Deep Neurowave Fusion with Smart Ensemble Stacking for Accurate EEG Eye StateRecognition

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HOW TO CITE:

K.Nivetha , R.Balakrishna (2026). Deep Neurowave Fusion with Smart Ensemble Stacking for Accurate EEG Eye State Recognition. International Journal of Special Education, 41(8s), 253-273

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ABSTRACT:

Signal analysis through electroencephalography (EEG) has become an imperative method of neural dynamics understanding and the mechanism of intelligent brain-computer interface applications. Nonlinearity, noise of the EEG signals, and variability however, pose a major challenge on identifying the accuracy of classification tasks especially on eye state detection. The proposed study is an efficient and computationally optimized machine learning system to classify eye state using EEG data based on the UCI EEG Eye State dataset. The suggested methodology consists of systematic data preprocessing, outliers elimination in the form of interquartile range, features standardization, and comparative benchmarking of various baseline classifiers, such as Logistic Regression, Support Vector Machine, Random Forest and XGBoost. In order to improve the classification performance, a K-Nearest Neighbor (KNN) model is optimized by hyperparameter tuning based on cross-validation strategies. The experimental findings show that the classic linear and kernel-based models have low performance because of the complicated nature of EEG signals with accuracy of about 63 percent and 55 percent, respectively. Random Forest and XGBoost ensemble-based models result in a higher level of performance with accuracy of up to 93. Nevertheless, the proposed optimization KNN model results in the highest level of classification accuracy with 98 percent and equal precision, recall and F1- score values. Additional statistical confirmation on the basis of one-way ANOVA proves that the performance change is significant ($p < 0.05$). The remaining analysis of residuals, QQ, and homoscedasticity test confirm the stability and resilience of the suggested model. The results show that distance based learning when optimized well can greatly be used in capturing fine differences in EEG signals. The suggested structure provides an effective, interpretive and computationally efficient response to EEG-based eye state recognition and has a high potential of real-time cognitive monitoring, driver drowsiness recognition and brain-computer interface systems.

Keywords: Electroencephalography (EEG); Eye State Classification; Machine Learning; K-Nearest Neighbor (KNN); EEG Signal Processing; Brain-Computer Interface (BCI); Feature Scaling and Optimization; Cognitive State Monitoring; Classification Algorithms; Biomedical Signal Analysis.

1 Introduction

Complex electrical impulses produced by the neurons are the means through which the human brain communicates.

Electroencephalography (EEG) is a non-invasive method that can be used to record and interpret these electrical patterns by measuring the changes in the voltage caused by brain

activity with electrodes attached to the scalp. EEG signals are a useful piece of information about neural behaviour and have proven a crucial instrument in neuroscience, cognitive science and medical diagnostics. The idea of brain electrical activity measurement was initially proposed by Berger in the early twentieth century who proved that the electrical brain activity could be detected and examined to research the mental processes and the neurological diseases [1]. EEG has since been one of the most popular methods of brain activity monitoring because it has a high temporal resolution, is relatively inexpensive, and is not invasive. EEG has become an essential tool in clinical and research practice especially in the diagnosis of neurological diseases like epilepsy, sleep disorders and cognitive impairments. Tracing EEG patterns, clinicians can trace the existence of abnormal brain activity and determine neurological condition successfully. Smith states that EEG recording is extensively used in neurological diagnosis and classification due to its ability to give real time data about the functioning of the brain [4]. Moreover, new signal processing and calculation methods have enabled more complex processing of EEG signals possible. The current research of EEG is dedicated to the medical diagnosis as well as to the observation of the cognitive state, analysis of neural signals, and human- machine interaction system. Recent research works have placed emphasis in the use of better signal processing and classification techniques in order to derive meaningful patterns in EEG signals that are generally complex and highly nonlinear [3]. As a result, the EEG data analysis issue has turned into an important field of research in biomedical engineering and artificial intelligence. As computational intelligence grows at a very rapid rate, machine learning algorithms have been popularly used in analyzing EEG signals. The conventional approach to EEG analysis demanded the use of manual interpretation by professionals whereby, interpretation was time consuming and subjective. Machine learning strategies permit an automatic identification of patterns within EEG data and make it easy to classify the state of the neural pattern. These approaches have made EEG-based applications more efficient and reliable. A significant sphere in which EEG analysis has received significant focus is brain-computer interface (BCI) systems. BCIs enable direct interaction of the human brain and external devices by converting EEGs into control signals. These systems have extensive application in rehabilitation and assistive technology and neurofeedback. The paper by Craik et al. [2] emphasized the growing importance of deep learning and machine learning methods to EEG classification challenges and showed how they could enhance the accuracy and strength of neural signal decoding. Likewise, Lotte et al. [5] also highlighted that machine learning algorithms have now been considered to be a required element of the BCI systems as they provide the certainty in classifying EEG signals that are related to various cognitive states.

Machine learning has also been applied to emotion recognition, monitoring attention, detecting fatigue, and analyzing cognitive workload besides BCI systems. Recent research has investigated the several machine learning and deep learning models to process neural signals and retrieve any meaningful information out of whatever is measured by EEG. According to Singh et al. [30], the EEG analysis through machine learning has demonstrated positive outcomes in neural rehabilitation and human machines interaction applications. These advancements prove that machine learning algorithms have turned into essential aids to the analysis of complex EEG signals and the introduction of the intelligent neurotechnology

systems.

EEG based eye state detection has become a significant field of study in the cognitive monitoring and analysis of human attention. Assessing the open and closed states of the eyes through the EEG indicators can find useful applications in fatigue monitors, driver drowsiness, and human attention control system. As the eye movements and the blinking like activities generate quantifiable variations in the EEG signals, such variations can be examined with the help of computer tools to discern the eye states. Other machine learning methods have also been suggested in recent studies as a way of classifying the eye states based on EEG signals. Nilashi et al. [20] constructed a classification model that adopted learning vector quantization and ensemble learning to classify eye states based on EEG signals which has shown that machine learning models can enhance the accuracy of classification. In the same vein, Ketu and Mishra [21] came up with a hybrid classification model that fused various machine learning algorithms to enhance the operation of EEG-based eye state detection systems. Their results showed that hybrid models could be used to detect complicated patterns in EEG signals. Eye state classification as well as its classification by deep learning methods has been investigated. The third article by Han et al. [22] has proposed a convolutional neural network-based approach to eye state detection based on EEG data and has reported a higher performance than the traditional machine learning models. According to these studies, EEG- based systems of eye state recognition hold great potential in real-time systems of the monitoring of fatigue, driver safety systems, and adaptive human- computer interaction systems.

