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Mental State Prediction Using Machine Learning and EEG Signal

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Abstract – One of the most exciting areas of computer science right now is brain-computer interface (BCI) research. A conduit for data flow between both the brain as well as an electronic device is the brain-computer interface (BCI). Researchers in several disciplines have benefited from the advancements made possible by brain-computer interfaces. Primary fields of study include healthcare and neuroergonomics. Brain signals could be used in a variety of ways to improve healthcare at every stage, from diagnosis to rehabilitation to eventual restoration. In this research, we demonstrate how to classify EEG signals of brain waves using machine learning algorithms for predicting mental health states. The XGBoost algorithm's results have an accuracy of 99.62%, which is higher than that of any other study of its kind and the best result to date for diagnosing people's mental states from their EEG signals. This discovery will aid in taking efforts [1] to predict mental state using EEG signals to the next level.

Keywords : BCI, EEG Signals, Support Vector Machine ,Random Forest , XGBoost.

I. INTRODUCTION

BCI technology is a potent tool for facilitating communication between people and machines. Issuing commands and completing the interaction does not necessitate any additional hardware or manual effort [1]. BCIs were first developed by the research community for use in the medical field, which then led to the creation of assistive devices [2]. They have made it easier to replace lost motor function and restore mobility for people who are physically disabled or confined [3].

Researchers have been inspired by BCI's bright future to investigate the technology's potential medicinal uses in people's everyday lives.Electrodeplacement on the scalp allows for electroencephalography (EEG), a noninvasive approach for recording the brain's electrical activity. These electrical impulses, or EEG waves, can be characterised by their frequency and amplitude. When a person is sleeping or otherwise at ease, brain waves have a low frequency, however as soon as they begin to react to their surroundings, the waves' frequency rises. More intense waves are generated when one's attention is focused [4]. Several international, interdisciplinary, and collaborative research projects are currently using a wide range of approaches to study the brain and emotional processing [5]. In particular, the gap between human and machine has been narrowed by indications of surface brain activity, which can be used to discern mental processes. Electrical activity in the brain takes the form of distinct patterns called "signals," which are formed by the coordinated firing of billions of neurons and reflect a person's current state of mind and actions [6]. When electrodes are implanted on a person's scalp, it's possible to observe and extract voltage patterns noninvasively; this method is called an electroencephalogram (EEG) [7].

However, it is difficult for doctors to correctly categorise EEG signals so that they may characterise the various mental states and recommend the most appropriate follow-up visit. The complicated time-frequency structure of nonlinear, nonstationary signals, which include a range of oscillating patterns, frequency bands, as well as noise components, can be used to identify them (artefacts) [8]. As artefacts, or non-brain-related physiological signals, render EEG signals unpredictable and diminish their clinical utility, they warrant special consideration. Since scalp EEG is a dynamic signal generated by a large number of cortical bases, investigations based on it can be quite rigorous in terms of data scale. Using an unpredictably huge number of signals, AI and ML can determine the subject's current state [9][10][11][12].

In order to generate results equal to manual analysis, artificial intelligence (AI)-based solutions, which are constrained by the amount of the data, depend on the identification of certain patterns within highly heterogeneous multimodal data sets[13][14][15]. Due to the fact that remote operations and quarantine have developed into industry standards during in the pandemic, these solutions can afterwards be made accessible to telemedicine-based applications[16].

II. RELATED WORK

In this discipline, a number of important studies have had a significant impact. When Bashivan et al. assessed mental reactions (emotional and logical) to movie playing, they found that wearable EEG sensors were quite significant in differentiating distinct cognitive states [17]. According to Agrawal et al., ANN and DNN often outperform conventional algorithms with more accuracy [18]. Three classification tests—emotional mood, guessing number, and concentration state—were the focus of another study by Bird et al. They were able to perform an Adaptive Boosted LSTM for the attention state test with up to 84.44% accuracy[19]. Richer et al. used the nave score as well as an entropy-based calculating score to determine the sensitivity, specificity, and ROC curves for real-time mental state recognition.[20].

