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# **Utilizing Embedded and Machine Learning Techniques to Classify EEG Eye States**

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#### Abstract

Numerous studies focus on epilepsy diseases in order to achieve the detection of eye states and classification systems because of the significance of automatically identifying brain illnesses. Eye condition recognition is essential for biomedical informatics applications like driving detection and smart home device control. Electroencephalogram signals are this problem. In this context, conventional methods and manually derived features are applied in several instances. The extraction of useful features and the choice of appropriate classifiers are difficult problems. This work suggests an ensemble system called "EEG Eye" that employs a new preprocessing stage. In this context, the base classifiers and the most significant classical works are compared to the ensemble approaches in the classification step. A publicly accessible EEG eye state dataset from UCI is used for assessment. At 100%, 100%, 100%, 100%, the maximum accuracy, precision, recall, and F1 are attained.

#### **Keywords**

Pre-processing, EEG eye state dataset, Ensemble method, Machine learning technique, Data mining, EEG

#### **INTRODUCTION**

The brain-computer interface is one of the trickiest aspects of human-computer interaction. It makes it possible for users to interact with computers mentally. Data from electroencephalography (EEG) is frequently used to measure this kind of activity. Categorizing eye states is a broad time series challenge for identifying human cognitive processes. Understanding human cognitive states can be very helpful for daily therapeutic applications. Analyses that are both subject-dependent and independent are used to classify the current ocular states [1, 2]. In subject-dependent classification, the model is trained using data from a subject, while no such criterion exists for a subject-neutral ensemble. There are issues with the EEG data because of noise and muscle movement. Researchers have used preprocessing, feature extraction, and ensemble techniques to overcome these issues. Machine learning (ML) techniques were employed by the writers.

The database, which was taken from the UCI machine learning repository, had the outlier removed by the authors. K-nearest neighbor (KNN) and multilayer perceptron NN (MPNN) yielded the best classification success rates, with 91.82 and 72.42%, respectively [2]. To improve classification performance, the authors proposed a computational model using the grey wolf optimization (GWO) technique. To categorize the best-generated feature by the GWO, they create an ensemble classifier. The suggested model provides notable performance increases in terms of sensitivity, specificity, accuracy, precision, and F1, i.e., 90.7, 96, 88.4, 94.9, and 92.7%, respectively, according to their findings [2].

The use of the several preprocessing steps together with four ensemble approaches results in the superiority of the suggested model. A classification model with high effectiveness was put forth using ensemble approaches including bagging, boosting, stacking, and voting. R programming was used to apply these principles, and positive outcomes were attained. By analyzing the data that we got from the UCI website, we have demonstrated that our work exceeds the prior

work in terms of assessment metrics and better prediction in improving heart disease. Our model is accurate and makes solid predictions about how this disease will progress.

#### **RELATED WORK**

A diagnosis of chronic kidney disease may occur between 2015 and 2021, according to many studies. There has been compiled a list of some of the most important works.

For the EEG eye dataset, the authors suggested a quick and precise classification algorithm in 2018. The database, which was taken from the UCI machine learning repository, had the outlier removed. The KNN and MPNN classifiers were used. The WEKA tool is used to evaluate the system with its default settings. The KNN and MPNN both had the greatest classification success rates, with 91.82 and 72.42%, respectively [1]. The authors put out a novel approach utilizing incremental attribute learning in 2014. Their findings demonstrated the value of thoughtful feature engineering. In comparison to their competitors, they demonstrated greater classification performance in terms of classification error rate. 27.4573% was the lowest categorization error rate. Additionally, other scientists proposed a novel approach for EEG eye states that integrates incremental attribute learning with neural networks (NNs). In terms of classification error rate, their results showed improved performance, with the lowest classification error rate being 27.3991% [3].

Here, a quick recap of the top works from 2021 is important. The writers looked into the use of mathematical operations including exponential, logarithm, multiplication, and division. They proposed the algebraic learning machine, a novel single-hidden-layer feed forward artificial neural network (SLFN) model (ALM). With the use of 60 distinct datasets, their ALM was assessed. 88.7% was the accuracy rating which was highest [4].

