European Journal of Technique

journal homepage: https://dergipark.org.tr/en/pub/ejt

Vol.15, No.1, 2025

Research Article

Eye State Classification from Electroencephalography (EEG) Signals Using the Extra Trees Classifier Algorithm

Suleyman Dal[1*]

[1*] Batman University, Rectorate, Energy Coordination Office, Batman, Turkey. (e-mail: suleyman.dal@batman.edu.tr).

ARTICLE INFO

Received: May., 22. 2025
Revised: Jun., 08. 2025
Accepted: Jun., 12. 2025

Keywords:
Electroencephalography
Extra Trees Classifier
Eye State
Machine Learning

Corresponding author: *Süleyman Dal*

ISSN: *2536-5010* | e-ISSN: *2536-5134*

DOI: https://doi.org/10.36222/ejt.1704397

ABSTRACT

This study aims to automatically classify the eye openness state (open/closed) of individuals from electroencephalography (EEG) signals. In the classification process, based on the knowledge that EEG signals reflect short-term cognitive states, the EEG Eye State dataset is used. The dataset contains 14,980 samples from 14 EEG channels and the eye state is labelled according to the binary classification problem. Within the scope of the preprocessing steps for the data, the scaling process was performed and then the classification model was created. In the modelling process, the Extra Trees Classifier (ETC) algorithm, which is an ensemble learning method based on decision trees, was preferred. The performance of the model was evaluated by 10-fold cross-validation method; accuracy, precision, sensitivity and F1 score metrics were calculated at each layer. The findings revealed that the model performed well in all metrics. In particular, the highest F1 score was achieved in Fold 1, and the width of the area under the ROC curve (AUC) confirmed the discriminative power of the model. In addition, in the feature importance analysis, it was observed that the signals obtained from occipital and parietal regions contributed more to the classification process. The results show that traditional machine learning algorithms, together with appropriate preprocessing strategies, can produce effective classification outputs on EEG data. This study contributes to the academic literature on EEG-based eye state detection and provides a meaningful basis for applications such as human-computer interaction, attention monitoring systems and neurocognitive assessment.

1. INTRODUCTION

Electroencephalography (EEG) is a neurophysiological recording method that measures the voltage changes in electrical signals that occur due to neuronal activity of the brain with high temporal resolution through (non-invasive) electrodes placed on the scalp [1-3]. The ability to examine EEG signals in more depth with analytical and signal processing methods has led to a significant increase in studies on human cognitive processes, moods and behavioral patterns in recent years; in this context, many studies have been carried out in the literature [2, 4, 5]. In this context, automatic classification of an individual's eye-openness state (eyes open or closed) over EEG signals is not only capturing a physiological response; it is of vital importance in attention level monitoring, driver drowsiness detection, state of consciousness tracking, personal identity verification, monitoring the sleep-wake cycle of infants, epileptic seizure detection and various clinical evaluation scenarios [6-10].

Eye state is not only a short-term motor response associated with the visual system, but also an important cognitive indicator that affects the dynamic structure of brain networks [4]. In particular, it is known that micro-movements such as blinking cause a dipole movement in the vertical direction with the electrical charge separation caused by the interaction between the cornea and the eyelid. This effect is observed as a positive wave lasting approximately 100 milliseconds in EEG recordings and is most prominently observed in the frontopolar region [11]. The meaningful analysis of such signals makes EEG-based eye state classification a high-potential application area both in neurocognitive research and in the design of real-time human-machine interfaces [12].

EEG signals provide an important biological data source for classification-based analyses because they have high temporal resolution and contain electrical patterns directly related to cognitive states [4,13]. Thanks to these features, many cognitive parameters such as an individual's mental state, emotional state or motor responses can be modelled through EEG signals by means of various algorithms [13, 14]. In this context, especially machine learning methods are effectively used in automatic classification processes by analysing the structural complexity of EEG data [15]. Recent studies have shown that various machine learning algorithms have been successfully applied to classify the open/closed eye state with EEG data [12,16]. The aim of this study is to classify the eye openness state (eyes open or closed) of individuals with high accuracy using EEG signals. For this purpose, the UCI EEG Eye State dataset was used in the experimental analyses [17]. The dataset consists of 14,980 samples and 15 features and contains eye state labels corresponding to EEG signals recorded at different time intervals. This time series data is a widely referenced source in the literature for the evaluation of EEG-based classification algorithms.

In this study, Extra Trees Classifier (ETC) method was applied to develop an effective model in terms of classification accuracy, sensitivity to class balance and computational efficiency. Extra Trees algorithm is an ensemble learning method consisting of randomised decision trees and attracts attention with its fast-training process and high accuracy potential, especially in high-dimensional data sets [18, 19]. The model used in the study was first trained by eliminating missing values and performing the necessary normalisation operations in the dataset and then tested with 10-fold cross-validation method. The results obtained show that the developed model exhibits high success in eye state classification. These results suggest that traditional machine learning methods, when applied with careful data preprocessing and feature management, can provide an effective alternative to more complex and computationally costly classification models in terms of both accuracy and computational efficiency. In addition, this study aims to make both academic and practical contributions by providing a faster, simpler and feasible alternative to the computationally expensive models in the literature for eye state detection based on EEG signals.

