Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

An Intelligent Computational Model to predict Eye Behaviour using EMD based Feature Extraction Technique

Dr. D. Narmadha[1], Ms. Sanooja Beegam M.A[2], Dr. G. Gifta Jerith[3], Dr. R. Poornima[4], Dr. G. Naveen Sundar[5*], Dr. S. Joyson Abraham[6]
[1]*Division of AIML, Karunya Institute of Technology & Sciences*
narmadha@karunya.edu
[2]*Assistant Professor, Department of Computer Science and Engineering, SCMS School of Engineering and Technology, Ernakulam*
sanooja@scmsgroup.org
[3]*Assistant Professor, Department of AI&ML, School of Engineering, Malla Reddy University, Hyderabad*
ggiftajerith@gmail.com
[4]*Assistant Professor, Department of AI&ML, School of Engineering, Malla Reddy University*
poorniom@gmail.com
[5*]*Division of CSE, Karunya Institute of Technology & Sciences, naveensundar@karunya.edu*
[6]*Associate professor, Department of Aeronautical engineering, Malla Reddy College of Engineering and technology, Hyderabad*
joysonabraham19@gmail.com

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

Monitoring human health using electroencephalogram (EEG) signal has become prominent research in recent times. The proposed research work focuses on assessing the EEG signal by incorporating EMD (Empirical Mode Decomposition) technique and deep learning model to forecast the future state of eyes based on understanding the characteristics of interactivity (open eyes and closed eyes). The relevance of the study is that it demonstrates how we can assess human body wellness by observing the status of the eyes for an extended period of time. The proposed method provides numerous beneficial supports for enhancing the accuracy of the information retrieval system. In this research work, we first extract the features of EEG data by combining EMD and then build DNN (Deep Neural Network) model for testing the real data set. The proposed model gives remarkable result than existing model in terms of accuracy, precision, recall, sensitivity and specificity. The proposed approach produces an accuracy of 96%, precision of 97%, recall of 93%, sensitivity of 93% and specificity of 97%.

Keywords: EEG(Electroencephalogram), EMD(Empirical Mode Decomposition), DNN(Deep Neural Network), VMD(Variable Mode Decomposition)

Introduction:

Electroencephalogram (EEG)uses electrodes connected to your scalp to capture the electrical impulses of your brain. EEG activity has been analysed primarily in clinical settings to discover diseases and epilepsies. Formerly, EEG interpretation was restricted to neurophysiologists trained to classify the types of EEG activity and to identify any anomalies found in EEG recordings. With the advancement of computers and related technology, it is now possible to successfully utilise a variety of approaches to measure EEG changes (Ochoa, J.B., 2002). The EEG is challenging for an inexperienced viewer to interpret when compared to other biological signals due to the geographic mapping of activities onto distinct parts of the brain and the location of electrodes. There are approximately 86 billion neurons in human brain (Iqbal et al., 2019), which comprise a sophisticated integrated information processing and control system that governs all everyday decisions. In medical diagnostics and Brain-Computer Interface (BCI) applications, the ability to detect biological motion sensations and physiological changes using EEG data is essential (Barachant, A, et. al, 2013). The relevance of studies that looked at the classification of eye states using EEG signals has been brought to light in different applications, such as automatic classification of walking patterns among children (Wei, P et al., 2021), drunken driving and drowsiness detection (Malar, E er. Al, 2011), (Bhowmick, B. and Kumar, K.C., 2009) and numerous neurological disease diagnosis (Alturki, F.A et al., 2020). According to recent estimates from the National Highway Traffic Safety Administration, driver weariness causes 1,800 deaths and 96,000 injuries each year.

Numerous methods have been used in recent times to obtain an improved classification accuracy, such as deep gradient Neural Network model to emotion classification (Wu, Q et al., 2021), power spectrum analysis is combined with minimum redundancy feature selection method and SVM classifier to attain faster classification of autistic children (Kang, J et al., 2020). In the research study by (Vettori, S et al, 2020), (Dong, Y et al, 2016) a fully automated model is used to predict social bias in boys by fusing EEG signals and ET signals is used to attain improved accuracy. Researchers (Ding, X et al, 2019) also focus on the study of classification between MDD patients and healthy patients by fusing EEG, eye tracking dataset and to improve the prediction accuracy. Researchers (Saghafi, A et al, 2017) have also used multivariate empirical mode decomposition (MEMD) and machine learning techniques for classification of eye state either open or close. Extensive literature analysis also has been done using Polynomial transform-based measures and SVM classifier for improved classification of EEG signals for Epilepsy detection (Nkengfack, L.C.D et al, 2021), (Zhao, L et al, 2018). Researchers (Wang, Y et al, 2020) have also done extensive analysis on data fusion strategies by combining EEG and Eye tracking dataset to bring an improvement in prediction accuracy. The power in the spectrum outcome has shown differences in study of people who are affected with disease and the people who are normal.

