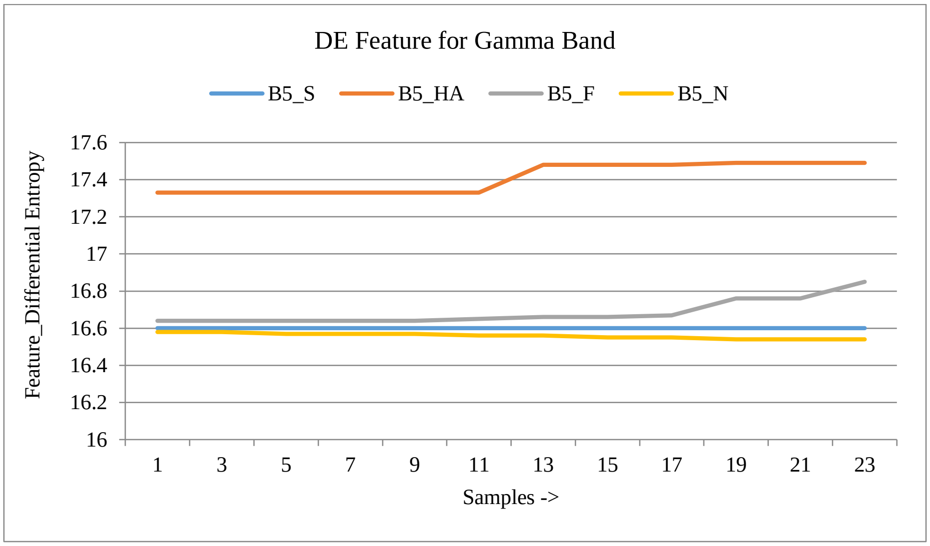


Fig. 6(b) Differential entropy of gamma band

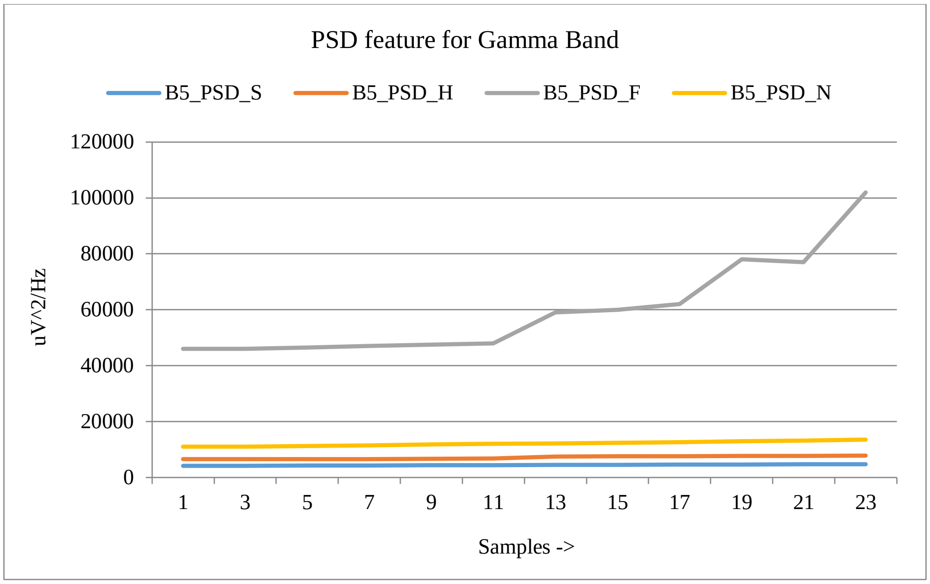


Fig. 6(c) PSD of gamma band

3.2. Feature Selection using PCA

After the feature extraction result,13 features were extracted in five bands. Among the five bands of the EEG signal, we got relevant features in the gamma band for further feature selection procedure. Figure 6(a) shows that the HC for all classes has significant differences and is thus useful for classification. Whereas Figures 6 (b) and (c) demonstrate the significance of the gamma band's remarkable differences in emotion classes, the vertical feature space reduces after applying ANOVA. Thus, the FVb and FVw are reduced to Equations (14) and (15).