The remaining sections of the paper are structured as follows: In the second section, current approaches and related works in the literature on eye state classification based on EEG signals are comprehensively reviewed. In the third section, the EEG Eye State dataset used in the study, the data preprocessing steps, and the methods applied in the classification process are presented in detail. In the fourth section, the modelling process performed using the Extra Trees Classifier algorithm and the metrics and results used to evaluate the success of the model are shared. In the fifth section, the feature importance levels of the classification model are analysed, and the relative contributions of the EEG channels are interpreted. In the sixth section, the study is discussed comprehensively in the light of the findings obtained; finally, in the seventh section, general conclusions are given and suggestions for future studies are presented.

2. LITERATURE RESEARCH

Classification of eye-openness state from EEG signals is considered as an important research area in many application areas such as human-computer interaction, driver attention systems and cognitive state analyses. In studies conducted in this direction, the effects of various machine learning modelling approaches on the classification performance of EEG-based signals have been extensively investigated. Hasan et al. (2021) proposed an ensemble model consisting of multilayer artificial neural networks to classify eye opening state using EEG signals, and obtained 89.2% accuracy and 91.24% F-measure in their experiments on the UCI EEG Eye State dataset. The study revealed that the proposed approach is effective not only in terms of classification accuracy but also in terms of its suitability for real-time applications [20]. Similarly, Jayadurga et al. (2024) compared various ensemble learning algorithms based on bagging and boosting on EEG data and stated that Bagged k-NN model offers the best results in terms of classification performance. In addition, the XGBoost algorithm was effective in increasing the interpretability of the model thanks to its capacity to evaluate feature importance levels. The study reveals that ensemble-based approaches provide high performance and stable solutions for EEG-based eye state classification [21].

Xiao et al. (2023) proposed a model based on continuous wavelet transform (CWT) and an improved convolutional neural network (CNN) for the classification of eye openness state from EEG signals. In this study, variational mode decomposition (VMD) algorithm is used for signal preprocessing, CWT method is used for time-frequency feature extraction, and then classification is performed with a CNN model developed with residual connections and attention mechanisms. Experiments on the UCI EEG Eye State dataset show that the proposed method provides high accuracy and generalisation. This study makes an important contribution to improve the classification performance of deep learning architectures by obtaining two-dimensional visual representation from EEG signals [22]. In another study, Hasan Adil et al. proposed a simple but effective machine learning approach using the K-Nearest Neighbour (KNN) algorithm for the classification of eye openness status based on EEG signals. The signals obtained with Emotiv EPOC EEG device were manually labelled with video support and used in model training. The KNN algorithm yielded successful results in terms of accuracy and classification performance, while attracting attention with its low processing time. The study shows that simple machine learning algorithms can provide a powerful alternative for EEG-based classification problems when configured correctly [23].

Fikri et al. (2021) systematically examined the opportunities and main challenges of machine learning and deep learning approaches for eye movement classification. In particular, the study comparatively analysed the methods used for the detection of basic eye movement events such as saccade, fixation and smooth pursuit, highlighting the limitations of threshold-based methods and emphasising the potential of machine learning algorithms and recent deep learning architectures in this field. The models in the literature are evaluated in terms of classification performance, interpretability, data balance and real-time application compatibility, and the limitations encountered at the application level such as data labelling processes, parametric adjustments and generalisation problems are discussed. In this respect, the study provides a useful resource for comparing the methods used in classification applications with eye movement data and understanding the methodological trends [24].

Although studies on eye state classification with EEG signals have an important place in the literature, there are also many studies for different purposes using EEG signals. In this context, EEG-based approaches have been successfully used in various applications such as epileptic seizure detection, mood analysis and mental state classification. Alkhaldi et al. (2024) presented a comprehensive review of the role of artificial intelligence and remote health applications in EEG-based epilepsy management. In the study, it was reported that algorithms such as CNN, SVM, Random Forest and stacking showed high performance in areas such as epileptiform activity classification, seizure prediction and surgical prediction. It was also emphasised that tele-EEG systems and AI-supported mobile applications offer significant advantages, especially in regions where access to healthcare services is limited. This study demonstrates the increasing impact of AI-based models in the diagnosis and treatment of epilepsy at the literature level [25].

Gaddanakeri et al. (2024) compared CNN and LSTM based deep learning models on DEAP dataset for emotion recognition with EEG signals. As a result of the preprocessing and modelling processes applied, it is stated that the LSTM architecture captures time-dependent patterns more successfully and provides superiority in classification performance. The study shows that deep learning is an effective method in EEG-based emotion recognition [26]. In this study by Wei-Yang Yu et al. (2024), a multi-model machine learning approach was developed by combining EEG signals and genetic data in the classification of Alzheimer's disease (AD). Within the scope of the study, both EEG-based biomarkers and a large number of single nucleotide polymorphisms (SNPs) and polygenic risk scores (PRS) were evaluated. Three different algorithms (SVM, Random Forest and XGBoost) were compared in the developed model and it was reported that the best performance was obtained with SVM. Significant differences were observed between AD patients and healthy individuals, especially in parameters such as EEG power, sample entropy and phase locking value (PLV). The findings reveal that the combination of EEG and genetic data provides an effective solution for early diagnosis of Alzheimer's disease and higher classification accuracy [27].

3. MATERIAL AND METHOD

3.1. Material

In this study, the open-access EEG Eye State dataset created by Oliver Roesler at Baden-Württemberg Cooperative State University was used in the analyses for the classification of individuals' eye openness state from electroencephalography (EEG) signals [17].