The use of ensemble classifiers was suggested as an efficient method. The cooperation values between the characteristics are first determined using a criterion. The structure of the collaboration graph is then established using the estimated cooperation values. Next, the community detection approach generates graph communities. AdaBoost is regarded as an ensemble classifier that combines different basic classifiers. Their research showed that the suggested strategy might increase classification accuracy by up to 65.23% [5]. For self-supervision on the EEG eye dataset, the authors presented work and termed the Statistical Self-Supervisor (SSS). To forecast the amount of additive isotropic noise, they utilized an NN. Various estimates of the SSS, ranging from one to 100%, were made. Precision, recall, F1, and accuracy scores that were highest were 45.95%, 41.78%, 61.99%, and 22.66%, respectively [6]. For self-supervision noise, they utilized an NN. Various estimates of the SSS, ranging from one to 100%, were made. Precision, recall, F1, and accuracy scores that were highest were 45.95%, 41.78%, 61.99%, and 22.66%, respectively [6]. For self-supervision noise, they utilized an NN. Various estimates of the SSS, ranging from one to 100%, were made. Precision, recall, F1, and accuracy scores that were highest were 45.95%, 41.78%, 61.99%, and 22.66%, respectively [6]. For self-supervision noise, they utilized an NN. Various estimates of the SSS, ranging from one to 100%, were made. Precision, recall, F1, and accuracy scores that were highest were 45.95%, 41.78%, 61.99%, and 22.66%, respectively.

The necessity to reduce dimensionality and the presence of duplicate and unnecessary characteristics in the EEG eye dataset are further issues. By using a meta-heuristic approach, the authors proposed a computational model to improve classification performance. The feature domain is first produced by using the information gain ratio. To determine the best feature, gray wolf optimization (GWO) is then used. To categorize the best-generated feature by the GWO, they create an ensemble classifier in combination with C4.5, random forest (RF), and Forest PA classifiers. On a number of datasets from the UCI Machine Learning Repository, they assessed their suggested model. The suggested model provides notable performance increases in terms of sensitivity, specificity, accuracy, precision, and F1, i.e., 90.7%, 96%, 88.4%, 94.9%, and 92.7%, respectively, according to their findings [7].

Authors in [8] proposed a hybrid classification model for eye state detection using EEG signals. The EEG signal is an essential source of Brain–Computer Interface (BCI) technology implementation. The basic concept of BCI is to enable the interaction among the neurological ill patients to others with the help of brain signals. It need for an efficient classification model that can deal with the EEG datasets more adequately with better classification accuracy, which will further help in developing the automatic solution for the medical domain. They have introduced a hybrid classification model for eye state detection using EEG signals. This hybrid classification model has been evaluated with the other traditional ML models, eight classification models. This proposed classification model establishes a ML-based hybrid model for the classification of eye state using EEG signals with greater exactness. It is also capable of solving the issue of outlier detection and removal to address the class imbalance problem, which will offer the solution toward building the robotic or smart machine-based solution for social well-being.

A novel method for EEG eyes state using recurrence plots and ML approach proposed [9]. The eyes-state classification from the EEG signals using nonlinear analysis tools is a new area of research. Based upon the theory of nonlinear analysis, recurrence plots (RPs) and recurrence quantification analysis (RQA) are of greater significance that help in understanding the chaotic and recurrence behavior of the dynamically occurring complex physiological signals. They proposed a new method combining the RPs with the ML based algorithms for automated classification of EEG signals. A dataset of 109 subjects has been acquired from the PhysioNet database. It is fed to different ML based algorithms such as logistic-regression (LR), support vector machine (SVM), RF, KNN, Gaussian naïve Bayes, and adaptive boosting. LR achieved the highest performance results in terms of accuracy, F1 score, precision, recall, and specificity of 97.27%, 97.17%, 98.26%, 96.36%, and 98.18%, respectively.

LSTM network as a screening tool used to detect moderate traumatic brain injury from resting-state EEG [10]. For the investigation of brain injury claims, the related insurance company may request medical images of the brain from the hospital and subsequently get opinions from the medical staff. The authors proposed a screening approach that uses

the resting-state EEG recordings as the input to a long short-term memory (LSTM) network. This LSTM architecture can classify the resting state EEG into two classes, which are either as a moderate traumatic brain injury (TBI) patient or a healthy person. Experimental results show that the proposed approach is able to outperform two similar recent works by achieving a classification accuracy of 74.33%.

Deep feature fusion based childhood epilepsy syndrome classification from electroencephalogram used in [11]. The authors presented a study on the classification of two most common epilepsy syndromes. A novel feature fusion model based on the deep transfer learning and the conventional time–frequency representation of the scalp EEG is developed for the epilepsy syndrome characterization. Experiments on the CHZU database show that the proposed algorithm can offer an average of 92.35% classification accuracy on the BECT and WEST syndromes and their corresponding normal cases.