$$FV_b = [IEEG, MAV, SSI, VEEG, MEDIAN(dastd), HA, HM, HC] \tag{14}$$

$$FV_w = [DE_g,\ PSD_g] \tag{15}$$

The Principal Component Analysis (PCA) method optimizes the features and improves classification. This provides a solution to dimensional reduction. Thus, PCA is applied to FVb and FVw to find final feature vectors for classification. Therefore, PCA provides two principal components, PC1 and PC2, which are further used for classification. The PCA is trained using ten features for two sessions, 24 trials, and 15 human subjects from the SEED dataset and 12 subjects from the MODMA dataset. The remaining dataset is used to test the model. PCA aims to obtain a new feature set that has a significant difference between depression and other emotions. From the above analysis, it was clear that more features reached the threshold value in the gamma band. Figure 7 shows the optimized principal component-based feature vector variation in classes.

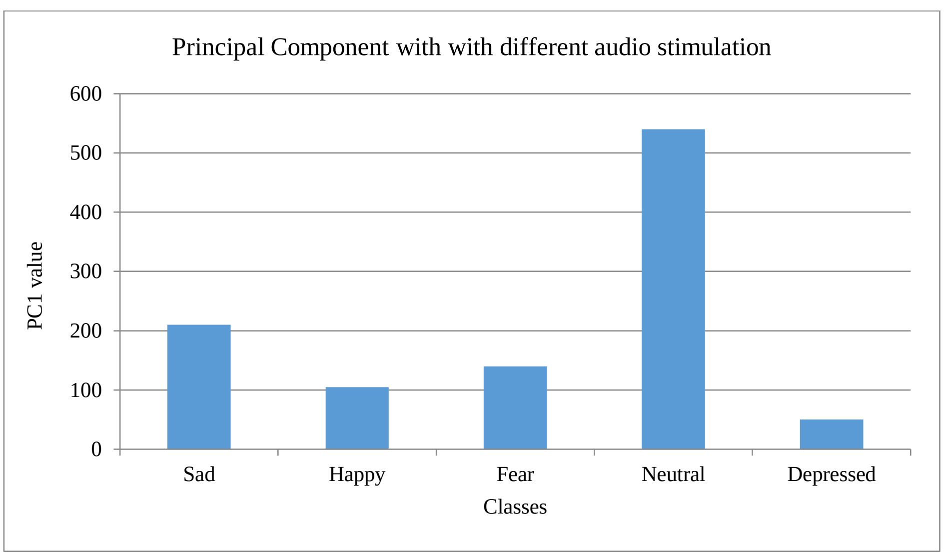


Fig. 7 Principal Component (PC1) for different classes

PCA aims to obtain a new feature set that has significant differences between depression and other emotions. The above analysis showed that the gamma band and related features reached the threshold value.