Ajith et al. proposed a method in their study utilizing the DEAP dataset that uses a convolutional neural network to categorize opinions into four groups based on the valence & arousal dimensions (CNN)[21]. Ghosh-Dastidar et al. classified seizure exposure using statistical analysis and their confounding neural net model was 92.5% accurate [22]. Didar D. Bos discovered a 64% accuracy rate for classifying emotional states using neural networks using EEG data[23]. Additionally, Koelstra et al. showed that Common Spatial Patterns are successful for categorising emotions, with a total optimal answer of 93.5% [24]. When Edla et al. tested their ensemble classifier-based BCI model on their dataset, they were able to achieve up to 75% accuracy in predicting concentration and meditation [25].

Additionally, Jin et al's investigation on mind-wandering found that the condition was distinct from the low vigilance state after training a support vector machine (SVM) classifier on EEG data [26]. In order to categorise mental states, Zeng et al. presented a DNN and demonstrated that their models regularly outperformed conventional LSTM and SVM-based classifiers [27]. Lee et al. likewise presented the study on this topic, and their accuracy percentage was around 72% [28].

In the meanwhile, SVM and CNN are the best candidates for classifying behavioural patterns, according to Gulhane and Sajana, who recently completed a review research on the subject of forecasting human behaviour using machine learning during the COVID-19 outbreak[29]. Bird et al., the creators of the dataset utilised in this study, tested a variety of feature selection methods and classifier models. In the end, they were successful in obtaining data accuracy for mental state sets of over 87%[30].The main goal of the current paper is to use 10 different ML algorithms to conduct an investigation and identify three different mental states.

As can be observed from the preceding studies, there is more potential for research into a subject's state of consciousness and focus than there is for investigating other goals like emotion classification. Due to the ambiguity in the nature of the study, these objectives frequently require a very careful approach and as a result, show only fair accuracy. This study uses an EEG dataset to classify patients into three concentration levels, resulting in a three-way categorization.

Logistic Regression (LoR), Gaussian Naive Bias (GNaB), K-Nearest Neighbor (KNN), Decision Tree (DeT), Random Forest (RaF), AdaBoost (AdaB), Support Vector Machine (SVM), Gradient Boosting (GrB), Multi-layer Perceptron (MuLP), and XGBoost are all laboriously simulated (XGB).The performance of these well-known algorithms is anticipated to be reliable for ML-based studies beyond the experts' area of expertise. The paper's Section III, which covers methods, presents additional discussion on enhancing performance. In Section IV, the classifiers' performances are shown, and a full comparison is shown. The last remarks are displayed in Section V.

III. METHODOLOGIES

The information utilised in this study originated from Kaggle' data set(https://www.kaggle.com/datasets/nnair25/Alcoholics)

This information was gathered as part of a large-scale investigation into the relationships between people's EEGs and their feelings. Includes data from 64 scalp electrodes recorded at 256 Hz (3.9 ms epoch) for 1 second.Subjects were divided into two categories: those in a positive mental state and those in a negative mental state. Both a single object photo (S1) and a pair of object pictures (S1 and S2) from the 1980 Snodgrass and Vanderwart picture collection were presented to each subject. There were two types of stimulus presentation: "matched," where S1 was the same as S2, and "non-matched," where S1 and S2 were different.

For the single stimulus condition, the average voltage, duration, and channel plots were taken from 10 separate trials.A total of 122 participants performed 120 trials, during which a variety of stimuli were presented. The electrodes were placed in the usual spots (American Electroencephalographic Association Standard Electrode Position Nomenclature, 1990). In the first step of data processing, the iloc function in Python was used to decouple

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the input and output processes. After that, the minmax scaler is used to normalise the inputs, and the k-best method is applied to select the most relevant features.
The next step is feature selection, when the most discriminative 500 features are chosen from a pool of 900.
Next, a 5-fold cross-validation was performed by splitting the Data into train and test sets at a ratio 80%:20%.After obtaining the confusion matrices, a wide range of model performance metrics became available for analysis. Additionally, the RandomSearchCV) technique has been utilised to optimise the performance of hyperparameters by random search cross-validation.

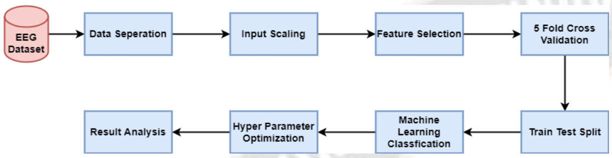

Figure 1 System Architecture

Instead than trying every possible combination of parameters, this approach just picks the ones that work best. In Fig. 1, the whole process flow is displayed. In the concluding section, a comparison of the various Machine learning models was provided to evaluate their applicability in developing an automated system for deriving mental states from EEG data. In this section, we go over the classification methods that can be utilised to make an educated guess.