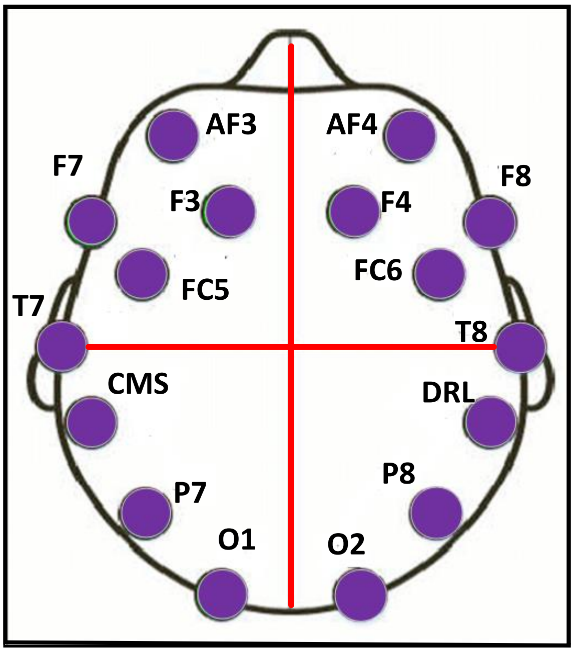

Figure 1. Electrode positions of the 14-channel Emotiv EPOC EEG system.

The dataset consists of observations matching EEG signals with the open or closed eyes of individuals and is suitable for binary classification problem. The target variable eyeDetection represents the closed eyes with a value of 0 and the open eyes with a value of 1. Accordingly, the target variable in the dataset consists of two categories and the number of samples corresponding to the moments when the eyes are closed is 8,257 and the number of samples corresponding to the moments when the eyes are open is 6,723. The dataset consists of 14,980 observations and 15 columns in total. The first 14 columns reflect the instantaneous values of EEG signals obtained from different electrodes. These signals were recorded using the Emotiv EPOC EEG headset and the electrodes used cover the following channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. The electrodes were placed in different regions of the brain, allowing data collection from the frontal, temporal, parietal and occipital lobes. This placement structure is visually presented in Figure 1.

3.2. Method

Data Preparation and Pre-processing: The EEG Eye State dataset used in this study is structured in ARFF (Attribute-Relation File Format) format. ARFF is a file format that is widely preferred especially in machine learning applications and contains both attribute definitions and data. This structure allows the features in the dataset and the target variable to be explicitly defined, ensuring data integrity. The dataset was imported in the appropriate format to enable the analysis and modelling processes to be carried out in the Python environment and then converted to DataFrame format using the pandas library. Thanks to this transformation, the data has been made flexible and suitable for processing in order to perform statistical analyses, select attributes and apply classification models.

Feature and Label Separation: Feature and label separation, which is one of the basic steps of the data preprocessing process, is a critical stage in terms of structuring machine learning algorithms. In this study, the variables in the EEG Eye State dataset are divided into two groups as independent variables (features) and dependent variables (target labels). The feature set (X) consists of numerical values corresponding to 14 different electrode channels from which EEG signals are obtained. These channels were recorded by electrodes placed in the frontal, temporal, parietal and occipital regions of the brain. The target variable (y) is called eyeDetection and is a binary classification variable representing the closed eyes with the label 0 and the open eyes with the label 1. This distinction enabled the model to predict eye state only from the explanatory variables and allowed the learning process of the algorithms to be structured correctly.

Feature and Label Separation: The first step in the data preprocessing process is the systematic separation of the explanatory variables and the target variable. In this study, numerical data representing EEG signals are set as independent variables (X), while the target variable eyeDetection is separated as dependent variable (y). The independent variable set contains the signals of 14 different electrode channels recorded by the EEG device, and the classification model is enabled to learn over these multidimensional data. The target variable contains the binary class information indicating whether the eyes are open (1) or closed (0).

Feature Scaling (Standard Scaler): Scaling is a critical part of the modelling process in order to increase the effectiveness of machine learning algorithms and to balance the effect of attributes on the model. In this context, the Standard Scaler method used in this study is a preprocessing technique that aims to fit the data into a standard distribution by setting the mean of each attribute equal to zero and the standard deviation equal to one. Thanks to this standardisation process expressed in Equation 1, the model is able to evaluate all variables at the same level of importance without discriminating between attributes of different scales. Thus, over-sensitivities and attribute biases that can be seen especially in distance and weight-based algorithms are prevented. The Standard Scaler application both increases the overall accuracy of the model and makes the training process more stable and faster [28].

$$X_{scaled} = \frac{X - mean(X)}{std(X)} \quad (1)$$

X_{scaled} represents scaled data with mean 0 and standard deviation 1, where X is the data value, $mean(X)$ is the mean of the dataset and $std(X)$ is the standard deviation of the dataset.

4. MODELLING AND EVALUATION

4.1. Extra Trees Classifier

In this study, the Extra Trees Classifier (ETC) algorithm was preferred in the modelling phase for classifying the eye-opening status of individuals from EEG signals. ETC is a classifier that stands out among tree-based ensemble learning methods and is known for its high level of randomness. The algorithm is based on the 'Extremely Randomised Trees' approach developed by Geurts et al [29]. This method is based on the collective construction of decision trees and the combination of the predictions obtained from these trees by majority voting. The difference of the Extra Trees Classifier from traditional methods such as Random Forest is that not only the attributes but also the split points are randomised. In addition, the entire training data is used in the construction of the model without bootstrap sampling, thus providing diversity among the trees and increasing the generalisation capacity of the model. This high level of randomisation strategy reduces the variance of the model and limits the risk of overfitting. At the same time, the no-sampling approach provides more balanced learning by reducing the systematic bias [30].