The previous research studies the use of EEG signal data and Eye tracking dataset for the prediction of neurological disorder, drunken driving and drowsiness detection. However, still the methodologies lack in the prediction accuracy. The objective of the research paper is to use a novel EMD (Empirical Mode Decomposition) technique to decompose a signal into several IMF (Intrinsic Mode Functions) and compute the residual value of the signal and obtain improved accuracy. The major contributions of the research paper are as follows,

The proposed approach uses an intelligent prediction model for predicting the eye behaviour using EMD based decomposition technique.

The extraction of statistical features and extracting the most optimal features for building the training data set.

The improved prediction accuracy is obtained using EMD decomposition technique. Section 2 provides a detailed description of the proposed methodology and the description of the dataset used for experimental analysis. Section 3 provides an overview of the exploratory study of the proposed method and the comparison with the existing methods. Finally, section 4 includes the conclusion and future work of the proposed research.

2. Materials and Methods:

2.1 Dataset:

The EEG eye state corpus from the UCI Machine Learning Repository was used in this study (Frank, A., and Asuncion, A., 2010). The dataset used in this research was captured by the experiment done by Rösler and Suendermann (2013) from Baden-Württemberg Cooperative State University (DHBW). The dataset consists of 14,980 instances and 15 characteristics in the corpus. 14 features represent the signals recorded from different positions on the scalp such as FC5, FC6, T7, T8, P7, P8, O1, AF3, AF4, F3, F4, F7, F8 and O2. The dataset uses EPOC headset for capturing the signals and the device is quite efficient and cost effective for capturing the signals.

2.2 Proposed Model:

The research work involves multiple steps right from the collection of EEG signal dataset from UCI machine learning repository. Figure 1 shows the step-by-step process involved in the prediction of eye state behaviour. The dataset was pre-processed such that the mean of the values is used to replace missing values. The pre-processed dataset was fed into decomposition module where the input signal was decomposed into number of IMF's until a residual value of the signal is obtained. The decomposed signal was fed into a number of feature extraction module to extract the features such as mean, maximum, skewness and kurtosis from the decomposed dataset. The optimal features of the proposed model are fed into deep learning models to predict the performance of the proposed model.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

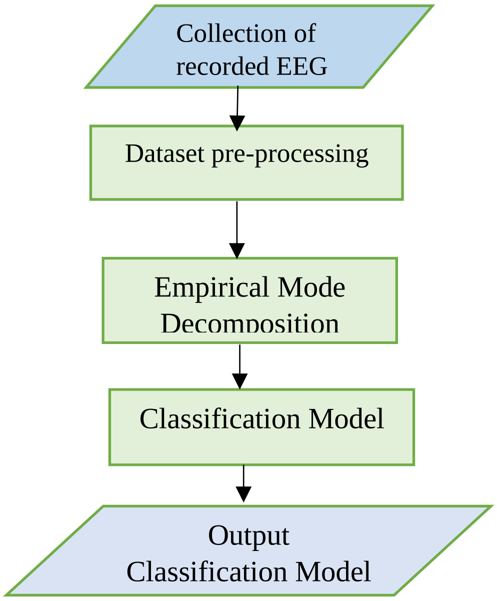


Figure 1: Flowchart of the proposed Model

2.3 Algorithms

Step 1: Pass the EEG signal data to the Empirical mode decomposition technique. It is an analysis technique used to process non linear input data and decompose the input signal into number of IMF(Independent intrinsic mode functions) and a residual value

Step 2: PCA(Principal Component Analysis) test is performed to extract the most correlated statistical features.

Step 3: The highly correlated features are fed into deep neural network model for accurate prediction of eye state.

Step 4: The decomposed signal is passed through deep neural network layer (14 features, ReLU activation function)

$$Yi = max(0,xi) \quad (1)$$

Step 6: The output of the previous layer is passed through the hidden layer of 14 feature maps using ReLU activation function

Step 7: The output of the hidden layer is pass to the output layer of sigmoid activation function.