- Support Vector Machine
- Random Forest
- XGBoost

3.1.Support Vector Machine
By creating a hyperplane with all samples belonging to one class situated on one side as well as all samples belonging to some other class located on the other, classification is accomplished. The distance between classes is maximised with the help of hyperplane optimization. The data points closest to the hyperplane form a support vector. [31].
Hyperplane can be created as given in the following equation:

$$H_0: w^T + b = 0 \ (1)$$

Two more hyperplanes $H1$ and $H2$ are created in parallel to the constructed hyperplane as given in the following equations:

$$H_1: w^T + b = -1 \ (2)$$
$$H_2: w^T + b = 1 \ (3)$$

Hyperplane should satisfy the constraints given by following equations for each input vector,

$$wI_j + b \geq +1 \ for \ I_j \ having \ class \ 1 \ (4)$$

And

$$wI_j + b \geq -1 \ for \ I_j \ having \ class \ 0 \ (5)$$

3.2. Random Forest
A bagging technique called Random Forest is used to merge many decision trees to improve prediction accuracy. Individuals are taught on their own in bagging. Each decision tree is trained using a different set of data samples in this method, and many data samples are formed from the original dataset using replacement. The features of the tree are also picked at random throughout the construction process. A majority vote can be used to combine the predictions of several trees.[32]. By changing variables like the number of estimators, a minimum node size, and the number of characteristics used to divide nodes, the random forest's accuracy can be increased.

3.3. XGBoost
It is a performance- and speed-focused gradient-boosted decision tree solution. To maximize efficiency, flexibility, and portability, XGBoost was developed as a distributed gradient boosting library. The Gradient Boosting framework is used to develop machine learning algorithms. XGBoost offers rapid and accurate parallel tree boosting (also known as GBDT, GBM) for a variety of data science challenges. XGBoost is a technique for boosting learning in a group. In some cases, relying just on a single machine learning model may not be enough.
The predictive capacity of numerous learners may be combined systematically through ensemble learning. In the end, you'll have a single model that combines the results of multiple other models.[33].Different learning methods may be used to build the ensemble, which is also known as a basic learner set. The two most common ensemble learning techniques are bagging and boosting. There are other statistical models in which these two approaches may be applied, but decision trees have been the most often employed.

IV. EVALUTION PARAMETER

On a scale of accuracy, sensitivity, specificity, precision, & recall, classifier performance was assessed [34][31]. False negatives are conceivable, but only in cases where the algorithm properly forecasts that the patient has heart disease. A true negative, as opposed to a false negative, happens when a person is anticipated to be disease-free.The system can create accurate predictions that are measured by the accuracy of its performance.

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$$Accuracy = \left(\frac{CorrectPrediction}{Total\ Prediction}\right) * 100 \qquad (6)$$

System sensitivity is a performance statistic that assesses a system's capacity to accurately forecast favourable outcomes.

$$Sensitivity = \left(\frac{True\ Positive}{(True\ Positive + False\ Negative)}\right) * 100 \qquad (7)$$

Performance parameter Specificity assesses the system's ability to correctly forecast negative outcomes.

$$Specificity = \left(\frac{True\ Negative}{(True\ Negative + False\ Positive\ )}\right) * \ 100 \qquad (8)$$

Precision refers to a system's ability to produce just the most relevant data.

$$Precision = \left(\frac{True\ Positive}{(True\ Positive + False\ Positive\ )}\right) * \ 100 \qquad (9)$$

F-Measure utilises the harmonic mean to combine accuracy and sensitivity measurements.

$$F - measure = 2 * \ \left(\frac{Sensitivity * Precision}{Sensitivity + Precision}\right) * \ 100 \qquad (10)$$

V. RESULTS AND DISCUSSIONS

According to preceding parts, performance measurements were acquired from simulations carried out in Python using a variety of machine learning classification techniques. The result validation has been done based on the accuracy, f1 score, precision etc. The results of all this classification algorithms have been shown in Table 1 and the confusion matrices of XGBoost Classification algorithm is shown as XGBoost algorithm had given the best results in terms of accuracy score. The estimation of a classifier's accuracy is made much easier by using these confusion matrices. These matrices make it simple to see how many occurrences the model correctly predicted as well as the actual values.