#### THE PROPOSED MODEL

Figure 1 depicts the suggested mode. Preprocessing and ensemble stages are two crucial phases of the model. The first step deals with the difficulties of missing values and outliers by using a separate normalization job in combination with the mean. Four ensemble approaches, including bagging, boosting, voting, and stacking, are utilized in the second step.

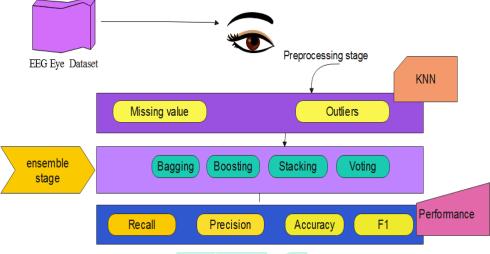


Fig. 1 The proposed Model

#### **Pre-processing Stage for Missing Values**

We were working with information we had obtained from the UCI website at this time. Even though some of the data contained missing values, we handled it in a variety of ways using the Weka and Rapid Miner tools. We successfully used the mean to identify outliers using new data. Since the proposed model performed better than we could have anticipated, we went above and beyond what we had done the previous weeks. The encouraging outcomes demonstrate that our approach accurately predicts instances of chronic nephritis. We aimed to boost the quality of this data to demonstrate relevant research that enhances and predicts categorization.

#### **Ensemble Stage through ML Methods**

A comprehensive meta-approach to machine learning seeks to enhance predictive performance by combining the predictions from several models. Even though you may design what seems like a limitless number of ensembles to solve your predictive modeling problem, there are just three strategies that dominate the realm of ensemble learning. In fact, rather than just algorithms per se, this area of research has given rise to a number of more specialized techniques. Each of the three main classes of ensemble learning techniques —bagging, stacking, and boosting— must be thoroughly understood in order to be considered in any project involving predictive modeling.

#### Bagging

To reduce variance within a noisy dataset, the ensemble learning approach known as bagging, also known as bootstrap aggregation, is widely utilized. Bagging involves randomly replacing and sampling data from a training set, allowing for numerous choices of the same data points. These weak models are individually trained after the development of several data samples, and depending on the task —for instance, classification or regression— the average or majority of those predictions yields a more accurate estimate. An extension of the bagging method, the random forest algorithm creates an uncorrelated forest of decision trees by combining feature randomness with bagging.

#### **Boosting**

An ensemble modeling strategy seeks to produce a powerful classifier by combining several weak classifiers. In order to construct a model, weak models are used sequentially. Initially, a model is built using the training data set. Then, in an effort to address the shortcomings of the first model, a second model is developed. Up until the whole training data set is correctly predicted or the maximum number of models is reached, this procedure is repeated and new models are added.

## Voting

The voting component of the voting approach, which is a sub-process, has at least two base classifiers. This method generates a high accuracy model, a classification model based on the learners, or a regression model where the majority choose the classification. It yielded results at a rate of 99% without preprocessing, however preprocessing with Rapid Miner resulted in results at a high rate of 100%. It was a good consequence for boosting classification performance and carrying out the prediction procedure, however, these datasets still need to be enhanced and work on better prediction.

# Stacking

We also applied the stacking method using the dataset as an extra option. The first stage is the training of fundamental learners. The second element is the process of testing the foundational learners. We applied it to the Rapid Miner tool, and as a result of our efforts, we were able to attain 100% accuracy in both data mining tools. It improved the performance of the classifier and predictor as well. The two sub-processes of the stacking approach, a fictitious process, were the base learners and the typical agglutinative sub-learner processes.

# **EXPERIMENTS AND RESULTS**

#### **Experiment I**

In Experiment I, we investigate the effects of ML methods on chronic renal illness without or with a preprocessing stage using the WEKA tool. As indicated in Table 2, we used the information that was retrieved from the UCI website. We downloaded some data with unusual and missing values. Excellent results were obtained. In addition to or instead of bagging, boosting, voting, and stacking, preprocessing was utilized. We achieved incredibly high results with the two experiments, which illustrate the preprocessing methods. In order to arrive at the high numbers, Table 2 was employed. An experiment without preprocessing attained the highest level of accuracy with a vote percentage of 100%. This figure is thought to have a very high level of predictive value for the progression of renal disease. We conducted a second experiment with respect to Table 2 using a preprocessing that involved locating outliers and replacing missing values with the mean. The algorithm's accuracy can go up to 100%. In terms of forecasting chronic renal illness and providing excellent results, this number is fairly high and outperforms past research. In this work, we proved that our model is suitable and improves ensemble performance.