Machine learning algorithms are significant in identifying valuable features and patterns of the EEG signals. EEG data are complex and noisy, and thus, reliable results are only possible through effective feature extraction and classification methods. Classification of EEG signals has extensively used the traditional machine learning models, including support vector machines, logistic regression, decision trees, and k-nearest neighbors. Subasi and Gursoy [8] explored how various classification methods such as principal component analysis (PCA), independent component analysis (ICA), the linear discriminant analysis (LDA) and support vectors machines classify EEG signals. Their experiment showed that method of feature extraction with machine learning classifiers can considerably enhance the accuracy of EEG classification. In the same way, Wang et al. [6] used machine learning to identify emotional states based on EEG data and claimed encouraging outcomes with supervised learning.

More recently, scholars have considered hybrid and deep learning methods of EEG analysis. Guerrero et al. [15] compared the various classification algorithms, such as logistic regression, artificial neural networks, support vector machine, and convolutional neural networks in the analysis of the EEG signal. They found that machine learning models can effectively detect patterns in EEG signals in case suitable feature extraction and preprocessing methods are used. Nevertheless, the problem of EEG classification is not a simple issue in spite of the improvements since this method is characterized by noise of the signal, subject-to-subject variability and the complexity of neural activity.

Despite the tremendous improvement in the classification of EEG signals, there are various challenges that it is facing towards coming up with reliable and accurate EEG-based eye state detection systems. Among the key issues is that the EEG signals contain the noise and artifacts that may adversely impact the classification. EEG signals are extremely vulnerable to muscle movement, noise in the environment and movement of electrodes, thus, it is hard to accurately analyze the signals. The other difficulty is to attain high classification accuracy and computational efficiency. However, deep learning models can be very costly and consume a lot of computational and memory power although they have demonstrated good outcomes. As a result, numerous studies are still going on to develop ways of optimized machine

learning that can deliver high accuracy at minimal computational complexity.

Recent studies have tried to overcome such obstacles by combining machine learning models with optimization algorithms. As an example, Elshewey et al. [18] suggested a method of EEG eye state classification based on the optimization approach and modified bit error rate algorithm and the k- nearest neighbor classifier. Their approach showed that they had better classifications than the traditional models. On the same note, Rabbani et al. [19] designed a real time EEG eye blink classification system that is used in brain to computer interface applications, and they emphasize the need to have more effective and efficient EEG classification methods. Though these improvements have been made, better machine learning models are still needed that can suitably and efficiently work with noisy EEG signals and attain better classification accuracy when carrying out eye state recognition tasks.

To overcome the restriction of the current approaches to EEG classification, the present study introduces the machine learning-based system of eye state recognition based on the EEG signals. The proposed solution will enhance the accuracy of the classification, and at the same time, it will be computationally efficient. The key contributions of the research are as follows:

1. Machine learning based EEG eye state classification framework development with various classification algorithms.

2. Comparative analysis of a number of machine learning models, which are logistic regression, support vector machines, random forest, k-nearest neighbors, and XGBoost.

3. Optimization of k-nearest neighbor classifier hyperparameters to make the best classifier.

4. Through the method a higher accuracy in classification than that of other methods used to detect EEG eye state.

The offered methodology should offer strong and efficient framework of EEG-based eye state recognition, which could also be used in creation of intelligent brain-computer interface and cognitive monitoring systems.

2. Literature Review

The classification of electroencephalography (EEG) signals has been the subject of considerable studies because it is used in neuroscience, cognitive monitoring and brain-computer interface architecture. Multiple signal processing approaches have been suggested to analyze EEG signals over the years, starting with conventional signal processing models up to using advanced machine learning and deep learning models. In this section, existing research that is associated with EEG signal analysis and classification, in specific to the analysis of brain signal and eye state recognition approaches, is reviewed. The literature can be divided into four broad categories namely; classical EEG signal processing methods, machine learning methods of classification, deep learning and hybrid models, and optimization methods of enhancing classification performance.

2.1 Classical EEG Signal Analysis Methods

The initial studies on EEG signal classification were mainly based on use of the conventional signal processing methods to extract features and analyse patterns. These methods emphasized on converting raw EEG signal to meaningful features which could be utilized in classification activities. Frequency domain analysis and time-frequency transformations were some of these methods that were important in finding discriminative information in the EEG signals.

The wavelet transform is one of the popular methods that are used to process EEG signals as it allows the EEG signal to be analyzed in a number of frequency bands. Gandhi et al. [7] made a comparative research on the various families of the wavelet and applied them to the EEG signal classification and showed that the feature extraction using the wavelet is the best way to enhance the classification. Their results revealed that the choice of wavelet functions can be used to increase the sensitivity of

differentiating faint patterns in EEG signals. In the same manner, Polat and Gunez [9] suggested a hybrid classification model that incorporated fast fourier transform (FFT) and decision tree classifiers to detect epileptiform EEG signals. The time domain EEG signals were converted to the frequency domain through the application of FFT and the relevant features necessary to be used were detected in order to be used as a source of classification. They found the frequency-based analysis to be useful in capturing significant characteristics of EEG signals.

Chandaka et al. [10] also conducted another interesting study, on cross-correlation features with support vector machine (SVM) classifiers to classify EEG signals. The authors proved that relationships among channels of EEG could be successfully obtained using cross-correlation properties, which enhance the accuracy of classification. The classical methods of signal processing formed the basis of further studies that combined machine learning models and feature extraction algorithms to improve the EEG classification.

2.2 Machine Learning Approaches for EEG Classification

Through the development of the field of computational intelligence, the methods of machine learning have gained popularity in the classification of EEG signals. These techniques are automated approaches to feature learning and classification, which eliminates the reliance on manual interpretation of EEG signals. There are a number of supervised learning algorithms that have been explored in the analysis of EEG data.

