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Real-Time Eeg-Based Cognitive State Detection Using Random Forest Classifier

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***Abstract*—Understanding a person's mental condition is important in many real-life situations such as driving, healthcare, and workplace environments. States like tiredness, stress, low attention, and distraction can reduce safety and performance. EEG is a simple non-invasive method that records brain signal activity and can be used to study these changes. In this work, an EEG-based Cognitive Monitoring System is developed using the Random Forest algorithm. Different EEG signal values such as Alpha, Beta, Theta, Delta, and Gamma are taken as input to predict the user's current condition. The predicted result is shown through a dashboard with details like behavior status, score, and risk level. The results show that the system can be used to observe changes in user condition and give simple feedback through the dashboard.**

***Keywords*—Brain Activity, Cognitive Monitoring, Driver Safety, EEG Signals, Random Forest, Real-Time Prediction**

I. Introduction

The state of mind of humans affects their ability to execute tasks that involve concentration, alertness, and fast decision-making. Drowsiness, fatigue, tension, and distractions can impact the performance of individuals leading to fatal outcomes, particularly in sectors like driving, medical field, and work environment. Hence, continuous monitoring of the cognitive state has become crucially necessary.

Electroencephalography (EEG) is a non-invasive technology to acquire the electrical activity of the brain with the help of sensors. Signals collected through this process provide valuable information regarding attention, mental tension, relaxation, and workload levels. Such signals can be processed via machine learning models to classify various states of mind.

Conventional monitoring technologies mainly use manual observation and sensors that are costly. Such techniques cannot be used in applications that need to occur in real-time situations. In order to address such concerns, this study proposes the use of an EEG based Cognitive State Monitoring System with Random Forest Algorithm. The model predicts the cognitive status of the individual along with providing the outcome via a dashboard interface.

Such a solution can find applications in transportation safety, health care monitoring, manufacturing units, and smart assistive technologies.

II. Related Work

EEG based cognitive monitoring is one of the emerging technologies used today, particularly in analyzing driver behavior and ensuring safety in transportation. Due to the fact that EEG signals measure the brain activity, it is possible to detect the condition of being alert, fatigued, distracted and intention of a reaction.

A review on the applications of EEG-based brain monitoring for driving state analysis was presented in [1]. Different approaches for detecting drowsiness, distraction, and mental workload using EEG signals were discussed. The study also highlighted the importance of EEG-based brain monitoring in intelligent transportation systems.

Emergency braking intention detection using EEG signals was explored in [2], where an EEG-based system was used to identify emergency braking intention during simulated driving. The results showed that changes in brain activity could be detected even before the actual braking action occurred.

[3] used non-invasive neural signals for classification of both soft and emergency brake intentions in drivers. It proved the effectiveness of EEG in early actions recognition.

Moreover, brain activity of drivers in case of sudden braking was considered in [4]. It describes EEG evoked by emergency braking when simulating driving process.In [5], a synchronous hybrid brain–computer interface was introduced for recognizing emergency braking intention with improved real-time performance.

Driver drowsiness detection has also been widely studied. In [6], improved drowsiness detection was achieved by selecting optimum combinations of EEG features and channels, which enhanced prediction performance. In [7], an EEG channel selection framework was proposed to simplify the detection model while maintaining reliable accuracy.

Although previous works reported promising results, challenges such as signal noise, sensor placement, and real-time deployment still exist.

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Therefore, the present work develops an EEG-based Cognitive Monitoring System using the Random Forest algorithm for efficient and practical real-time monitoring.

III. Methodology

The proposed system uses EEG signal values to understand the user's mental condition and provide real-time monitoring results. The working process includes collecting EEG data, preparing the data, selecting useful features, training the model, and predicting the final state. For classification, the Random Forest algorithm is used because of its stable and efficient performance.

A. Data Collection

The data used for the EEG data consists of an existing dataset which is used for cognitive state prediction analysis. There are about 50,000 samples of the dataset which represents brain activity during a particular instant.

There are five EEG features in the dataset which are referred to as EEG_0 to EEG_4, which are as follows:

EEG_0 – Alpha (a state of calmness and relaxation)
EEG_1 – Beta (state of active thoughts)
EEG_2 – Theta (a drowsy state with low attention)
EEG_3 – Delta (deep rest state)
EEG_4 – Gamma (high-level thoughts)

These values refer to the intensity of the particular brain waves and can be used as features of the dataset.

Also, there is a class feature in the dataset that represents the cognitive state of the user and it consists of three classes as follows:

0 - low cognitive load
1 - medium cognitive load
2 - high cognitive load

B. Preprocessing

The raw EEG data might have some noise or anomalies. Therefore, to increase the quality of the input data, preliminary steps of preprocessing are conducted. The process involves removal of missing data and duplicates, along with data arrangement.

C. Feature Selection

The significant EEG bands considered for this experiment include:

- Alpha
- Beta
- Theta
- Delta
- Gamma

These features are useful for identifying states such as calmness, focus, tiredness, and stress.