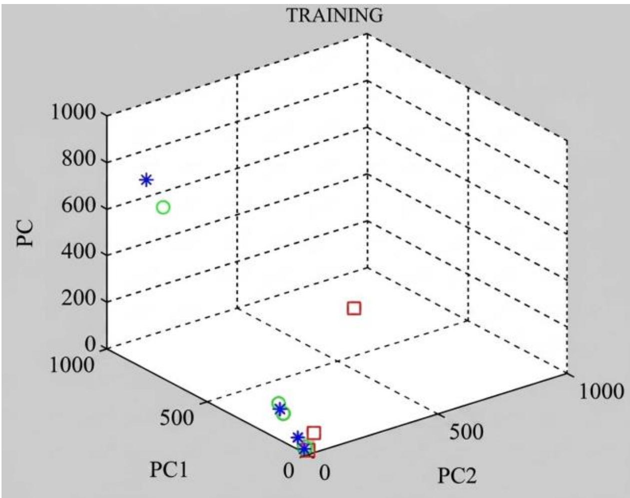


Fig. 8(a) Training accuracy

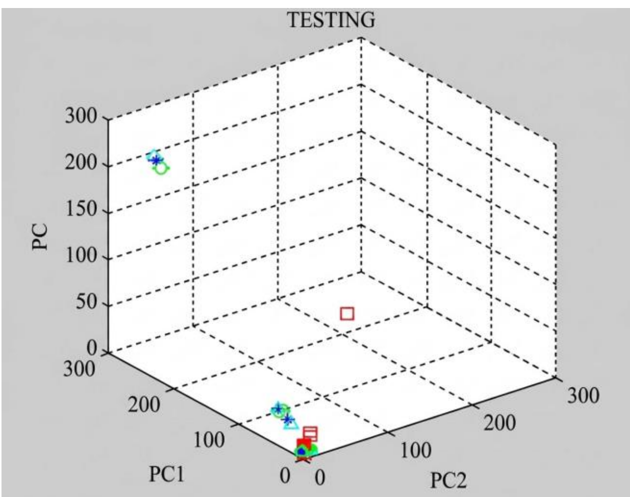


Fig. 8(b) Testing accuracy

Figure 8(a) shows the training of the dataset in which the system is trained with patients with 400 samples for each emotion.

In training, PC1 shows fear and sad emotions in the range of 300 to 400, happy emotions classified in the range of 0 to 200, depressed emotions classified in the range of 400 to 500, and PC2 classifies Fear emotions in the range of 500 to 600. Thus, features are observed to be classifiable. The feature vector is constructed by PCA based on training samples. The same feature vector is used to test the features.

Above, Figure 8 (b) shows a data set that was tested with 22 patients, with 500 samples for each emotion. The training and testing data set was reduced into two principal components: i,e. PC1 and PC2.

In testing, PC1 classifies fear and happy emotions in the range of 0 to 200; the remaining emotions are classified in the range of 200 to 500, and PC2 classifies fear, happy, and sad emotions in the range of 0 to 500.

3.3. Classification results for ANFIS

The principal components PC1 and PC2 are observed to be significant. Thus, the FIS, ANN, and ANFIS classification models are used for classification, and their performance is compared.

The output of PCA is provided to the ANFIS model. In the ANFIS model, x is the PC1 input, and y is the PC2 input. In layer 1, it processes to find the membership function. In layer 2, both membership functions multiply each other. In layer 3, it performs normalization. Layer 4 produces the normalized firing strength and a first-order polynomial product.

In Layer 5, it performs the addition of all layers and results in a set of emotions like Happy, Sad, Fear, and Depressed; according to the proposed methodology, the happy emotion is considered as not depressed analysis.

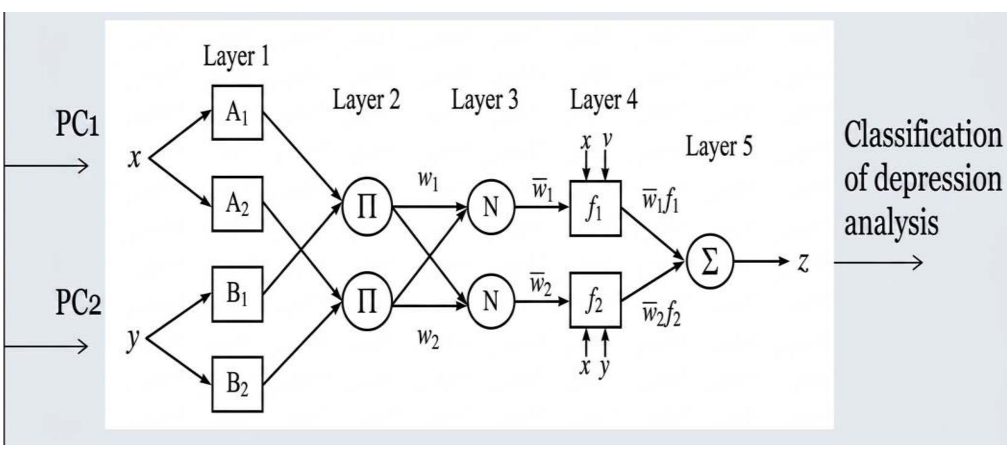


Fig. 9 Classification model for emotion and depression detection using ANFIS

Figure 10 shows the classification of emotion for Happy. It was tested with 75 samples (1 session of 15 subjects, 5 sample files) for happy. It correctly tested 85% of the samples from them. The X-Y-Z planes show variation in features, variation in amplitudes between 0 and 8 microvolts, and the sample no. of Happy, which is between 0 and 100, respectively.