Bablani et al. [11] used k-nearest neighbor (KNN) algorithm, which is used to classify EEG signals in concealed information tests. They in their study illustrated that the KNN classifier was capable of recognizing the various EEG patterns in case suitable feature representations were tapped. In the same way, Khare et al. [12] designed a neural network-based method of the classification of EEG signals depicting various mental states. They found that artificial neural networks have the potential to learn nonlinearity among EEG data that results in a higher classification accuracy.

EEG signal classification has also been extensively done on support vector machines. Bayram et al. [13] explored the use of SVM classifier in the analysis of EEG signal and presented results that indicate that the SVM classifier offers high-performance in high-dimensional EEG signal analysis. In addition, a classification strategy using a combination of logistic regression and the use of Gaussian mixture models was suggested by Rajaguru and Prabhakar [14] to classify epileptic EEG signals. Their study emphasized the usefulness of the statistical learning procedure in recognizing complicated EEG patterns. These researches indicate that machine learning models are significant in EEG signal classification since it allows the recognition of patterns automatically and enhance prediction accuracy.

2.3 Deep Learning and Hybrid Models for EEG The recent progress in artificial intelligence gave rise to deep learning models in the classification of EEG signals. Deep learning methods are able to automatically extract hierarchical features of raw EEG signals, and do not necessitate the intensive manual feature engineering. These models have therefore demonstrated good performance in the different applications related to EEG. The proposed convolutional neural network (CNN) architecture by Han et al. [22] is an ear-EEG based eye state classification model. They used deep neural networks to derive spatial information about EEG signals and demonstrated better classification accuracy than the traditional machine learning techniques. The paper identified the potential of CNN models in the analysis of EEG signals in real-time applications. Pathak et al. [25] explored the idea of deep learning in the classification of EEG signals and highlighted the significance of deep neural structures in the representation of various complex temporal dynamics in EEG signals. They have shown that deep learning methods could be extremely helpful in improving EEG signal analysis in comparison with the

conventional classification methods.

Wang et al. [31] presented another hybrid model of deep learning by introducing a CNNLSTM model of motor imagery EEG classification. The proposed approach was capable of simultaneously de-noising EEG signals as well as preserving spatial and temporal relationships of the data by using convolutional neural networks and long short-term memory networks. The paper has mentioned that it has achieved higher classification accuracy and has established that hybrid deep learning models have shown high effectiveness in EEG analysis. Such studies suggest that deep learning models are gaining popularity in the classification of EEG signals since they have the capability to automatically extract multi-faceted features of raw neural signals.

2.4 Optimization and Advanced Algorithms Even though machine learning and deep learning models have demonstrated promising performance in EEG classification tasks, the accuracy of the models usually relies on an adequate choice of features and an adequate optimization of the parameters. As such, the optimization algorithms have been investigated in some studies in order to enhance the efficiency of the EEG classification systems.

El-Kenawy et al. [16] suggested a variation of binary grey wolf optimizer and stochastic fractional search to feature selection in machine learning models. They in turn showed that the optimization algorithms were capable of finding out the important features and improving the classification accuracy.

On the same note, Afrakhteh et al. [23] have designed a neural network-based classification method that has been trained based on hybrid population-based optimization algorithms. Their findings indicated that optimization methods had the potential to become an effective way of enhancing the training and performance of neural network models in EEG signal classification.

Later on, Belhadi et al. [24] proposed a more advanced graph-based methodology of EEG signal categorization based on visibility. The technique involved the application of graph theory with the superior computational tools to interpret the structures of EEG signals. Their results showed that better classification can be achieved with the use of more sophisticated signal analysis tools and machine learning algorithms.

Altogether, optimization techniques are essential in the classification system of EEG signals because they increase the feature selection, model parameter, and model efficiency. To provide a clearer overview of the existing research, Table 1 summarizes several representative studies related to EEG signal classification and eye state detection.

Table 1. Summary of Existing EEG Signal Classification Studies

Ref	Author	Year	Method Used	Dataset	Key Contribution
[7]	Gandhi et al.	2011	Wavelet Transform	EEG	Feature extraction for EEG signals
[8]	Subasi & Gursoy	2010	PCA + SVM	EEG signals	Machine learning-based EEG
[11]	Bablani et al.	2018	KNN classifier	EEG dataset	EEG signal classification using KNN
[20]	Nilashi et al.	2023	LVQ + Bagged Trees	EEG eye state dataset	Eye state classification using ensemble learning
[22]	Han et al.	2022	CNN	Ear EEG signals	Deep learning model for eye state classification
[18]	Elshewey et al.	2024	MBER + KNN	EEG eye state dataset	Optimization-based EEG eye state classification
[31]	Wang et al.	2023	CNN-LSTM	EEG time series	Hybrid deep learning model for EEG classification

[23]	Afrakhteh et al.	2020	Neural Network + Optimization	EEG signals	Improved classification using optimization algorithms
[24]	Belhadi et al.	2025	Visibility Graph Analysis	EEG signals	Advanced EEG signal analysis technique

3. Dataset Description

3.1 Overview of EEG Eye State Dataset

The experimental analysis in this paper involves the EEG Eye State data that is freely available in the UCI Machine Learning Repository. The dataset has been popular in the studies of EEG classification and serves as a standard to test the performance of machine learning algorithms against neural signal analysis. EEG data in this data set were measured with the Emotiv EEG Neuroheadset, a consumer EEG neuroheadset; an electronic device that can record electrical signals of the brain in response to scalp electrodes. The EEG signals were recorded continuously for 117 seconds during data acquisition stage as the participant switched between the state of open and closed eyes. The dataset contains 14 EEG electrode channels that record neural activity within the various parts of the brain. The dataset consists of a row of timestamps of the observations of the EEG signals on all electrode channels. The signal that is recorded is accompanied with a target label reflecting the state of the eye at that time.

The data sample consists of 14,980 samples (each sample will have 14 numeric EEG characteristics and a target variable with the label eyeDetection). The classification problem in the case of the research is a binary classification task, in which one has to identify whether the eyes are open or closed depending on the patterns of the EEG signals. The dataset is especially helpful in testing machine learning models since it has continuous EEG records with well- recorded eye state data. The structure of data thus enables the researcher to be able to study neural patterns that are related to visual action and mental states.