Step 8: The model has been trained using ADAM optimizer and binary cross entropy function is used to calculate the loss.

Step 9: The model is evaluated using various performance parameters such as accuracy, sensitivity, specificity to evaluate the performance of the proposed model.

2.4 Outline of Proposed Model:

Figure 2 shows the block diagram of the overall functionality of the proposed model. The functionality of the model is described in the following section

Block 1: The dataset used for the experiment consists of EEG measurement recorded using EEG Neuroheadset. The dataset has been recorded for 117 seconds and state of eye has been recorded using a camera. Outcome of the recording has been given as '1' to indicate open state and '0' to indicate closed eye state. The dataset used for the experiment has been taken from UCI machine learning repository.

Block 2: The recorded EEG signal has been cleaned to remove the instances that has missing values. In this analysis, four of the instances such as 899, 10,387, 11,510, and 13,180 have been removed.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Block 3: Pass the EEG signal data to the Empirical mode decomposition technique. It is an analysis technique used to process non-linear input data and decompose the input signal into number of IMF (Independent intrinsic mode functions) and a residual value.

Block 4: PCA (Principal Component Analysis) test have been performed to extract the most optimal features in order to improve the performance of the proposed model.

Block 5: Evaluate the performance of the models using various performance metrics.

2.4.1 Decomposition using EMD

The EMD method is a step used to reduce any given data into a collection of intrinsic mode functions (IMF) and Hilbert spectral analysis is applied to decomposed data. The process of extracting IMF from the signal is known as sifting. Figure 3 shows the sample of observed IMF.

(i) *The upper and the lower envelope covers all the data points between them. The first value is obtained by calculating the difference between the mean and the data.*