The ETC model used in this study was trained with an ensemble of 100 decision trees. This number of trees was chosen to improve both the stability of the model and the classification performance. A large number of trees improves decision reliability and supports overall accuracy, especially for biosignals that may contain noise such as EEG. A visual representation of the general operation of the model is presented in Figure 2. Among the hyperparameters of the algorithm, variables such as the number of trees, minimum sample size and the number of random features to be evaluated at the node are critical factors that directly affect the decision diversity and generalisation performance in the learning process. On the other hand, since the node splitting process is randomised due to the structure of ETC, the computational cost remains low, which makes the method a computationally efficient solution. Thanks to these features, Extra Trees Classifier is considered as a powerful, fast and balanced learning tool for binary classification problems such as eye state in high-dimensional, multivariate and structurally complex EEG data.

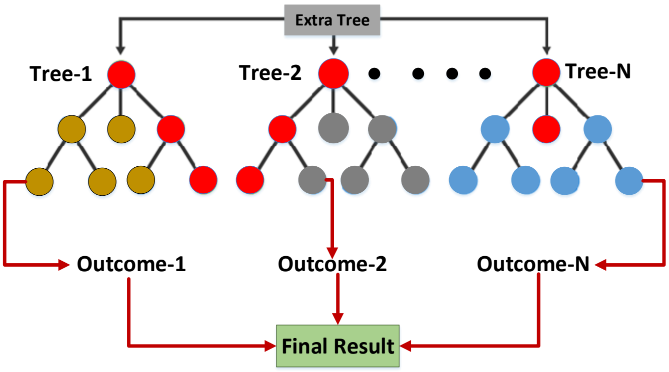

Figure 2. Extra Trees Classifier

4.2. Evaluation Metrics

Cross Validation: In this study, the 10-Fold Cross-Validation method was used to reliably assess the generalisability of the classification model. This method allows the model to be tested independently in each subset by dividing the entire dataset into ten subgroups of approximately equal size, thus providing more robust and statistically significant performance measures. The StratifiedKFold approach was adopted in the cross-validation process. This method stabilises the validation process of the model in data sets with class imbalance, by preserving the class distribution proportionally in each layer and enables the evaluation criteria to be calculated fairly across classes.

Performance Evaluation Metrics: The success level of the classification model developed in this study is evaluated with basic performance measures that are widely used in classification problems and are considered statistically significant. These metrics quantitatively reveal both the overall and class-based discrimination capacity of the model and allow inferences to be made regarding the practical applicability of the model.

Accuracy: Accuracy is a key indicator of success that expresses the overall accuracy of the classification model. It is calculated as the ratio of the number of data correctly classified by the model out of all instances to the total number of instances. Since this metric includes correct predictions in both positive and negative classes, it is a holistic evaluation measure that reflects the overall classification competence of the model. Accuracy is calculated as the ratio of the sum of True Positive (TP) and True Negative (TN) predictions, plus false positive (FP) and false negative (FN) predictions, to the total number of samples. In Equation 2, the accuracy measure is expressed mathematically [28].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Precision: Precision is an evaluation metric that expresses the proportion of samples that the model predicts belong to the positive class that are actually positive. This metric is especially critical in cases where the model has a high tendency to generate false positives (FP). This is because it reflects the level of accuracy in the model's positive forecasts and reveals its forecast reliability. In other words, it measures how many of the samples that the model marks as "positive" class actually belong to that class. In Equation 3, the Precision criterion is expressed mathematically [28].

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Recall: Recall is one of the key classification metrics that measures the model's ability to recognize true positive examples. In other words, it refers to the proportion of all instances belonging to the positive class that the model correctly classifies as positive. This metric plays a decisive role, especially in applications where it is critical to reduce the number of False Negative (FN), i.e. missed positive examples. The sensitivity value is expressed mathematically in equation 4 [28].

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

F1-Score: The F1 score is a composite metric that quantitatively reflects the balance between the precision and recall metrics of a classification model. By taking the harmonic mean of both values, this metric summarizes in a single value both the model's ability to detect true positives and its success in avoiding false alarms. Especially in datasets with imbalance between classes, where general measures of success such as accuracy can be misleading, the F1 score provides a more accurate representation of the model's true performance. Due to its computational methodology, the F1 score can reach high values not only with high precision or high sensitivity, but by optimizing both together. As such, it is one of the key success indicators of choice, especially in scenarios where both false positive (FP) and false negative (FN) results are critical (e.g. medical diagnostics, security systems, fraud detection). The F1 score is mathematically formulated in equation 5 [28,31].

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

This ratio takes a value between 0 and 1, with a value closer to 1 indicating that the model has a strong balance in terms of both precision and sensitivity. Therefore, the F1 score is considered as an indispensable performance criterion for the reliability and application success of classification systems.