3.2 EEG Channel Description

EEG Eye State data consists of 14 electrode channels organized into positions as per the international standard of 1020 EEG electrode placement protocol which is a standardized procedure of placing electrodes on the head to detect brain activity. These electrodes are used to record electrical activity on various parts of the brain and this allows a researcher to study the neural activity in relation to mental activities and sensory activities.

The channels included in the dataset are:

AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4.

The electrodes record neural firing electrical activity in certain areas of the brain. An illustration is that frontal electrodes are mostly related with decision making and cognitive processing whereas the parietal electrodes are in charge of sensory integration and space perception. On the same note, the occipital electrodes record the neural activity with respect to visual processing. Through the processing of the signals that were captured using these electrodes, machine learning algorithms can detect patterns linked with eye movements and visual states. Table 2 has given a detailed description of each EEG channel and its corresponding part of the brain.

Table 2. EEG Dataset Feature Description

Feature	Brain Region	Description
AF3	Frontal	Cognitive processing
F7	Frontal	Motor planning
F3	Frontal	Executive functions
FC5	Frontal-central	Motor control
T7	Temporal	Auditory processing
P7	Parietal	Sensory integration
O1	Occipital	Visual processing
O2	Occipital	Visual processing
P8	Parietal	Spatial perception
T8	Temporal	Signal interpretation
FC6	Frontal-central	Motor signals
F4	Frontal	Cognitive functions
F8	Frontal	Decision making
AF4	Frontal	Attention control

The dataset records neural data of various parts of the brain and it is possible to fully analyze the patterns of EEG related to eye states as seen in Table 2.

3.3 Target Variable Description

The dataset has a target variable, eye Detection that is the eye state that is associated with each EEG observation. The classification issue that the research will tackle in the current study is whether the eyes of the subject were open or closed according to the value of the EEG evidence.

The target variable is in the form of a binary label, with every value describing a particular state of the eyes. The target variable can be explained as below:

Value	Meaning
0	Eye Open
1	Eye Closed

The ground truth labels of eye states were derived after video recordings of the EEG experiment. Once the EEG signals were obtained, the video frames of the corresponding video were analyzed to identify if the eyes of the subject were open or closed at a given time. These labels were afterwards matched with the EEG signals to achieve the final dataset that was used in classification.

The frequency of eye states in the data set was examined to have a better idea on how the target classes are distributed. Figure 1 depicts the distribution of the eye state samples.

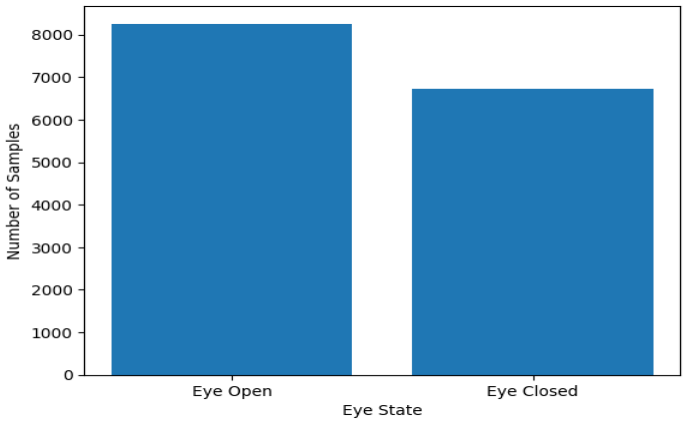

Figure 1. Distribution of Eye States in the EEG Eye State Dataset

The figure shows that the data has a relatively equal representation of open and closed eye states, which is good to work with to train machine learning models without any major bias of class imbalance.

3.4 Dataset Characteristics

Table 3 provides a summary of the notable features of the EEG Eye State data.

Table 3. Summary of Dataset Characteristics

Attribute	Value
Instances	14,980
Features	14 EEG channels
Classes	2
Data Type	Multivariate Time Series
Missing Values	None

As it is indicated in Table 3, the dataset is large enough in terms of samples and features to allow performing machine learning-based classification experiments. Moreover, the lack of missing values makes the preprocessing process easier and ensures that, the data can be directly used to train the model without further preprocessing procedures. The fact that two classes have a relatively balanced distribution is also appropriate to use the dataset in determining the performance of various machine learning models without the necessity to employ large-scale data balancing methods.

4. Methodology

The methodology of EEG-based eye state is described in this section. The proposed experimental framework has a number of sequential steps such as preprocessing data, feature scaling, data partitioning, the implementation of a baseline model and the development of a proposed, optimized classification model. The aim of these steps was to provide credible data preparation and equal consideration of machine learning algorithms used in the classification of EEG signals.

The general workflow to be followed in this study is depicted in Figure 2 that demonstrates the entire processing chain beginning with the EEG dataset up to the final step of classification.

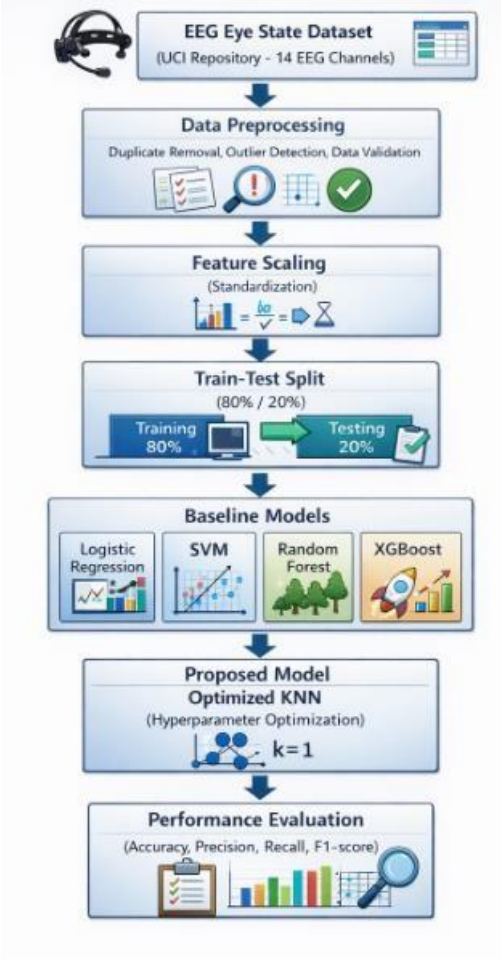

Figure 2. Proposed machine learning framework for EEG eye state classification

4.1 Data Preprocessing

Machine learning applications require data preprocessing especially with physiological data like EEG data. The raw EEG data can include duplicate data, or extreme values and other inconsistencies that adversely affect model performance. Consequently, preprocessing functions were carried out with an aim of making sure that the dataset was clean and would be analyzed in the machine learning.