Table 1 With the Rapid Miner tool, the categorization pre-processing results paired with DT and RF					
Classifier	Precision	Recall	Accuracy	F1	
Bagging	99 %	99 %	99 %	99 %	
Boosting	97.88%	97.88%	97.17 %	97.88 %	
Voting	99 %	99 %	99 %	99 %	
Stacking	100 %	100 %	100 %	100 %	

Table 1 demonstrates our unplanned approach to working on it. Then, we examined it and kept making improvements utilizing ensemble techniques like bagging, boosting, voting, and stacking. The results showed exceptionally high accuracy and an improvement in the prediction of this disease, with the highest accuracy in Table 1 approaching 100%.

# **Experiment II**

We walk through our third illustration of this process using extremely exact algorithms. When anticipating the best outcomes, it often produces pleasant findings, but when put into practice. It typically does not. We analyze the downloaded data in relation to diabetes utilizing bagging and boosting, voting, and stacking while using the Rapid Miner program. The recall, precision, accuracy, and f-measure values for categorization, RF, and DT are shown in Table 2. The results of our labor were excellent. 100% accuracy at a high level was reached. We anxiously anticipate these procedures, which are among the most well-liked methods for enhancing group performance.

Table 2 The results of RF and DT preprocessing ensemble using the Rapid Miner tool					
Classifier	Precision	Recall	Accuracy	<b>F1</b>	
Bagging	100 %	100 %	100 %	100 %	
Boosting	100 %	100 %	100 %	100 %	
Voting	100%	100 %	100 %	100 %	
Stacking	100%	100%	100%	100%	

We produced high values for accuracy, recall, precision, and F1 that displayed good and differentiating findings using the methods indicated in Table 2. The highest accuracy rate was achieved with voting and stacking and bagging and boosting at 100 %. These are regarded as high values that were obtained from our research and used in this study, where high-precision adjustments were performed to enhance and anticipate the problematic and common diabetes at younger ages. Additionally, it proves that our effort is better than others and will be successful. Additionally, it will outperform rivals and produce trustworthy outcomes.

#### EVALUATION METRICS AND DISCUSSION

Accuracy, precision, recall, and F1 were used to evaluate. These criteria are listed in Table 3.

Table 3 Parameters definitions				
Metrics	Evaluation			
Accuracy	(TP + TN) / (P + N)			
Precision	( <i>TP</i> ) / ( <i>TP</i> + <i>FP</i> )			
Recall	TP / P			
F1	2×precision×recall precision+recall			

Using the Rapid Miner tool, we applied ensemble methods in this case, such as bagging and voting, boosting, and stacking, both with and without preprocessing. These methods exhibit exceptional talent and modest efficacy in producing results. Our task was further broken into two components for each of the two halves. In the first portion, we paired DT and RF using ensemble approaches without any preprocessing. Recall, precision, accuracy, and F1 scores are all 100% as shown in Table 1. This validates the accuracy, value, and dependability of our research. As shown, we employed boosting and stacking, the second branch of the first part of bagging and voting, to get positive results without making therapy more challenging. The performance and prediction accuracy of the classifier is greatly enhanced by this amazing number. The categorization scheme in Table 2 produced the best results, with a DT accuracy of 100%. However, as Table 2 shows, we now employed the preprocessing, DT, and RF classification techniques. The findings in Table 2 were rather good; the highest accuracy was 100% for bagging and voting, boosting, and stacking. Our rating system will perform far better than expected and will provide the finest value in our sector. Table 3 contrasts our labor with that of other employees. Compared to other persons, our efforts were 100% more precise and successful. Since our study has demonstrated that utilizing such algorithms will result in the right course of action and advantageous outcomes, it is very desirable for improved prediction. By using such algorithms, you show off your good job since your predictions are more exact and your conclusions more accurate. It is well known that the results of our study significantly improved the way the data were presented.

Table 3 A comparison of the outcomes of pre-processing, categorization, and other tasks.

W	Precision	Recall	Accuracy	<b>F1</b>
[2]	90.7 %	96%	94.9%	92.7%
[7]	90.7 %	96 %	88.4 %	94.9 %
[6]	45.95 %	41.78 %	61.99 %	22.66 %
Our work	100 %	100 %	100 %	100 %

Our work is contrasted with past attempts on this subject in Table 3. Because our paper had a maximum accuracy of 100%, performance has to be improved. Our model performs classification more effectively than others while paying more attention to its development and prediction. Figure 2 displays a comparison between our findings and those of their equivalents.