Figure 11 shows the classification of a depressed state. It was tested with 134 samples for depression. It correctly tested 129 samples from them. It was considered a depressed analysis. The X-Y-Z planes show variation in features. variation in amplitudes between 0 and 25 microvolts, and the sample number of depressed people between 0 and 100, respectively.

Figure 12 shows the classification of sad emotions. It was tested with 120 samples for sad emotion. It correctly tested 95 samples from them. It was considered prone to depression analysis. The X-Y-Z planes show variation in features, variation in amplitudes between 0 and 20 microvolts, and the sample number of depressed states between 0 and 100, respectively.

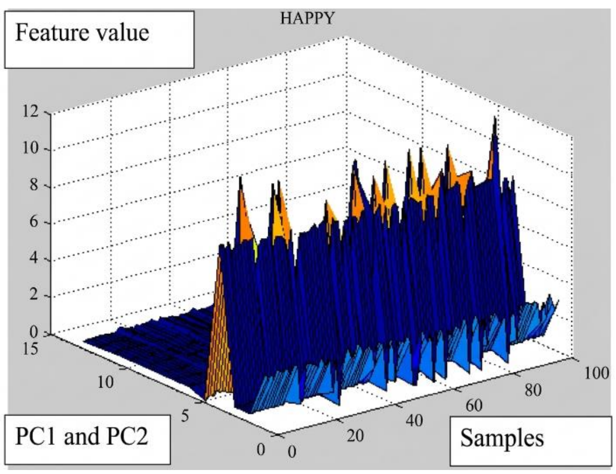


Fig. 10 Classification of the happy state by ANFIS

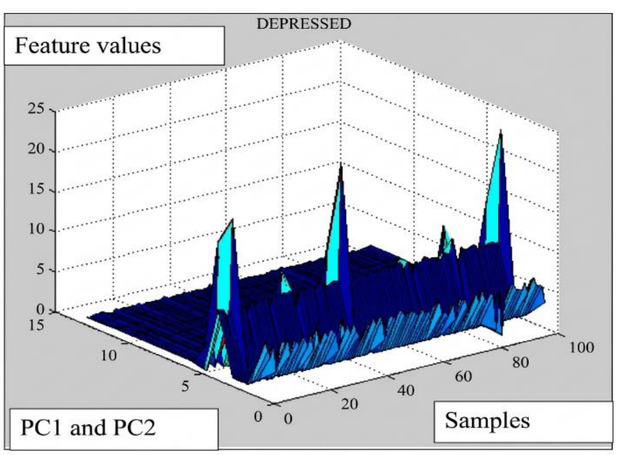


Fig. 11 Classification of the depressed state by ANFIS

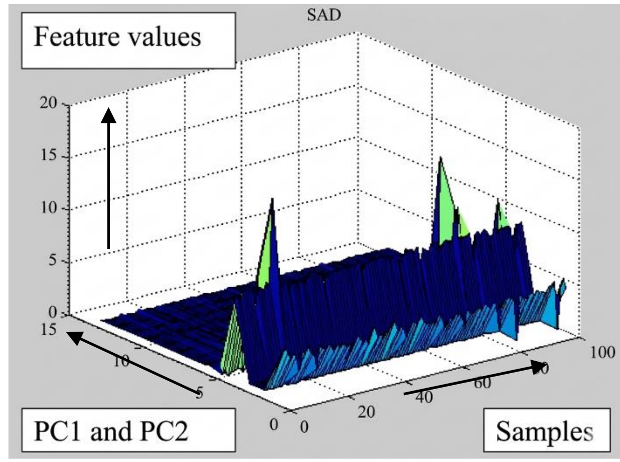


Fig. 12 Classification of sad state

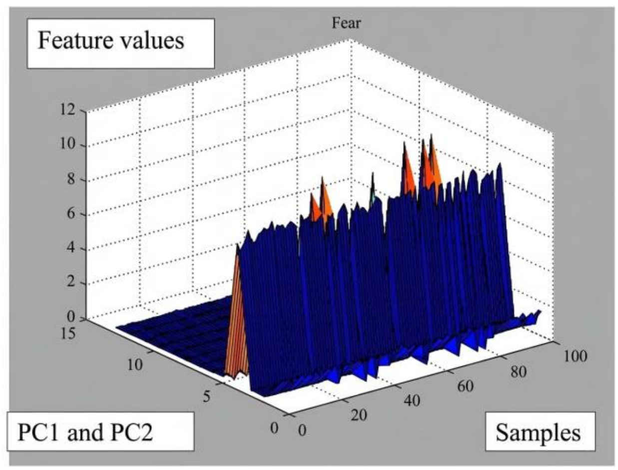


Fig. 13 Classification of fear state