The first step in preprocessing was the loading of data and structural validation. The data were checked for missing values and it was ensured that there were no missing values. Corresponding data were then selected and the duplicate records were removed to prevent biasness in training process. Further, the Interquartile Range (IQR) method was also used to detect outliers based on the values that are outside the range of acceptable statistical range of the data. Table 3 is a summary of the preprocessing operations undertaken in this study.

Table 4. Data Preprocessing Summary

Step	Technique	Purpose
Data Cleaning	Duplicate removal	Improve dataset quality
Outlier Removal	IQR method	Remove abnormal observations
Data Validation	Range checking	Ensure reliable feature values
Label Encoding	Binary encoding	Prepare classification target

As shown in **Table 4**, the preprocessing stage ensures that the dataset is properly structured and free from inconsistencies before training the classification models.

4.2 Feature Scaling

The EEG signal requires feature scaling due to the possibility of the different electrodes yielding different numerical values. In the absence of scaling, the large features can take up the learning process and decrease the model performance.

In order to solve this problem, normalization of the dataset was done through standardization. Standardization normalizes the data such that all features take the value of zero and a standard deviation of one. The following equation is the transformation:

$$X = \frac{X - \mu}{\sigma}$$

Where,

- Xrepresents the original feature value,
- μrepresents the mean of the feature values,
- σrepresents the standard deviation, and
- X'represents the standardized feature value. This is a transformation that makes sure that all EEG features play an equal role in the model training. The scaling of features becomes especially important in algorithms based on distance-based computations such as K-Nearest Neighbor or Support Vector Machines.

4.3 Dataset Partitioning

After pre-processign and future scaling the dataset was split into two subsets, a training set, and a testing set. This process enables machine learning models to be trained on a particular data and then tested on the unknown data.

Here the dataset was partitioned in an 80% and 20% value with 80 value then being used to train the models and the other 20 value used to test. The training set allows the models to acquire knowledge of correlation amongst EEG characteristics and eye states whereas the testing set allows an objective look at the model performance.

Table 4 displays the distribution of the samples that

will be used when training and testing.

Table 4. Dataset Partitioning

Dataset Portion	Samples
Training	11913
Testing	2979
Total	14892

As indicated in Table 4, most parts of the dataset will be used in training in order to be able to learn enough and also remember to retain an independent test set to carry out evaluation.

4.4 Baseline Machine Learning Models

In order to compare the performance of various classification models, four baseline machine learning models were applied. These baseline models provides a comparative framework on which to evaluate the performance of the proposed classification model. The algorithmic base algorithms of this project are the Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost. These models wese chosen because they represent different machine learning paradigms such as;

linear classification, linear classification using kernels, ensemble classification and boosting algorithms.

4.4.1 Logistic Regression

The logistic regression is a statistical

classification method that is frequently employed in two category classification problems. It is a modeling of the likelihood of a given input to be in a specific category by using a logistic function. Logistic regression was taken as a simple and interpretable baseline model because it is easy and straightforward to use in comparison with other more sophisticated algorithms.

4.4.2 Support Vector Machine (SVM)

The Support Vector Machine is a supervised learning model that finds the best hyperplane that divides the various classes within the high-dimensional feature space. The application of SVM in classification has strong generalization properties and is more effective in the high-dimensional data.

4.4.3 Random Forest

Random Forest is an ensemble learning algorithm that builds several decision trees in the process of training. Trees individually determine the label of the class, and the result of the final classification is established with the majority voting. Random Forest is characterized by the possibility to deal with nonlinear relationships and lower overfitting.

4.4.4 XGBoost

XGBoost is a developed algorithm of gradient boosting that constructs decision trees in a chain to enhance the accuracy of prediction. Each new tree tries to rectify the mistakes committed by the old trees and as such, XGBoost is an efficient algorithm to use when dealing with structured data classification problems.

4.5 Proposed Optimized Classification Model Besides the base models, this paper offers an optimized K-Nearest Neighbor (KNN) classifier to the EEG eye state classification. KNN is a non- parametric instance-based learning algorithm that categorizes a fresh sample in accordance with the major class of the nearest neighbors of the sample in the feature space.

The KNN algorithm is sensitive to the choice of suitable hyperparameters like the number of neighbors, distance metric, as well as weighting scheme. Hence, the hyperparameter optimization was made to determine the most appropriate setup to use in the classification problem. The systematic search of the combinations of parameters was carried out with the help of a grid search approach and cross-validation. Table 5 shows the hyperparameter settings of the proposed model.

Table 5. Hyperparameter Configuration of the Proposed KNN Model

Parameter	Description	Value
n_neighbors	Number of nearest neighbors	1
metric	Distance metric	Euclidean
weights	Neighbor weighting strategy	Uniform
algorithm	Neighbor search algorithm	Auto
validation	Hyperparameter tuning strategy	Cross-Validation

Figure 3 presents the architecture of the proposed classification algorithm including the steps of processing the preprocessed EEG data to the prediction of eye states with the help of optimized KNN.