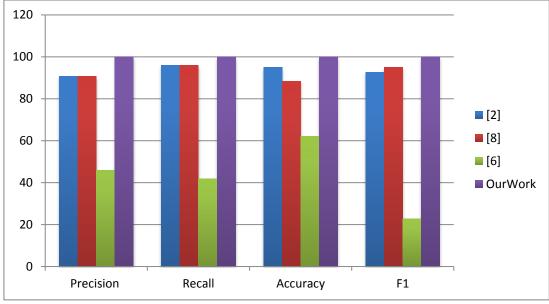


Fig. 2 The results of comparing our work with those of others

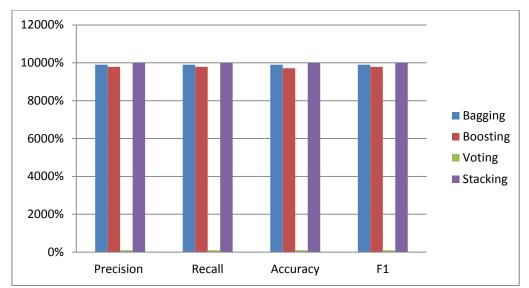


Fig. 3 The Comparison results among our work through ensemble without pre-processing in conjunction with DT and RF

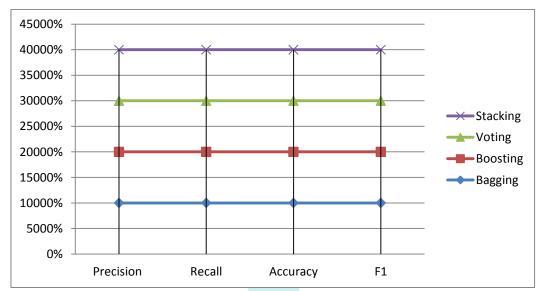


Fig. 4 The Comparison results among our work through ensemble with pre-processing in conjunction with DT and RF

#### CONCLUSION

Since the used statistics were taken from the UCI website, they were incomplete and had incorrect values. In this investigation, we ran two tests. The WEKA tool's Bagging and Boosting and Voting Stacking methods, either with or without preprocessing, were utilized in the first trial. These preprocessing techniques included locating outliers and substituting the missing value with the mean. We had positive outcomes in the initial trial. His research found that f1, precision, recall, and accuracy all reached high values, with Table 2 displaying the highest result. When using the voting process, they get close to 100%. It is thought to offer outstanding values in the best manner. Our findings showed a significant improvement in classification performance, proving the superiority of our approach over earlier research. We have significantly enhanced the performance of categorization and prediction using these results. Chronic nephrotic syndrome, one of today's most common disorders, is also one of the deadliest for the elderly and people with other chronic conditions. In the second experiment, we employed the Rapid Miner tool and the following algorithms. Preprocessing is optional when it comes to voting, stacking, bagging, and boosting. When we got high numbers, preprocessing was accomplished to spot outliers and use the mean to fill in the gaps left by missing data. Without any preprocessing, the outcomes for the metrics listed below are shown in Table 3 Our findings showed a significant improvement in classification performance, proving the superiority of our approach over earlier research. We have significantly enhanced the performance of categorization and prediction using these results. Chronic nephrotic syndrome, one of today's most common disorders, is also one of the deadliest for the elderly and people with other chronic conditions. In the second experiment, we employed the Rapid Miner tool and the following algorithms. Pre-processing is optional when it comes to voting, stacking, bagging, and boosting. When we got high numbers, pre-processing was accomplished to spot outliers and use the mean to fill in the gaps left by missing data. Without any pre-processing, the outcomes for the metrics listed below are shown in Table 3. Since chronic nephrotic syndrome is a serious and hazardous ailment that affects individuals, it is clear that this article was successful and achieved exceptional results since it is much superior to the prior studies. Our study will improve classification performance and show the viability of our theory. Additionally, it will improve his performance and foresee chronic nephrotic. Table 3 displays the results of the voting

algorithm, with all metrics being 100%. This value, which is the highest in this piece, has significantly enhanced chronic nephrotic and allowed us to foresee a significant improvement in classification performance. Since the chronic nephrotic syndrome is an uncomfortable and difficult illness that puts people in danger, it is clear that this study was successful and achieved remarkable results since it is far better than the prior attempts. Our research will improve classification accuracy, show that our theory is true, locate chronic nephrotic, and improve accuracy.

#### **AUTHOR BIOGRAPHIES**

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