Receiver Operating Characteristic Curve (ROC): It is an evaluation tool that visualizes the extent to which the model can correctly distinguish the positive class depending on the classification thresholds in binary classification problems. The ROC curve shows the relationship between the model's True Positive Rate (TPR), or sensitivity, and False Positive Rate (FPR). These two ratios change as the threshold is varied, and the ROC curve graphically presents the discrimination performance of the model across this variability. The points on the curve represent the behaviour of the model at different thresholds, while the Area Under the Curve (AUC) is a singular metric that summarizes the overall classification ability of the model. The AUC value ranges between 0 and 1, with values close to 1 indicating that the model can distinguish between positive and negative classes with high accuracy. AUC value: 0.5 means performance equivalent to random guessing and 1.0 means excellent classification performance. In this context, ROC-AUC analysis offers a more robust and reliable metric to assess the true discrimination capacity of the model, especially in scenarios where classical metrics such as accuracy can be misleading, especially in the presence of class imbalance [28].

Confusion Matrix: The Complexity Matrix is a fundamental evaluation tool that allows analysing the performance of classification models not only in terms of overall accuracy, but also in terms of class-based patterns of success and error. This structure details the classification process by comparing the predictions produced by the model with the actual class labels through four main components: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). These four components categorically reflect both the model's accuracy and its tendency to be wrong at the class level. Especially in binary classification problems, the structure of this matrix is usually 2x2 in size, allowing a direct comparison of the performance of the model for different classes [28].

The complexity matrix is the main data source for calculating not only overall accuracy but also important derivative metrics such as precision and recall. In this respect, the complexity matrix provides the opportunity to analyse the decision quality of the model in more detail, especially in data sets with class imbalance or in clinical, financial or security-based applications where certain classes (e.g. positive class) are more critical. It also provides a more comprehensive perspective on what types of errors the model is prone to make and the operational consequences of these errors in the application domain. Thus, not only quantitative success but also qualitative evaluation becomes possible [31].

5. FEATURE IMPORTANCE

In order to increase the interpretability of machine learning models and to quantitatively reveal which variables contribute more to the classification process, feature importance ranking was performed in this study. This analysis allows for a more transparent evaluation of not only the output of the model but also the decision-making process [32,33]. Especially when working with multidimensional and structurally complex data such as biological signals, knowing the relative importance levels of attributes plays a critical role in understanding the internal logic of the model and increasing its interpretability [34]. In this study, attribute importance scores are computed from the decision trees of the Extra Trees Classifier algorithm using a model-based approach. This method statistically evaluates the contribution of the EEG data obtained from each electrode channel to the classification decision. Due to the natural structure of tree-based algorithms, direct interaction between features is taken into account and the features that contribute the most to the learning process of the model are ranked according to their relative weights.

6. RESULT AND DISCUSSION

6.1 Result

This study aims to classify the eye openness (open/closed) of individuals using the EEG Eye State dataset, which is made openly available by Baden-Württemberg Cooperative State University through the UCI Machine Learning Repository. The dataset consists of a total of 14,980 observations corresponding to 14 channels of EEG signals recorded at different time points; each sample is labeled in a binary classification format according to whether the eyes are open (1) or closed (0). In the modeling process, Extra Trees Classifier (ETC), an ensemble learning algorithm based on decision trees, was used and the

 ISSN 2536-5010 | **e-ISSN** 2536-5134

classification performance of this model, which was configured with 100 trees, was analysed based on various criteria.

In order to evaluate the generalizability and stability of the model, the Stratified 10-Fold Cross-Validation method was used and key performance metrics such as accuracy, precision, recall and F1 score were calculated for each layer. According to the results presented in Table 1, the model performed consistently above 90% in all layers, especially in layer 1 (Fold 1), where the F1 score of 0.9521 was the highest among all layers. This result indicates that the model maximizes the model's ability to predict the positive class both accurately and consistently in this layer. Overall, the average accuracy of the model is 0.9511, average precision is 0.9645, average sensitivity is 0.9252 and average F1 score is 0.9444. These metrics reveal that the model performs a high performance and reliable classification by balancing between classes. In particular, the high average F1 score shows that the model is able to distinguish both positive and negative classes in a balanced way and exhibits a stable behavior in decision processes.

TABLO 1
CROSS-VALIDATION PERFORMANCE METRICS

Fold	Accuracy	Precision	Recall	F1 Score
1	0.9579	0.9736	0.9315	0.9521
2	0.9526	0.9574	0.9360	0.9466
3	0.9566	0.9691	0.9330	0.9507
4	0.9526	0.9659	0.9271	0.9461
5	0.9506	0.9614	0.9271	0.9439
6	0.9473	0.9640	0.9167	0.9397
7	0.9493	0.9571	0.9286	0.9426
8	0.9426	0.9666	0.9034	0.9339
9	0.9526	0.9703	0.9227	0.9459
10	0.9493	0.9599	0.9257	0.9425

Feature importance evaluation, which is used to analyse which features are more decisive in the classification decisions of the model, plays an important role in making the internal decision structure of the model more transparent and interpretable. In this context, the relative importance scores calculated by the Extra Trees Classifier algorithm over the decision trees are analysed. As presented in Table 2, the attributes that the model gives the most weight in the classification process are the data belonging to the O1 and P7 electrodes. The fact that these two channels stand out with importance scores of 0.1154 and 0.1000, respectively, indicates that the EEG signals obtained from the occipital (O1) and parietal (P7) regions have high discriminative power in distinguishing the eye-opening status.