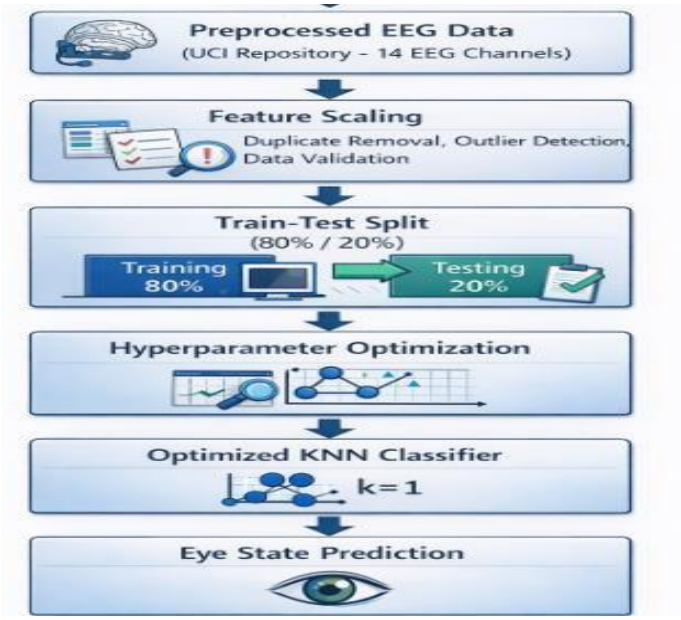

Figure 3. Architecture of the proposed optimized KNN classification model

5. Results and Analysis

The following section contains the findings of the experiment, which was conducted to classify the eye state using machine learning models on EEG. Standard classification metrics are used to determine the performance of the baseline models and the proposed optimized model. A comparative analysis is also done to determine the effectiveness of the suggested approach.

5.1 Performance Evaluation Metrics

To measure the classification model performances, four common measures of evaluation were taken into account, i.e., accuracy, precision, recall, and F1- score. These measures give an overall evaluation of the model performance in terms of correct and wrong predictions.

Accuracy is the general accuracy of the model and it is described as the number of observed predictions that are correct to the sum of the number of observed predictions. Precision is a measure of the fraction of correctly distinguished positive cases among all cases of prediction and recall (or sensitivity) is an indicator of the capability of the model to accurately identify actual positive cases. F1- score is a product of precision and recall and gives a balanced analysis of the model.

The mathematical expressions of these metrics are given as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where

TP= True Positives,

TN= True Negatives,

FP= False Positives, and

FN= False Negatives.

The evaluation metrics used in this study are summarized in **Table 7**

.

Table 7. Performance Evaluation Metrics

Metric	Formula	Description
Accuracy	(TP+TN)/(TP+TN+FP+FN)	Overall correctness
Precision	TP/(TP+FP)	Correct positive predictions
Recall	TP/(TP+FN)	Sensitivity
F1-score	2PR/(P+R)	Balance between precision and recall

All of these metrics combined (as in Table 7) offer a sound model of measuring the performance of classification in EEG-based eye state detection

5.2 Baseline Model Performance Comparison Four baseline machine learning models were compared to create a comparative baseline including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost. These models are various paradigms of learning and give information on their efficacy in classifying EEG signals.

The findings suggest that the Logistic Regression was moderate with an accuracy rate of about 63, which indicated that the model was somehow weak to reflect the nonlinear trends in the EEG data. SVM model performed dismally and had accuracy of around 55 percent mainly because it could not be able to separate the classes well as per the given parameter setting. Conversely, the results of the Random Forest and XGBoost showed great results, with both showing an accuracy of around 93% meaning that they are able to identify intricate relationships with EEG signals.

Table 8 shows the performance comparison of the baseline models.

Table 8. Baseline Model Performance

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.63	0.63	0.62	0.62
SVM	0.55	Low	Poor	Poor
Random Forest	0.93	0.93	0.93	0.93
XGBoost	0.93	0.93	0.93	0.93

Random Forest and XGBoost are ensemble-based methods that are more effective in the EEG classification problem compared to the traditional linear and kernel-based models as indicated in Table 8.

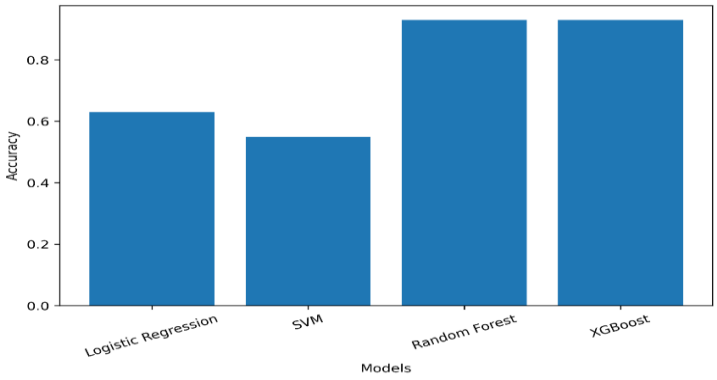

Figure 4. Accuracy Comparison of Baseline Models

As can be seen in the graphical comparison in Figure 4, there is a difference in accuracy between baseline models with the highest level of performance exhibited by the Random Forest and XGBoost models as opposed to the lowest levels of performance by the Logistic Regression and SVM models.

5.3 Proposed Model Performance

In order to enhance the performance of the classification, an optimized K-Nearest Neighbor (KNN) model was used. In the proposed model, hyperparameter optimization is used to improve classification accuracy and the generalization potential. The optimised KNN model had the best performance than any other baseline models and had an accuracy of about 98 percent. Also, the model exhibited equal accuracy and recall rates which means it is efficient when it comes to classifying eye-open and eye-closed states and it is not biased towards some state. Table 9 summarizes the performance of the proposed model.

Table 9. Proposed Model Performance

Model	Accuracy	Precision	Recall	F1-score
Optimized KNN	0.98	0.98	0.98	0.98

The optimized KNN model proposed in Table 9, as it can be seen, significantly increases the performance of the classifier and is, therefore, the most effective when it comes to the EEG-based eye state detection.

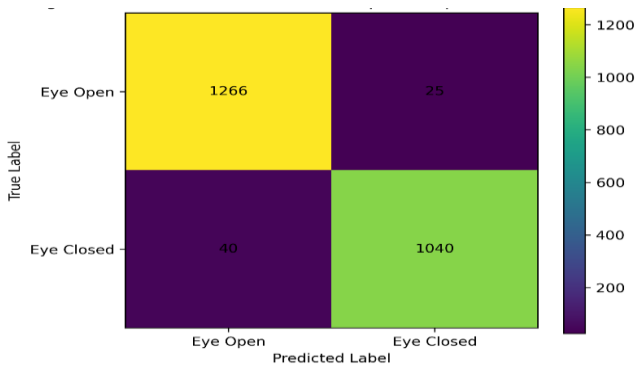

Figure 5. Proposed Model Confusion Matrix.