$$Y_1 = Xi(t) - u_1 \qquad (1)$$

Y_1: Output value
$Xi(t)$: Input Features
u_1 : Mean of all the values

(ii) *In the next iteration, Y_1 is treated as the data*

$$Y_1 - u_{11} = Y_{11} \qquad (2)$$

After iterating the process for n times, Y1 becomes an IMF

$Y_{1(n-1)}\, u_{1n} = Y_{1n}$

Y_{1n} is defined as the IMF of the data

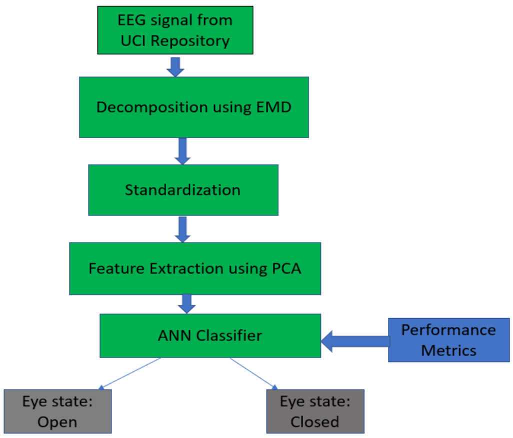
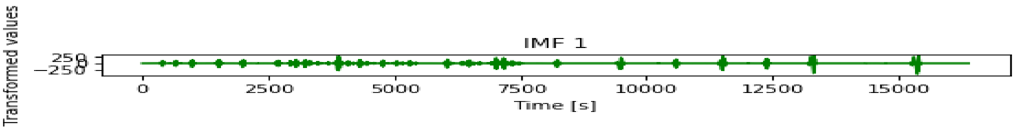
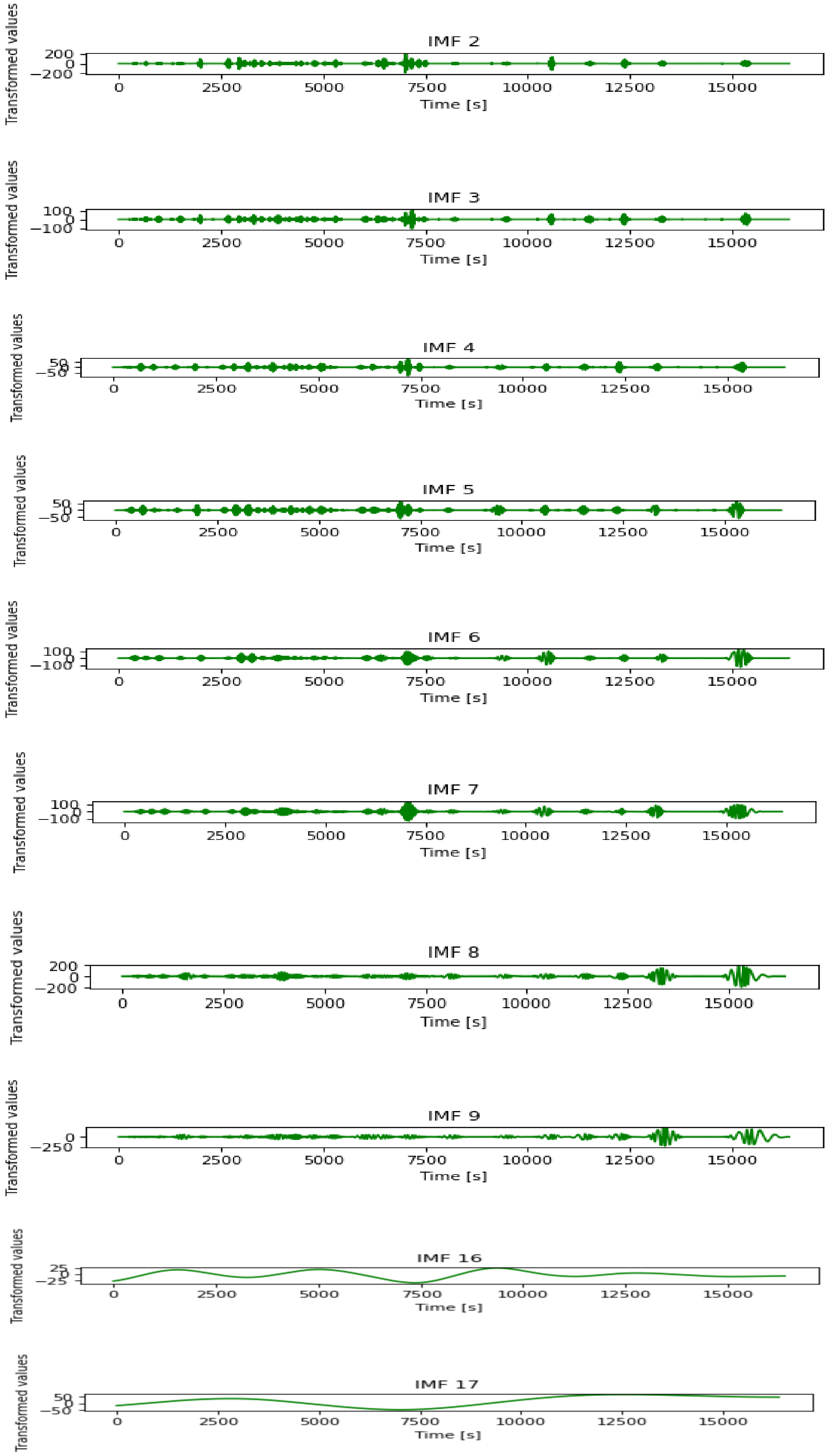


Figure 2 Block diagram of proposed methodology



Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article



Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

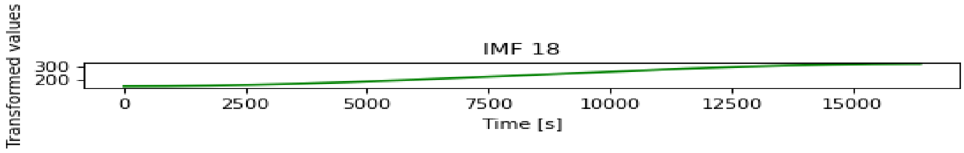


Figure 3 : Observed data, IMF's and Final residual for Eye state prediction

2.2 Feature scaling using Standard Scalar Function:

The features are standardized using standard scalar function where the feature is subtracted by the mean and divided by the standard deviation of all the values of the features.

It is represented by the following equation

$$zi = \frac{xi-\mu i}{\sigma i} \quad (3)$$

2.3 Feature Extraction using PCA:

Feature extraction helps to reduce the complexity involved in classifying the open and closed state of eyes. Some of the features contribute well for classifying the eye state and some of the features do not contribute well for classifying eye state. In this experimental analysis PCA (Principal Component Analysis) was conducted to identify the most significant features for classifying the open and closed state of eyes. This test can be applied to find the correlation between dependent and independent features.