TABLE 2
FEATURE IMPORTANCE SCORES

Feature	Importance Score
O1	0.1154
P7	0.1000
F7	0.0857
F8	0.0782
AF3	0.0772
AF4	0.0761
FC6	0.0650
FC5	0.0617
F4	0.0614
T7	0.0587
T8	0.0583
F3	0.0571
O2	0.0568
P8	0.0482

Moreover, channels such as F7, AF3 and AF4, which correspond to the frontal region, ranked high with scores of 0.0857, 0.0772 and 0.0761, respectively, suggesting that the model also considers frontal lobe activities as an important determinant in the decision-making process. This supports that brain regions associated with visual attention, eye movements and cortical activation processes are critical for the detection of eye openness via EEG signals. Channels with low importance scores, such as O2, P8 and F3, contributed less to the model's classification process, which may be instructive for future regional analyses in relation to the topographic distribution and signal characteristics of the data.

In order to visually and statistically evaluate the classification performance of the model, the Receiver Operating Characteristic (ROC) curve was analysed. The ROC curve shows the accuracy of the model at different thresholds, indicating the extent to which the positive class is correctly separated. As presented in Figure 3, the ROC curve for Fold 1 clearly shows that the model has a high discriminative power, with its structure almost leaning towards the upper left corner. The Area Under Curve (AUC) value was calculated as 0.9926 in this sample. This value indicates that the classification performance is almost perfect, confirming that the model works with both high accuracy and low false positive rate. In this context, the obtained ROC curve and AUC score show that the model is highly successful not only in terms of average metrics but also in terms of its sensitivity in class discrimination. As the reduction of false positives is critical, especially in biomedical classification problems, this result supports the suitability of the model for practical applications.

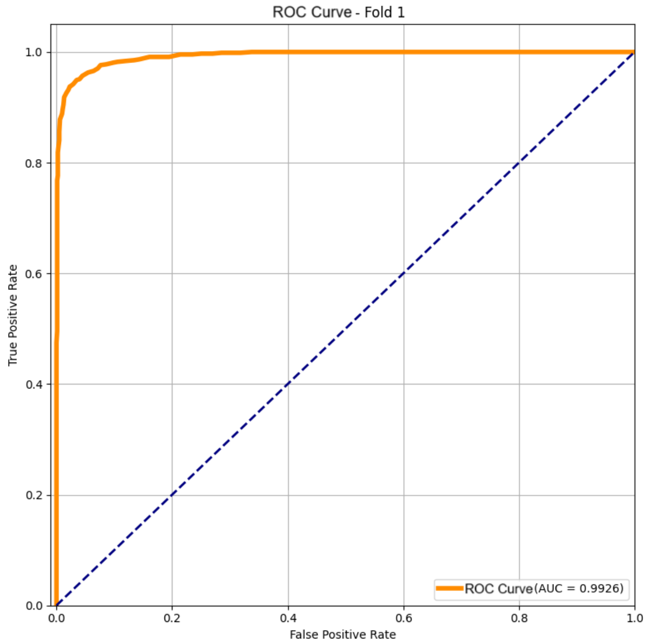

Figure 3. ROC Curve and AUC Value for Fold 1

In order to further analyse the classification performance of the model, the confusion matrix for Fold 1 is examined. As presented in Figure 4, the four main components of the model's correct and incorrect classifications are clearly visible. The model produced 809 True Negative and 17 False Positive predictions for the negative class (label 0), which represents when the eyes are closed. On the other hand, 626 True Positive and 46 False Negative predictions were made for the positive class (label 1). According to these results, the model was able to discriminate both classes with high accuracy and demonstrated its discriminative power by making very low false positive predictions, especially for the negative class. The relatively high number of false negatives (FN = 46) suggests that the model is more cautious when classifying the positive class (eyes open). This distribution reveals that the model exhibits a balancing structure that contributes to its overall performance and keeps the misclassification rates to a minimum. Hence, these findings from the confusion matrix are consistent with previous performance metrics and ROC analysis, numerically confirming the model's consistent success in class discrimination.

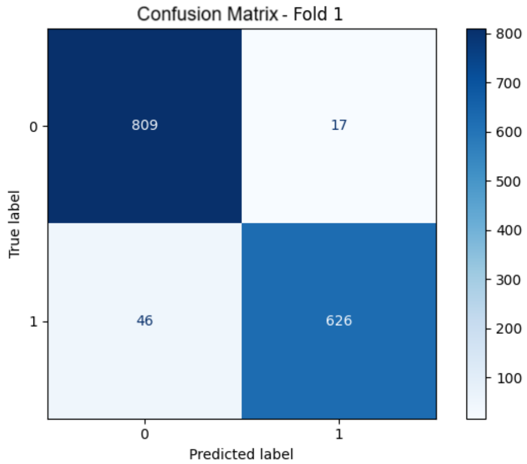

Figure 4. Confusion Matrix for Fold 1

6.2 Discussion

In this study, it is aimed to classify the eye openness state (open/closed) of individuals using EEG signals. For this purpose, the EEG Eye State dataset was used; the dataset contains 14,980 observations labelled for binary classification, consisting of 14 attributes in total. In the modelling process, data normalization was applied, and all variables were evaluated on the same scale. In the classification phase, the Extra Trees Classifier (ETC) algorithm, an ensemble method based on decision trees, was preferred and the model was tested with a 10-fold cross-validation method. The model gave consistent results in each fold and demonstrated an overall successful classification performance. In particular, Fold 1 showed the highest success in terms of F1 score.