TABLE I.
EEG PARAMETERS USED FOR ANALYSIS

Parameter	Meaning	Condition
Alpha	Relaxed Activity	Calm
Beta	Active thinking	Alert
Theta	Slow activity	Drowsy
Delta	Deep rest	Sleepy
Gamma	Fast activity	Focus / Stress

D. Model Training

The input data set is split into the training and testing sets. The training of the Random Forest model is carried out based on the EEG features. This model comprises the combination of decision trees and predicts the output based on majority votes.

E. Prediction

Once the training has been done, the system receives the inputs from the EEG values to predict the cognitive state of the user. The inputs are comprised of five brain waves represented in EEG readings.

On the basis of the above inputs, the classification done by the Random Forest Model determines whether the cognitive load is low, medium, or high. The predicted output will be transformed to system outputs like safe, warning, and alert.

There are also other outputs that will be produced, namely behavior status, risk level, and final state.

IV. Results And Discussion

The design of the proposed Cognitive Monitoring System utilizing EEG features was successfully implemented using the Random Forest algorithm. Training was carried out based on several important EEG characteristics like Alpha, Beta, Theta, Delta, and Gamma values. As a result, the prediction of the user's cognitive condition was performed according to the input values.

An interface was created for presenting the predicted state of users with an output like behavior status, present state, score value, confidence level, and risk condition. Testing showed various cognitive conditions like Safe Driving, Focus Work, Distracted, and Drowsiness depending on the pattern of EEG signals.

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High values of Beta and Gamma suggest the person being focused, while high levels of Theta and Delta characterize the fatigued and distracted state. That means that the EEG signals represent the changes in cognitive state properly.

The quality of prediction of the Random Forest classifier was assessed based on the accuracy. The training accuracy was found to be 81.82%, while the testing one amounted to 75.45%. From the confusion matrix below, it can be seen that the distribution of classification outcomes is done accurately.

From the classification report, it is observed that Class 0 and Class 2 were performed excellently by having their F1-score values as 0.82 and 0.81 respectively while Class 1 had its value as 0.63. This means that there was some scope for improving this score.

This proves the efficiency of the proposed system in detecting cognitive states from the EEG data collected, although improvements could be done using big data analysis and better feature selection methods. The poor performance seen in Class 1 may be attributed to the similarity of the EEG data for different cognitive states.

TABLE II.
SYSTEM OUTPUT STATES

Behavior	State	Risk Level
Safe Driving	Active Monitoring	Safe
Distracted	Low Attention	Medium
Drowsy	Fatigue Detected	High
Focused Work	Productive	Safe

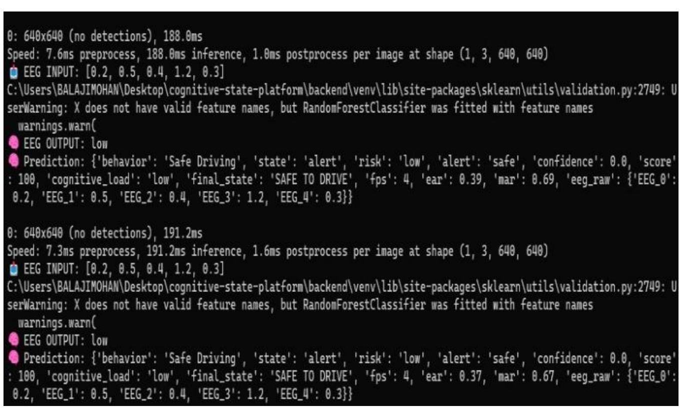

Fig. 1. EEG output Low

The results given in Fig. 1 have been generated based on the EEG signal [0.2, 0.5, 0.4, 1.2, 0.3]. The model recognizes the cognitive load as low, meaning that there is a normal status.

The behavior pattern can be identified as Safe Driving with a low threat level, and the resultant state is SAFE TO DRIVE.

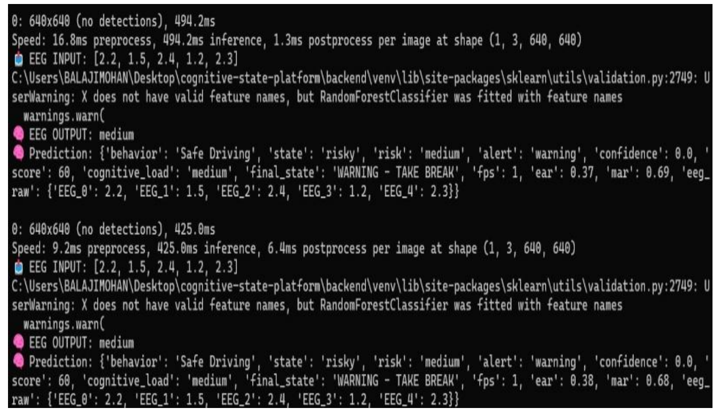

Fig. 2. EEG output Medium

The above results in Fig. 2 are obtained using the EEG inputs [2.2, 1.5, 2.4, 1.2, 2.3]. The cognitive load in the system has been predicted as MEDIUM, which represents a moderately challenging condition. The behavior in question has been identified as SAFE DRIVING, but with MEDIUM risk, resulting in the final condition as WARNING – TAKE BREAK.