Model	Accuracy		F1 Score	Precision	Recall
Logistic Regression	97.93	0	0.95	0.99	0.97
		1	0.99	1	0.99
		2	0.99	0.95	0.97
Support Vector	96.66	0	0.93	0.99	0.96
		1	0.98	0.99	0.99
		2	0.98	0.92	0.95
Random Forest	99.06	0	0.99	0.99	0.99
		1	0.99	0.99	0.99
		2	0.99	0.98	0.99
Decision Tree	97.73	0	0.98	0.95	0.96
		1	1	0.99	0.99
		2	0.95	0.98	0.96
XG Boost	**99.62**	**0**	**1**	**0.99**	**0.99**
		1	**1**	**0.99**	**1**
		2	**0.98**	**1**	**0.99**

Table 1 Performance Evaluation of Classification Model

The multi-class structure of this research is what led to the scoring pattern that can be seen below. Other performance indicators, as opposed to binary sorting, are more forgiving when estimating the correctness of the analysis. As a result, a classifier with a high accuracy score will also have greater precision and recall scores.Table 2 shows a contrast with earlier studies that addressed the identification of mental states. The dataset used to create this paper's first 3 rows of references is the same one.

According to a different strategy proposed by Ashford et al., CNN is used to conduct the picture classifiers and express the statistical data as 2D images, achieving up to 89.38% accuracy[6]. AdaBoosted LSTM, which was employed in another study by Bird et al., achieved the best accuracy (84.44%) when it came to classifying data using bioinspired computing techniques[19].Richer et alrecognition .'s of mental states (Neutral, Focus, Relax) using wearable EEG used eleven subjects and produced a successful recall score of 0.82 as additional performance measurements [20].

However, Zeng et al. showed that the suggested deep learning model could outperform SVM and LSTM classifier, with an accuracy of 84.38% [27]. Of these feature sets & models developed by Bird et al., a Random Forest classifier based on the OneR attribute selector was shown to be the most correct (87.16%) (of the classifiers)[35].

A.A. Rehman and others Hyperparameter tuning was carried out using the RandomSearch CV method, and both tuning and tuning without hyperparameters were compared. Support Vector Machine (SVM) showed the highest accuracy (95.36%) after analysing the performance parameters[36]

References	**Algorithms**	**Results**
[6]	Convolutional Neural Network	89.38 %
[19]	Ada Boost LSTM	84.44 %
[25]	Random Forest	75.00 %
[35]	Random Forest	87.16 %
[36]	Support Vector Machine	95.36 %
[37]	K-Nearest Neighbour	78.80 %

Proposed Methodology	(XGBoost)	99.62 %

Table 2 Comparative Analysis

Using the XGBoost algorithm, the technique used in this study finally achieved the best accuracy of 99.62%. To the of our knowledge, using the RandomSearchCV technique to adjust the hyperparameters greatly helped produce comparatively better performance for all the outcomes [35]. The dataset may have been overfitted based on the results, as certain methods still had lower values even after hyperparameter adjustment.

VI. CONCLUSION

It has the ability to identify hidden patterns & psychiatric diseases such as human mental state disorder by classifying mental states using EEG data produced from brain neural activity. This research aimed to identify the most effective classifier by utilising the Kaggle mental state dataset. Here, XGBoost Classifier's 99.62% precision was the highest of any classifier tested. The results can help the early adopters find the most effective method of detecting a person's mental state by analysing their electroencephalogram (EEG). As a result, ML models can help specialists by providing the insights they need to accomplish their jobs, which can have a huge impact not only on the economy but also on the healthcare sector. Future research on deep learning techniques will highlight how well these models function in many scenarios.briefhistoryofFEhasbeensketched,withafocusonitsearliest,pioneeristicdevelopments,followedbyabibliographical analysisonthenumberofFEpapersin open literature in general on IEEE journals and on*ACES Journal* in particular. The latter, being committedtocomputationalelectromagnetics,hostedinthislast 20years a remarkable number of papers dealing with FEsanditsapplications.

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