Figure 13 shows the classification of Fear emotion. It was tested with 129 samples for sad emotion. It correctly tested 115 samples from them. It was considered prone to be depressed analysis. The X-Y-Z planes show variation in features, variation in amplitudes between 0 and 12 microvolts, and the sample no. of fear, which is between 0 and 100.

3.4. Classification Results for ANN

In terms of the network layer, data sets consist of different ages of people, where 13 males and 11 females from MODMA and 15 unknown subjects from SEED Dataset are taken as input; thus, the network contains sixty-four input and hidden nodes. The input layer is constructed with three nodes: 13 males, 11 females, and 15 Unknowns.

The network classifies selected datasets' emotions into happy, fearful, depressed, and sad. MATLAB platform and neural network toolbox are used to build, train, and test. Figure 14 above shows the ANN architecture representing six input nodes consisting of 2 nodes from 11 females, two from 13 males, and two from 15 unknowns. Emotions are classified as Happy, fearful, sad, and depressed in the output layer.

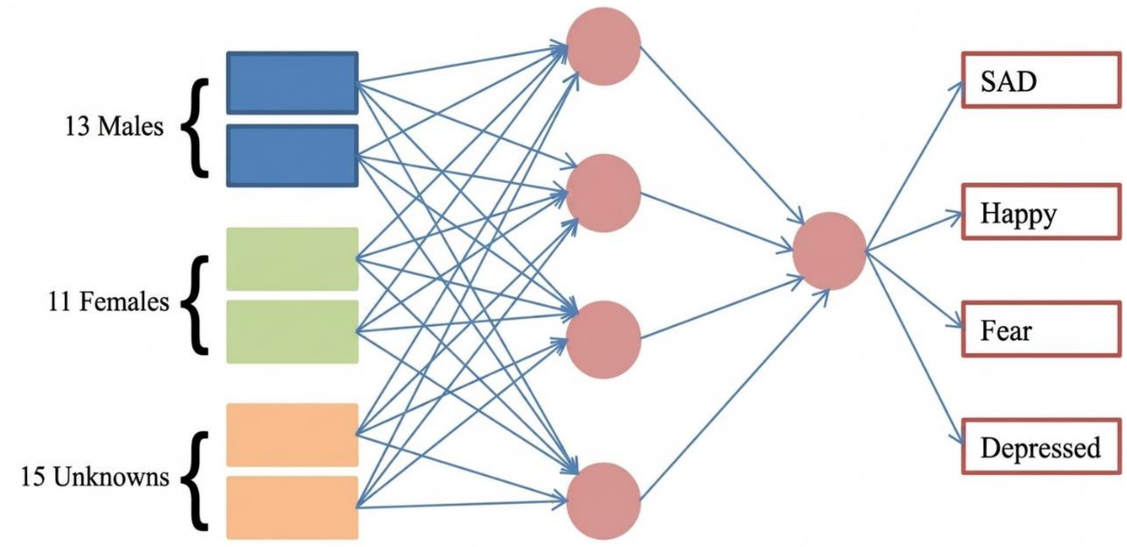


Fig. 14 Classification model for emotion and depression detection using ANN

3.5. Classification Results for FIS

Fuzzy logic represents an excellent mathematical framework for dealing with uncertainty in features.