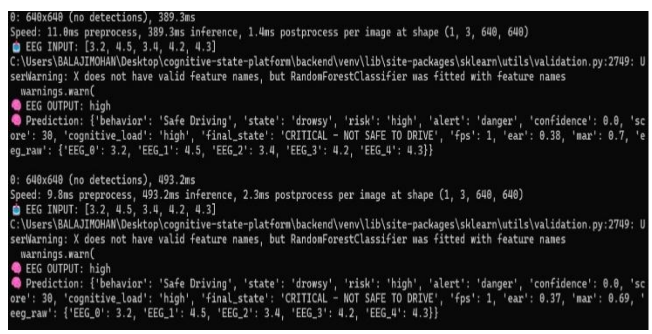

Fig. 3. EEG output High

Output in Fig. 3 relates to higher values of input in EEG, wherein the system determines that there is high cognitive load in the individual. It suggests that the person might be under stress or fatigue. The risk involved in such a situation is considered high, and the final status of the model is shown as “ALERT – NOT SAFE.”

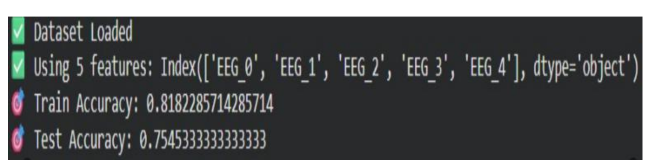

Fig. 4. Model Accuracy Results

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Training and Testing Accuracy of the Random Forest classifier with EEG features is shown in Fig. 4. As evident from the graph, the classifier has performed quite satisfactorily with training accuracy at 81.82% and testing accuracy at 75.45%.

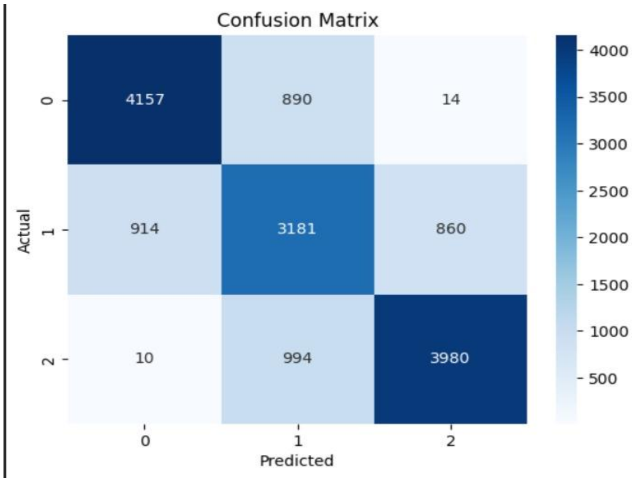

Fig. 5. Confusion Matrix

Confusion Matrix of the model as shown in Fig. 5 gives an insight into the accuracy of various classifications by the model. Values mostly lie in the diagonal region, suggesting correctness of predictions.

Misclassifications are minimal but occur here and there, with a fair performance of the model being achieved in Classes 0 and 2. Confusion in classification is mostly present in Class 1.

TABLE III.
Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.82	0.82	0.82	5061
1	0.63	0.64	0.63	4955
2	0.82	0.80	0.81	4984
Accuracy	—	—	0.75	15000
Macro Avg	0.76	0.75	0.75	15000
Weighted Avg	0.76	0.75	0.76	15000

Classification report as shown in Table III. provides information regarding the Precision, Recall, and F1-Score of each class. From the classification report, it can be seen that Classes 0 and 2 achieve relatively high scores, while Class 1 scores low when compared. Overall accuracy of the system stands at 75% with weighted average F1-score as 0.76.

V. Conclusion

An EEG-based Cognitive Monitoring System was developed using the Random Forest algorithm to identify user mental conditions in real time. EEG signal features such as Alpha, Beta, Theta, Delta, and Gamma were used to analyze cognitive states including alertness, focus, and fatigue.

The system successfully predicted user conditions and displayed the results through a dashboard showing behavior status, confidence score, and risk level. The classification process by using the Random Forest algorithm was found to be simple and efficient. The application of the system is possible in the field of driver safety, health care monitoring, office monitoring, and intelligent guidance system. In the future, the model will be further improved through the use of live EEG sensors and modern technology.

VI. Future Scope

There is a lot of room for improving the suggested model in the future. Live EEG equipment can be incorporated in order to measure brain waves in real-time. The algorithm might prove even more effective if additional amounts of data are trained and different methods of machine learning are used. The dashboard might also be transformed into an app for greater convenience. Other variables such as stress, distraction, anxiety, and mental workload may be taken into account in the future.

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