The ROC curve of the model shows that the classification sensitivity is high, while the confusion matrix reveals low levels of misclassifications. Moreover, the feature importance analysis shows that the model gives more weight to some EEG channels in the classification process. This supports the effect of topographical diversity of EEG signals on classification success. However, the study also has some limitations. Since the dataset used was obtained from a single group of participants, it may be limited in terms of generalizability. In addition, only one basic machine learning algorithm was used for classification, and different model comparisons were not included. The lack of integration of deep learning or other signal processing techniques may have limited the ability of the method to recognize more complex patterns. In these respects, the study has demonstrated the effectiveness of machine learning methods in EEG-based eye state classification, but it is recommended to be supported by studies with larger participant profiles, different algorithms and multiple data sources.

7. CONCLUSION AND FUTURE STUDIES

In this study, we aim to automatically classify the eye openness state (open/closed) of individuals from EEG signals and develop a machine learning model on the EEG Eye State dataset. In the modelling process, the Extra Trees Classifier method, an ensemble learning algorithm based on decision trees, was preferred and the performance of the model was analysed in detail by applying 10-fold cross-validation on the dataset. The findings show that the model offers a consistent classification success. In particular, the highest success in terms of F1 score was observed in Fold 1, while the ROC curve and confusion matrix revealed that the model has a strong discrimination ability in terms of both sensitivity and specificity. Feature importance analysis revealed that some EEG channels play more decisive roles in the classification process, emphasizing the contribution of regional EEG activity to classification success. These findings suggest that traditional machine learning algorithms, when combined with appropriate preprocessing techniques and balanced modelling strategies, can provide effective solutions to classification problems based on biological signals such as EEG.

Despite the findings of this study, some limitations need to be addressed in future research. First of all, since the dataset used was obtained from a single device and under limited conditions, the generalizability of the model should be re-evaluated with EEG data collected from different populations and conditions. Furthermore, comparative performance analysis of different machine learning algorithms (e.g. LightGBM, XGBoost) and deep learning-based models (e.g. CNN, LSTM) can be performed to reveal more robust classification structures. On the other hand, this line of research can be further deepened by extending studies such as time series-based feature extraction, advanced filtering techniques for signal noise removal, and classification of cognitive states other than eye state. In particular, the development of low latency and high accuracy models for real-time applications will contribute to practical applications such as EEG-based human-computer interfaces and driver attention systems.

REFERENCES

[1] Piatek, Ł., Fiedler, P., & Haueisen, J. (2018). Eye state classification from electroencephalography recordings using machine learning algorithms. Digital Medicine, 4(2), 84-95.

[2] Bharati, S., Podder, P., & Raihan-Al-Masud, M. (2018, November). EEG eye state prediction and classification in order to investigate human cognitive state. In 2018 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE) (pp. 1-4). IEEE.

[3] Nilashi, M., Abumalloh, R. A., Ahmadi, H., Samad, S., Alghamdi, A., Alrizq, M., ... & Nayer, F. K. (2023). Electroencephalography (EEG) eye state classification using learning vector quantization and bagged trees. Heliyon, 9(4).

[4] Ketu, S., & Mishra, P. K. (2022). Hybrid classification model for eye state detection using electroencephalogram signals. Cognitive Neurodynamics, 16(1), 73-90.

[5] Saeid Sanei, Jonathon A. Chambers, " EEG Signal Processing," John Wiley & Sons, 2013.

[6] Peter Wolf (M.D.), "Epileptic Seizures and Syndromes: With Some of Their Theoretical Implications," John Libbey Eurotext, 1994.

[7] Aleksandar Čolić, Oge Marques, Borko Furht, "Driver Drowsiness Detection: Systems and Solutions," Springer, 2014.