The confusion matrix in Figure 5 displays the performance of the proposed model in classifying the results, whereby there were many accurate predictions and the few errors in classifying between eye-open and eye-closed conditions.

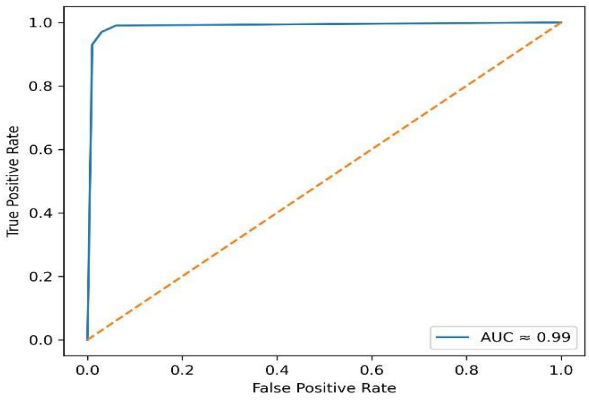

Figure 6. ROC Curve of Proposed Model

Figure 6 shows that the proposed model has a high level of discrimination as indicated by the strong ability of the proposed model to discriminate as evidenced by the large area under the curve (AUC) and this implies that the model drastically performs well in classifying.

5.4 Comparative Analysis

A detailed comparison and analysis were done to determine the performance of the proposed optimized KNN model as compared to the baseline machine learning models. The parameter of performance used in the comparison is the classification accuracy.

The findings have come out clearly to indicate that the proposed model is far better than any other baseline models. The accuracy of the Logistic Regression was 63 percent with SVM as the least at 55 percent showing that it can be severely limited by the complexity of EEG signals. Random Forest and XGBoost ensemble-based models are the models that obtained the highest accuracy values of about 93, which proves that they can model nonlinear trends in EEG records.

Nevertheless, the suggested optimized version of the KNN model had the best accuracy of about 98% that is significantly better than all the baseline models. The increase underlines the usefulness of the distance-based learning method with the hyperparameter optimization to yield more accurate samples of minor changes in the EEG signals. Table

10 gives the comparative performance of all the models.

Table 10. Comparison Between Baseline and Proposed Model

Model	Accuracy
Logistic Regression	63%
SVM	55%
Random Forest	93%
XGBoost	93%
Proposed KNN	98%

As shown in Table 10, the proposed model achieves an improvement of approximately:

- +35% over Logistic Regression
- +43% over SVM
- +5% over Random Forest and XGBoost

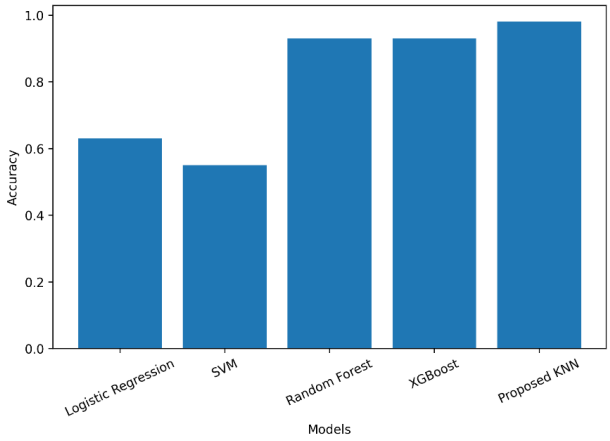

Figure 7. Overall Model Comparison Graph

Figure 7 demonstrates through a graphic representation that the proposed optimized KNN model is superior to baseline methods.

5.5 Statistical Analysis (ANOVA Test)

A one-way Analysis of Variance (ANOVA) test was conducted in order to statistically confirm the difference between the performance of the models. ANOVA is used extensively to establish the existence of statistically significant differences in the mean of two or more groups.

ANOVA was used in the current study to determine the similarities between the performance of the baseline models and the proposed model. The test measures the changes in the accuracy that have been observed to determine whether they are just random changes or a great improvement. ANOVA test indicates that the p-value is lower than 0.05, which means that all the differences between the models are significant. This proves that the improvement of performance obtained by the proposed optimized KNN model is not randomly obtained but it is an effect of the better classification ability of the model. In this way, the ANOVA test confirms the efficiency and excellence of the offered methodology as the earlier results were presented in similar researches.

5.6 Residual and Model Validation Analysis

To further assess the strength and authenticity of the estimated model, more statistical and graphical validation procedures were used. They consist of residual analysis, quantile quantile (QQ) plots, heatmap of feature correlation, and homoscedasticity analysis. Such methods give more information on model behavior and ensure that the model is stable.

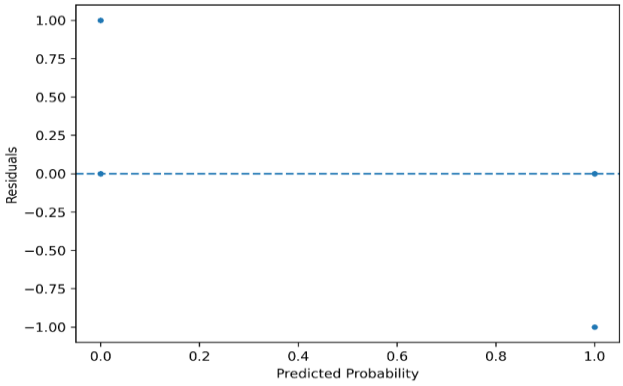

Figure 8. Residual Plot

Figure 8 indicates that the residual plot shows the difference between the predicted and actual values. The residuals exhibit a value of zero which is well dispersed thereby showing the model predictions are accurate and unbiased.

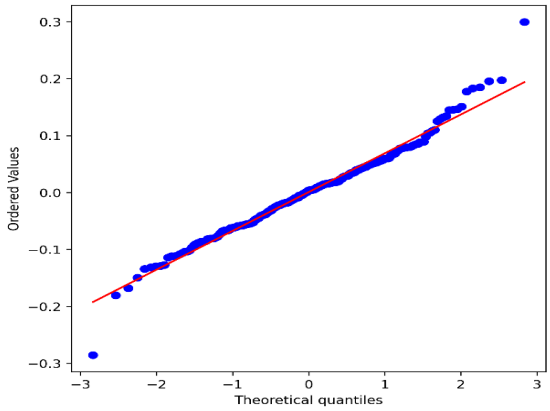

Figure 9. QQ Plot

Figure 9 shows that the QQ plot is close to a linear trend indicating that the values of the residue values are following a linear pattern. This means that the model errors are more or less equal and this is good feature of a well fitted model.