(i) *Evaluate the mean of the input features Ω(1), Ω(2), Ω(3), Ω(4)... Ω(n) related to eye state classification*

(ii) *Evaluate the covariance matrix Ω(1,1), Ω (1,2), Ω (1,3).. Ω (1,n) from the input features*

Compute Ω^2ordered pairs.

(iii) *Evaluate the covariance of all the ordered pairs of input features related to eye state classification*

using the following equation

$$cova(\Omega_1, \Omega_2) = \frac{1}{M-1} \sum_{k=1} M(\,\Omega i - \Omega i\,)^2 \quad (4)$$

(iv) *Evaluate covariance matrix of size M*M*

$$A = \begin{matrix} cova(\,\Omega(1),\ \Omega(1)) & cova(\,\Omega(1), \Omega(n)) \\ cova(\,\Omega(m),\ \Omega(1)) & cova(\Omega(n),\ \Omega(n)) \end{matrix} \quad (5)$$

(v) *Evaluate eigen value, eigen vector and normalized eigen vector using the following equation*

Determinant(A-£€) = 0 *(6)*

2.4 Deep Neural Network Classifier

The proposed model uses deep neural network architecture to classify the eye state. The architecture is arranged as sequence of layers. The layers are made up of individual neurons. The neurons perform mathematical computation to convert input signal to an equivalent output function.

Table 1 Parameters of Deep Neural Architecture

Parameters	Values
Count of Input Neurons	10
Count of Hidden Neurons in layer1	6

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Count of Hidden Neurons in layer2	6
Count of Hidden Neurons in layer3	6
Count of output Neurons	1
Activation Function in Hidden layer1	ReLu
Activation Function in Hidden layer2	ReLu
Activation Function in Hidden layer3	ReLu
Activation Function in Hidden layer4	ReLu
Activation Function in output layer	Sigmoid

Table 1 shows the summary of the parameters setting of the deep neural architecture.

3. Experimental Results and Discussion

The performance of the proposed model was evaluated using performance parameters such as tru_pos(True positive), tru_neg(True negative), fal_pos(False Positive), fal_neg(False negative)

$$Accuracy(Acc) = \frac{tru_{\_pos}+tru\_neg}{tru\_pos+tru\_neg+fal\_pos+fal\_neg} \quad (7)$$

$$Recall(Rec) = \frac{tru\_pos}{tru\_pos+fal\_neg} \quad (8)$$

$$F-meaure(F-mea) = 2.\frac{Pre.Rec}{Pre+Recaa} \quad (9)$$

$$Specificity(Spec) = \frac{tru\_neg}{tru\_neg+fal\_pos} \quad (10)$$

$$Precision(Pre) = \frac{tru\_pos}{tru\_pos+fal\_pos} \quad (11)$$

Sensitivity specifies the rate of open eye state classification exactly predicted as positive and Specificity specifies the rate of closed eye state prediction exactly predicted a negative. Accuracy specifies the overall classification rate.

The ultimate objective of the proposed model was to see how the binary pattern recognition approaches influenced the ability to distinguish closed eye state from open eye state. Three different signal decomposition techniques were used for feature extraction, which leads to good performance in eye state classification. Table 2 shows the results of classification by including all features of the dataset.

Table 2 Results of classification Phase(I) – All features fed into DNN architecture

Techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F-score (%)
EMD	96	93	97	97	93	95
EEMD	93	89	96	89	89	92
VMD	92	91	93	93	91	91