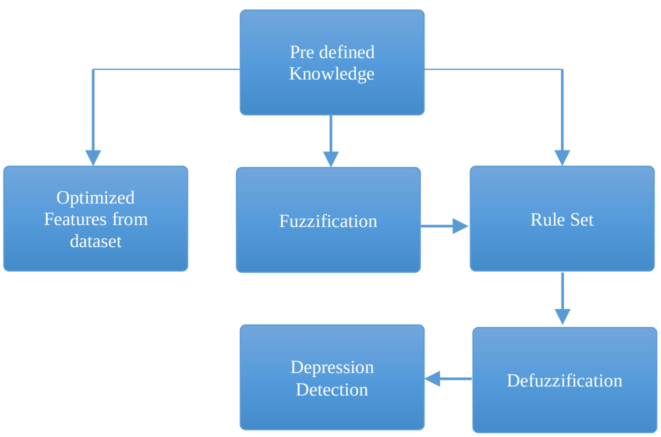


Fig. 15 Classification model for emotion and depression detection using FIS

After feature extraction, the crisp input was provided to the knowledge base. It applies if-then rules, and the inference process uses the membership functions of fuzzy sets in the fuzzy rules. Fuzzification transforms precise values into fuzzy values, while de-fuzzification is used to revert fuzzy values back into exact quantities. Output reacted as crisp output for classifying emotions as happy, sad, fear, and depressed.

4. Comparative Analysis

This study focused on the ANFIS performance in comparison to the FIS and ANN classification. The performance metric for ANN, ANFIS, and FIS is shown in Table 3. It is observed that the ANFIS model gives good performance for all classes. Table 4 demonstrates the performance of the Normal vs Depressed class.

Table 3. Performance matrix for ANN, ANFIS, and FIS (Vs Neutral) (SEED and MODMA Dataset)

Classification Model	Sad	Happy	Fear	DD
ANN	82.2%	81.5%	80.7%	84.1%
FIS	79.6%	80.6%	82.9%	81.7%
ANFIS	89.5%	90.1%	88.7%	92.4%

**DD is Depressive Disorder*

The limitations of FIS and ANN are recovered in the ANFIS model, such as optimization of membership function and interpretability, or uncertainty. The ANFIS model proves it better in random signals like EEG and thus gives good classification accuracy.

Table 4. Accuracy of ANFIS, ANN, and FIS (MODMA Dataset)

Classification model	Normal	Depressed
ANFIS	96.56%	89.55%
ANN	72.03%	82.08%
FIS	64.45%	78.35%

Table 5. Comparative analysis with recent research work

Method used	Dataset	Accuracy
RF and CNN (2023) [3]	MODMA	>95%
Graph Convolution Network and attention (2024) [17]	MODMA	92.87
Proposed PCA+ANFIS	MODMA+ SEED-IV	Average = 93%

5. Conclusion

Depressive disorder is a very common neurological disorder observed in all ages. The EEG is the most reliable tool for understanding the state of mind or emotions. The study extracts and processes the EEG using a machine-learning approach. The significant observations are baseline features extracted from the EEG raw signal and wavelet features extracted at the level of four, contributing better to the classification of emotions. Out of the five bands of the EEG signal, the gamma band was most suitable for feature extraction. The extracted signal selects the features using ANOVA and PCA. ANFIS, FIS, and ANN classification models are implemented for analyzing the depression state. The ANFIS classification model is found to be the most accurate. The classification accuracy observed is 89.55%,78.35%, and 82.08% for ANFIS, FIS, and ANN, respectively, and for the SEED and MODMA datasets, the maximum accuracy observed as 92.4%. The study's contribution is that the experimentation is performed on musically induced emotions measured with EEG signals. As the MODMA dataset gives the reference of foreign music and EEG signals, the framework will be used for a real-time database created using Neurosky Mindwave while listening to Indian Music. The work is extended to understand the impact of Indian music on brain waves and also as a music therapy for diabetic patients who suffer from anxiety, stress, depression, and mood swings.

Conflicts of Interest

We assure that there are no known conflicts of interest associated with this publication.