[8] Mardi Z, Ashtiani SNM, Mikaili M (2011) EEG-based drowsiness detection for safe driving using chaotic features and statistical tests. J Med Signals Sens 1(2):130
[9] Khurram I.Qazia, H.K.Lama, BoXiao, Gaoxiang Ouyang, XunheYinc, "Classification of epilepsy using computational intelligence techniques", CAAI Transactions on Intelligence Technology, Volume 1, Issue 2, Pages 137-149, April 2016.
[10] Correa AG, Orosco L, Laciar E (2014) Automatic detection of drowsiness in EEG records based on multimodal analysis. Med Eng Phys 36(2):244–249.
[11] Sanei, S., & Chambers, J. A. (2013). EEG signal processing. John Wiley & Sons.
[12] Laport, F., Castro, P. M., Dapena, A., Vazquez-Araujo, F. J., & Iglesia, D. (2020, August). Study of machine learning techniques for eeg eye state detection. In Proceedings (Vol. 54, No. 1, p. 53). MDPI.
[13] Mumtaz W, Ali SSA, Yasin MAM, Malik AS (2018) A machine learning framework involving EEG-based functional connectivity to diagnose major depressive disorder (MDD). Med Biol Eng Comput 56(2):233–246
[14] Zhang T, Chen W, Li M (2019) Classification of inter-ictal and ictal EEGs using multi-basis MODWPT, dimensionality reduction algorithms and LS-SVM: a comparative study. Biomed Signal Process Control 47:240–251.
[15] Chatterjee R, Maitra T, Islam SH, Hassan MM, Alamri A, Fortino G (2019a) A novel machine learning based feature selection for motor imagery EEG signal classification in Internet of medical things environment. Future Gener Comput Syst 98:419–434
[16] Gajbhiye, P., Singh, V., Saharan, S., & Joshi, S. (2024). Artificial neural network-based classification of eye states using electroencephalogram signals: a comparative analysis of algorithms and artifact removal techniques. In Artificial Intelligence: A tool for effective diagnostics (pp. 5-1). Bristol, UK: IOP Publishing.
[17] O. Roesler, "UCI Machine Learning Repository [EEG Eye State]," Baden-Wuerttemberg Cooperative State University (DHBW), Stuttgart, Germany, 2013. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State
[18] Keerthi Latha, C. V., & Kezia Joseph, M. (2024, June). Enhancing Depression Detection Using EEG Signals Through Adaptive Feature Weighting in Extra Trees Classifier. In International Conference on Frontiers of Intelligent Computing: Theory and Applications (pp. 583-592). Singapore: Springer Nature Singapore.
[19] Shafique, R., Mehmood, A., & Choi, G. S. (2019). Cardiovascular disease prediction system using extra trees classifier. Res. Sq, 11, 51.
[20] Hassan, M. M., Hassan, M. R., Huda, S., Uddin, M. Z., Gumaei, A., & Alsanad, A. (2021). A predictive intelligence approach to classify brain–computer interface based eye state for smart living. Applied Soft Computing, 108, 107453.
[21] Jayadurga, N. P., Chandralekha, M., & Saleem, K. (2024, May). Leveraging Ensemble Techniques for Enhanced Eye State Classification with EEG Data. In 2024 2nd International Conference on Advancement in Computation & Computer Technologies (InCACCT) (pp. 570-576). IEEE.
[22] Xiao, Q., Yang, M., & Yuan, K. (2023). Eye state recognition based on continuous wavelet transform and improved convolutional neural network.
[23] Adil, S. H., Ebrahim, M., Raza, K., & Ali, S. S. A. (2018, August). Prediction of eye state using knn algorithm. In 2018 International Conference on Intelligent and Advanced System (ICIAS) (pp. 1-5). IEEE.
[24] Fikri, M. A., Santosa, P. I., & Wibirama, S. (2021, October). A review on opportunities and challenges of machine learning and deep learning for eye movements classification. In 2021 IEEE International Biomedical Instrumentation and Technology Conference (IBITeC) (pp. 65-70). IEEE.
[25] Alkhaldi, M., Joudeh, L. A., Ahmed, Y. B., & Husari, K. S. (2024). Artificial intelligence and telemedicine in epilepsy and EEG: A narrative review. Seizure: European Journal of Epilepsy, 121, 204-210.
[26] Gaddanakeri, R. D., Naik, M. M., Kulkarni, S., & Patil, P. (2024, April). Analysis of EEG signals in the DEAP dataset for emotion recognition using deep learning algortihms. In 2024 IEEE 9th International Conference for Convergence in Technology (I2CT) (pp. 1-7). IEEE.
[27] Yu, W. Y., Sun, T. H., Hsu, K. C., Wang, C. C., Chien, S. Y., Tsai, C. H., & Yang, Y. W. (2024). Comparative analysis of machine learning algorithms for Alzheimer's disease classification using EEG signals and genetic information. Computers in Biology and Medicine, 176, 108621.
[28] Hazar, Y., & Ertuğrul, Ö. F. (2025). Process management in diabetes treatment by blending technique. Computers in Biology and Medicine, 190, 110034.
[29] Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. Machine learning, 63, 3-42.
[30] Hussein, N., & Zeebaree, S. R. (2024). Performance Evaluation of Extra Trees Classifier by using CPU Parallel and Non-Parallel Processing. The Indonesian Journal of Computer Science, 13(2).
[31] A. G´eron, Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow, O'Reilly Media, Inc, 2022.
[32] M.A. Jamil, S. Khanam, Influence of One-Way ANOVA and Kruskal–Wallis Based Feature Ranking on the Performance of ML Classifiers for Bearing Fault Diagnosis, Journal of Vibration Engineering & Technologies, 2023, pp. 1–32.
[33] A. Al Imran, A. Rahman, H. Kabir, M.S. Rahim, The impact of feature selection techniques on the performance of predicting Parkinson's disease, Int. J. Inf. Technol. Comput. Sci. 10 (11) (2018) 14–29.
[34] N. Silpa, V.M. Rao, M.V. Subbarao, R.R. Kurada, S.S. Reddy, P.J. Uppalapati, An enriched employee retention analysis system with a combination strategy of feature selection and machine learning techniques, in: 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, 2023, May, pp. 142–149.

BIOGRAPHIES

Süleyman Dal Dr. Lecturer. Assist. Süleyman Dal is an academic specialised in the field of electrical and electronics engineering. He completed his undergraduate education at Çukurova University, Department of Electrical and Electronics Engineering in 2018, completed his master's degree at Batman University, Institute of Science and Technology in 2020, and completed his doctorate education at the Institute of Graduate Studies of the same university in 2021. He is currently working as a Dr. Lecturer in the Energy Coordination Department within the Batman University Rectorate. His research interests include machine learning, signal processing and optimisation algorithms.