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

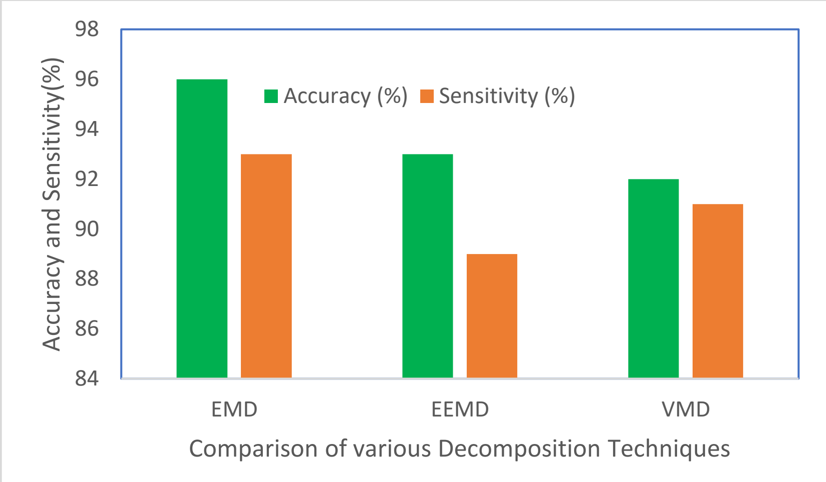


Figure 4: Performance comparison in terms of Accuracy and Sensitivity

It is observable from Figure 4 the proposed research work shows an improvement of 3% improvement than EEMD based decomposition technique and 4% improvement than VMD based decomposition technique in terms of Accuracy. Similarly, the proposed approach shows an improvement of 4% than EEMD based decomposition techniques and 2% improvement than VMD based decomposition techniques.

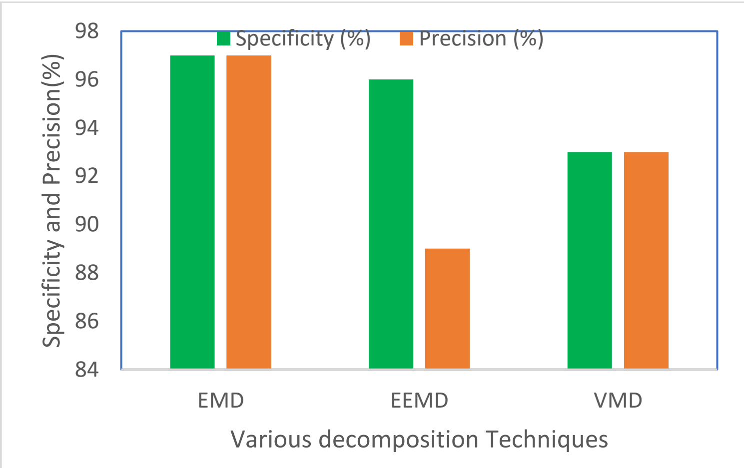


Figure 5: Performance comparison in terms of Specificity and Precision

Figure 5 shows performance comparison of the proposed approach in terms of specificity and Precision. It is observable from the figure, the proposed approach brings an improvement of 1% than EEMD and 4% than VMD in terms of specificity. Similarly, for precision the proposed approach brings an improvement of 7% than EEMD and 4% than VMD in terms of precision.

Table 3 Results of classification Phase (II) – Selected features fed into DNN architecture

Techniques	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F-score (%)
EMD	97.2	94.17	96.23	96.23	94.17	96.4
EEMD	91	87.23	92.1	92.1	87.23	91.2
VMD	90.2	90.3	91	91	90.3	90.2

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 3 summarizes the performance evaluation of the proposed methodology. It is observable from table 3, the proposed method brings an improvement of 6.2% than EMD and 7% than VMD in accuracy, 6.94% improvement than EEMD and 3.87% improvement than VMD in sensitivity, 4.13% than EMD, 5.23% than EEMD for specificity, 4.13% than EMD, 5.23% than EEMD for precision, 6.94% improvement than EMD and 3.87% improvement than EEMD, 5.2% improvement than EMD and 6.2% improvement than EEMD.

Decomposition Technique	Performance Metrics	Decision Tree	SVM	KNN	DNN
EMD	Accuracy	87	82.3	89	**97.2**
	Sensitivity	77.2	77.3	85.4	**94.17**
	Specificity	82.3	84	87.9	**96.23**
EEMD	Accuracy	81	82.6	80.7	92.3
	Sensitivity	83.2	85	78.9	93
	Specificity	80	82.4	80	94.6
VMD	Accuracy	83	82.3	80	90.2
	Sensitivity	80.5	81.3	82	91.6
	Specificity	88.4	78.9	83	92