Funding Statement

No Financial Support for the work

References

[1] Ruggero G. Bettinardi, Mohamed Rahmouni, and Ulysse Gimenez, "BioSerenity-E1: A Self-Supervised EEG Model for Medical Applications," *arXiv preprint*, pp. 1-20, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ajit P. Gosavi, and S.R. Khot, "Emotion Recognition using Principal Component Analysis with Singular Value Decomposition," *2014 International Conference on Electronics and Communication Systems (ICECS)*, Coimbatore, India, pp. 1-5, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[3] Amel Ksibi et al., "Electroencephalography-based Depression Detection using Multiple Machine Learning Techniques," *Diagnostics*, vol. 13, no. 10, pp. 1-39, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Muhammad Umair et al., "Decentralized EEG-based Detection of Major Depressive Disorder Via Transformer Architectures and Split Learning," *Frontiers in Computational Neuroscience*, vol. 19, pp 1-15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] Mandar Deshpande, and Vignesh Rao, "Depression Detection using Emotion Artificial Intelligence," *2017 International Conference on Intelligent Sustainable Systems (ICISS)*, Palladam, India, pp. 858-862, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[6] Raid M. Khalil, and Adel Al-Jumaily, "Machine Learning based Prediction of Depression Among Type 2 Diabetic Patients," *2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*, Nanjing, China, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[7] Mudiana Binti Mokhsin et al., "Automatic Music Emotion Classification using Artificial Neural Network based on Vocal and Instrumental Sound Timbers," *Journal of Computer Science*, vol. 10, no. 12, pp. 2584-2592, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[8] Philippe Dondon et al., "Implementation of a feed-forward Artificial Neural Network in VHDL on FPGA," *12th Symposium on Neural Network Applications in Electrical Engineering (NEUREL)*, Belgrade, Serbia, pp. 37-40, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[9] Sasikumar Gurumurthy, and B.K. Tripathy, "Classification and Analysis of EEG Brain Signals for Finding Epilepsy Risk Levels using SVM," *World Applied Sciences Journal*, vol. 33, no. 4, pp 631-639, 2015. [Google Scholar]

[10] Bo Liu et al., "An End-to-End Depression Recognition Method based on EEGNet," *Frontiers in Psychiatry*, vol. 13, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Georgi Georgiev et al., "Structure Synthesis of ANFIS Classifier for Teletraffic System Resources Identification," *2016 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)*, Varna, Bulgaria, pp. 1-5, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[12] P. Geethanjali, Y. Krishna Mohan, and Jinisha Sen, "Time Domain Feature Extraction and Classification of EEG Data for Brain Computer Interface," *2012 9th International Conference on Fuzzy Systems and Knowledge Discovery*, Chongqing, China, pp. 1136-1139, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[13] Dingyin Hu, Wei Li, and Xi Chen, "Feature Extraction of Motor Imagery EEG Signals based on Wavelet Packet Decomposition," *The 2011 IEEE/ICME International Conference on Complex Medical Engineering*, Harbin, China, pp. 694-697, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[14] Hamid Behnam et al., "Analyses of EEG Background Activity in Autism Disorders with Fast Fourier Transform and Short Time Fourier Measure," *2007 International Conference on Intelligent and Advanced Systems*, Kuala Lumpur, Malaysia, pp. 1240-1244, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[15] A. Akrami et al., "EEG-based Mental Task Classification: Linear and Nonlinear Classification of Movement Imagery," *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, Shanghai, China, pp. 4626-4629, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[16] Wei-Long Zheng et al., "EmotionMeter: A Multimodal Framework for Recognizing Human Emotions," *IEEE Transactions on Cybernetics*, vol. 49, no. 3, pp. 1110-1122, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[17] Zhongyi Zhang et al., "A Novel EEG-based Graph Convolution Network for Depression Detection: Incorporating Secondary Subject Partitioning and Attention Mechanism," *Expert Systems with Applications*, vol. 239, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[18] H. Cai et al., "MODMA Dataset: A Multi-Modal Open Dataset for Mental-Disorder Analysis," *arXiv Preprint*, 2020. [Google Scholar]
[19] Wei Gan et al., "TSF-MDD: A Deep Learning Approach for Electroencephalography-based Diagnosis of Major Depressive Disorder with Temporal-Spatial-Frequency Feature Fusion," *Bioengineering*, vol. 12, no. 2, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[20] T. Thamaraimanalan et al., "Exploiting Adaptive Neuro-Fuzzy Inference Systems for Cognitive Patterns in Multimodal Brain Signal Analysis," *Scientific Reports*, vol. 15, no. 1, pp. 1-28, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[21] Jianli Yang et al., "Depression Detection based on Analysis of EEG Signals in Multi Brain Regions," *Journal of Integrative Neuroscience*, vol. 22, no. 4, pp. 1-9, 2023. [CrossRef] [Google Scholar] [Publisher Link]