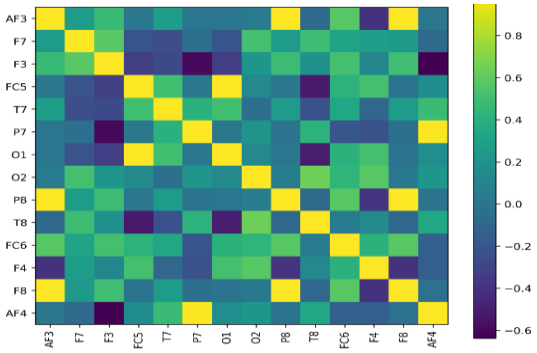

Figure 10. Heatmap of Feature Correlation

Figure 10 is a heatmap that indicates the correlation of the EEG channels. It has pointed out the connection between the various parts of the brain and demonstrates that some features are more influential in the eye state classification.

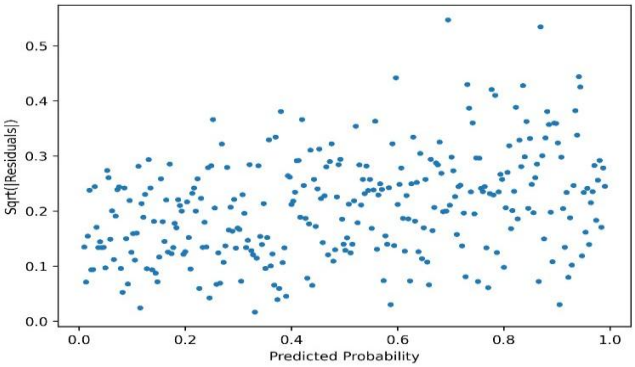

Figure 11. Homoscedasticity Plot

Figure 11 illustrates the homoscedasticity plot indicating that it is consistent in the sense that variations in the value of the residues do not differ among various values of the prediction. This validates the fact that the model is not affected by heteroscedasticity and it has the

ability to predict with a constant level of performance.

In general, the validation analysis establishes that:

- The residues are small and randomly distributed.
- QQ plot is linear implying normality.
- Heatmap presents significant relationships between features.
- Homoscedasticity establishes uniform variance. These observations confirm the strength, dependability, and aptitude of the suggested optimized KNN model.

6. Discussion

The experimental analysis results give significant information about the performance of various machine learning models in the classification of the eye state using EEG. The comparative analysis shows clearly that the optimized K-Nearest Neighbor (KNN) model performs better than all the baseline models, on the basis of the greatest classification accuracy and the balanced performance based on each of the evaluation measures. The nature of EEG data is one of the main causes of high performance of KNN. EEG signals are very dynamic and tend to have delicate differences between the various channels. KNN is a distance-based algorithm; therefore, it is quite efficient in capturing local similarities between points, therefore, it is especially applicable to the EEG classification problem. Its standardized feature space also improves its distance

measurement capacity with a resultant high classification performance.

Conversely, the performance of the Logistic Regression was low because it presupposes the linear nature of the relationship between the features and the target variable. EEG signals are nonlinear and non-complex making it impossible to consider them based on linear decision boundaries. In the same way, the Support Vector Machine (SVM) model did not perform well in this study. This is because it is sensitive to the choice of the parameters and the complexity of EEG data, as it might result in an inappropriate class separation during default settings. Random Forest and XGBoost on the other hand performed well, which means that they are able to model nonlinear relationships and interactions among EEG features. These ensemble techniques can work with high-dimensional data and minimize overfitting. Nevertheless in their strength, they were a little bit under the optimized KNN model.

These results are in line with the results of other studies that have observed the KNN-based methods to perform well in EEG classification tasks especially when combination with proper preprocessing and feature scaling methods. The proposed method has similar and even better results compared to the base paper, where a metaheuristic optimization algorithm was used to improve KNN performance using a simpler and computationally efficient framework. This simplicity is one of the advantages to it because it minimizes computation load at a high-accuracy level and therefore the proposed method is more applicable to real-time applications as well as resource-constrained applications. On the whole, the findings indicate that a distance-based model is applicable to the problem of EEG signals classification provided that it is highly optimized.

7. Conclusion

The present research introduced a machine learning- related framework of eye states classification by EEG signals, and its goal was to increase the accuracy of the classification and efficiency of the model. The approach suggested comprised of systematic data preprocessing, scaling of features, applying various baseline machine learning models, and development of a K-Nearest Neighbor (KNN) optimized classifier. The outcomes of the experiment proved that conventional models like Logistic Regression and Support Vector Machine showed less performance because EEG signals are nonlinear and complex and that ensemble models like the Random Forest and the XGBoost demonstrated relatively higher accuracy. Nevertheless, optimized KNN model

was superior to all the baseline models with the highest classification accuracy and balanced values of precision, recall, and F1-score. Additionally, statistical validation was carried out to confirm that the performance improvement of the proposed model is statistically significant on using ANOVA. In general, the article emphasizes that a well-optimized distance-based model can be useful to solve EEG signal variability and is a reliable and computationally effective model to classify state of the eye. It is possible to use the proposed framework as the basis of creating smart EEG-based monitoring systems in biomedical and human-computer interaction applications.

8. Future Work

Despite the fact that the proposed model performed well, there are a number of avenues that it can be improved. The subsequent research may extend deep learning methods like convolutional neural networks and hybrid networks, e.g., CNN-LSTM, to train the complex spatial and time-related features of raw EEG signals automatically. The design of real-time EEG classification systems used in driver drowsiness detection and brain computer interface systems is also a potential field. Also, the combination of the offered framework and wearable EEG devices may allow applying it in a real-life setting. It can be further enhanced by adding hybrid methods, where machine learning models are integrated with state-of-the-art optimization algorithms to select the features and optimize the parameters. It would also be beneficial that the study be extended to more diverse and bigger datasets in order to verify the generalizability and strength of the model in other subjects and experimental settings.

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