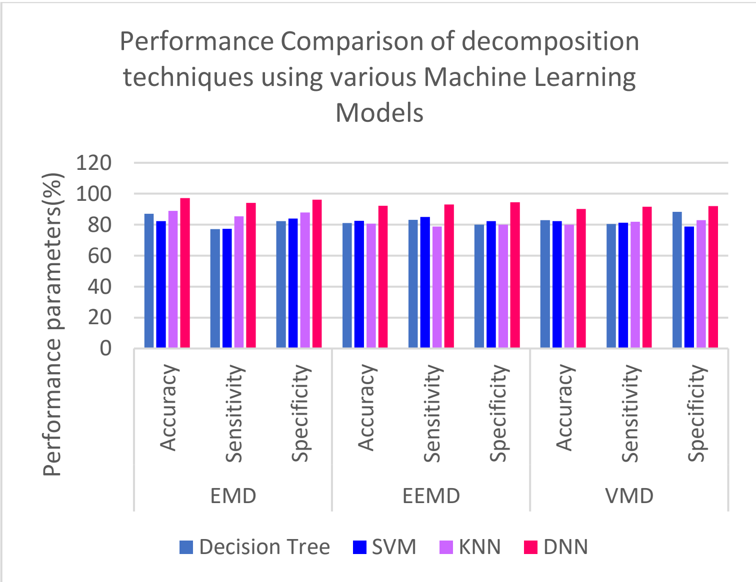


Figure 6 Performance comparison of different decomposition techniques on various ML techniques

Figure 6 shows the performance assessment of the various decomposition techniques on different machine learning approaches. It is observable from Figure 6, the proposed EMD-Deep learning technique brings an improvement of 4.9% than EEMD-Deep learning technique and 7% improvement than VMD-Deep learning technique in accuracy performance metric. It is observable for sensitivity, the proposed approach brings an improvement of 4.2% than EEMD and 5.6% than VMD based deep learning approach. Also, the proposed approach brings an improvement of 2.6% than EEMD and 5.2% than VMD based decomposition technique. There is also significant improvement in eye state classification that other machine learning approaches like decision tree, SVM classifier and KNN based classifier.

Table 3 Performance comparison using proposed and existing Eye state classification techniques

References	Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
(Pengcheng Ma and Qian Gao, 2020)	EEG Signal and Feature Interaction Modeling-Based Eye Behavior Prediction Research	93	92	90
(Abolfazl Saghaf et al., 2017)	Random eye state change detection in real-time using EEG signals	88	86	87
Our study	An Intelligent Computational Model to predict Eye Behaviour using EMD based Feature Extraction Technique	97.2	94	96

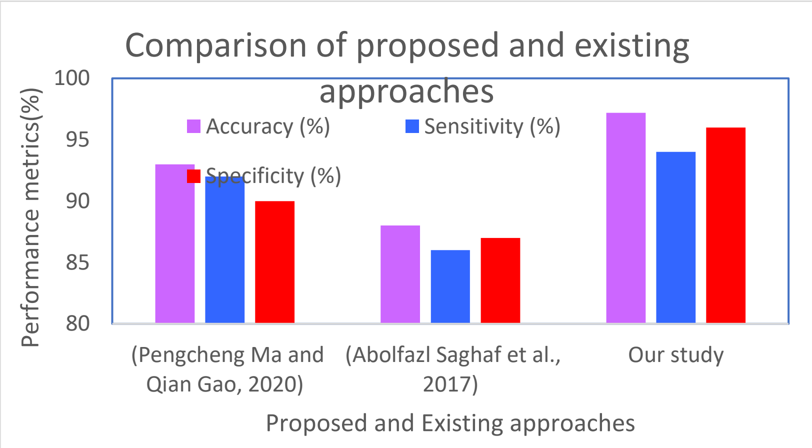


Figure 7: Comparison of proposed and existing approaches

Figure 7 shows the chart for the performance comparison of proposed and existing approaches. It is observable that the proposed approach. In accuracy, the proposed approach gives an improvement of 4.2% than the approach proposed by (Pengcheng Ma and Qian Gao, 2020) and 9.2% improvement than (Abolfazl Saghaf et al., 2017). Similarly for sensitivity and specificity the proposed approach shows remarkable improvement that existing approaches.

4. Conclusion

The purpose of the research is to predict the state of eye whether open or closed using EEG signal data. The outcome of the research is to automatically diagnose the overall health of eyes by detecting state of eye for long time. Initially, Empirical mode decomposition technique was used to decompose the signal into several IMF's and generate residual value from it. The decomposed signal was fed into Principal Component Analysis approach for feature selection. The selected features are fed into various machine learning approaches and deep learning technique. The EMD-Deep learning approach brings remarkable improvement than existing decomposition and Machine Learning based approaches.

REFERENCES:

[1] Ochoa, J.B., 2002. EEG signal classification for brain computer interface applications. *Ecole Polytechnique Federale De Lausanne*, *7*, pp.1-72.

[2] Kreiman, G., Koch, C. and Fried, I., 2000. Imagery neurons in the human brain. *Nature*, *408*(6810), pp.357-361.

[3] Iqbal, A., Sheikh, A. and Karayannis, T., 2019. DeNeRD: high-throughput detection of neurons for brain-wide analysis with deep learning. *Scientific reports*, *9*(1), pp.1-13.
[4] Barachant, A., Bonnet, S., Congedo, M. and Jutten, C., 2013. Classification of covariance matrices using a Riemannian-based kernel for BCI applications. *Neurocomputing*, *112*, pp.172-178.
[5] Wei, P., Zhang, J., Tian, F. and Hong, J., 2021. A comparison of neural networks algorithms for EEG and sEMG features based gait phases recognition. *Biomedical Signal Processing and Control*, *68*, p.102587.
[6] Malar, E., Gauthaam, M. and Chakravarthy, D., 2011. A novel approach for the detection of drunken driving using the power spectral density analysis of EEG. *International Journal of Computer Applications*, *21*(7), pp.10-14.
[7] Alturki, F.A., AlSharabi, K., Abdurraqeeb, A.M. and Aljalal, M., 2020. EEG signal analysis for diagnosing neurological disorders using discrete wavelet transform and intelligent techniques. *Sensors*, *20*(9), p.2505.
[8] Wu, Q., Dey, N., Shi, F., Crespo, R.G. and Sherratt, R.S., 2021. Emotion classification on eye-tracking and electroencephalograph fused signals employing deep gradient neural networks. *Applied Soft Computing*, *110*, p.107752.
[9] Kang, J., Han, X., Song, J., Niu, Z. and Li, X., 2020. The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data. *Computers in biology and medicine*, *120*, p.103722.
[10] Vettori, S., Dzhelyova, M., Van der Donck, S., Jacques, C., Van Wesemael, T., Steyaert, J., Rossion, B. and Boets, B., 2020. Combined frequency-tagging EEG and eye tracking reveal reduced social bias in boys with autism spectrum disorder. *Cortex*, *125*, pp.135-148.
[11] Ding, X., Yue, X., Zheng, R., Bi, C., Li, D. and Yao, G., 2019. Classifying major depression patients and healthy controls using EEG, eye tracking and galvanic skin response data. *Journal of affective Disorders*, *251*, pp.156-161.
[12] Saghafi, A., Tsokos, C.P., Goudarzi, M. and Farhidzadeh, H., 2017. Random eye state change detection in real-time using EEG signals. *Expert Systems with Applications*, *72*, pp.42-48.
[13] Nkengfack, L.C.D., Tchiotsop, D., Atangana, R., Louis-Door, V. and Wolf, D., 2021. Classification of EEG signals for epileptic seizures detection and eye states identification using Jacobi polynomial transforms-based measures of complexity and least-square support vector machine. *Informatics in Medicine Unlocked*, *23*, p.100536.
[14] Wang, Y., Yu, S., Ma, N., Wang, J., Hu, Z., Liu, Z. and He, J., 2020. Prediction of product design decision Making: An investigation of eye movements and EEG features. *Advanced Engineering Informatics*, *45*, p.101095.
[15] Frank, A., Asuncion, A., 2010. UCI machine learning repository. 2010 http://archive. ics.uci.edu/ml.
[16] Saghafi, A., Tsokos, C.P., Goudarzi, M. and Farhidzadeh, H., 2017. Random eye state change detection in real-time using EEG signals. *Expert Systems with Applications*, *72*, pp.42-48.
[17] Ma, P. and Gao, Q., 2020. EEG signal and feature interaction modeling-based eye behavior prediction research. *Computational and Mathematical Methods in Medicine*, *2020*.
[18] Dong, Y., Zhang, Y., Yue, J. and Hu, Z., 2016. Comparison of random forest, random ferns and support vector machine for eye state classification. *Multimedia Tools and Applications*, *75*(19), pp.11763-11783.
[19] Zhao, L., Wang, Z., Zhang, G., Qi, Y. and Wang, X., 2018. Eye state recognition based on deep integrated neural network and transfer learning. *Multimedia Tools and Applications*, *77*(15), pp.19415-19438.
[20] Bhowmick, B. and Kumar, K.C., 2009, November. Detection and classification of eye state in IR camera for driver drowsiness identification. In *2009 IEEE International Conference on Signal and Image Processing Applications* (pp. 340-345). IEEE.