International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Eye State Classification with EEG using Machine Learning

Alavala Vinay[1], Allacheruvu Srikanth[2], Abburi Venkata Rao[3], Ms. G. Priyanka[4], Dr. R. Shoba Rani[5], Dr. M. Manikandan[6]

Department of Computer Science and Engineering,
Dr. M. G. R Educational and Research Institute, India

Abstract

Through machine learning to monitor eye statuses and set off an alarm as appropriate, this project focuses on creating a real-time classification system for eye states. The main goal is to create a device able to distinguish between open and closed eyes on the fly using image data, track the length of time the eyes remain open, and warn should the eyes be constantly open for more than one minute. For accurate classification of eye states, the system uses OpenCV for real-time video input and eye detection in addition to a trained Convolutional Neural Network (CNN). While the model examines and predicts the state of the eyes, haar cascades are used for localizing the eye region. The project also combines an alarm system utilising Python libraries to sound an audible alert once particular conditions are met. This solution is meant to be pertinent for situations when long periods of eye openness could indicate weariness or reduced attention, such as driver drowsiness detection, user attention monitoring, and so on. Developed in Python, the system uses machine learning frameworks including TensorFlow/Keras and OpenCV for efficient real-time processing.

Keywords: EEG, Machine Learning, Eye State Detection, Convolutional Neural Networks, OpenCV, Keras, HaarCaascade, TensorFlow

I. Introduction

The field of wide-ranging research called electroencephalography (EEG)-based eye state classification is an emerging one that combines neuroscience and artificial intelligence. Applicability of knowing whether a person's eyes are open or closed exists in several areas including medical diagnostics, cognitive neuroscience, and assistive technology. Mainly based on infrared cameras or optical sensors capturing eye movements and gaze direction, conventional eye-tracking systems These techniques have significant restrictions, how- ever including susceptibility to poor illumination, facial obstructions such as glasses or eyelashes causing occlusion, and possible privacy issues stemming from the invasive character of camera-based observation.

The approach based on machine learning for categorizing eye states with EEG data is discussed in this document. We investigate several preprocessing techniques, feature extraction approaches, and classification algorithms for improving the dependability and accuracy of system. Through thorough testing and analysis, we show the suitability of EEG-based eye state classification over conventional eye-tracking techniques.

II. Literature Review

A. EEG-Based Eye State Detection and Its Applications

Zhang and others showed how the Deep-Learning powered technique forecasts eye state from the EEG's data. Their re- search revealed that convolutional neural networks (CNNs) can efficiently extract spatial features from EEG signals, potential direction for raising classification accuracy. Jain et al. also use the same approach. emphasizing the benefits of including both spatial and temporal feature extraction, given a CNN-LSTM approach to identify driver drowsiness based on EEG signals.

B. Feature Extraction Methods for EEG Signals

In EEG-based classification, feature extraction is extremely important. Li et al. extensively investigated characteristic ex- traction methods for brain-computer interfaces (BCI) based on EEG. Especially in terms of increasing classification accuracy, their research emphasized the need of deep learning-based au- tomatic feature extraction and time-frequency domain features.

C. Comparison of Classification Algorithms

Khan and others compared several classification approaches, including support vector machines, random-forest, and Deep Learning models. In their findings, deep learning algo- rithms—especially CNN-based methods—produced excellent results.
Records of brain activity, known as EEG, provide an ex- citing answer for eye state classification. The human brain

D. *Brain computer interfaces*

Shows different neural activity patterns linked to varied eye conditions. For instance, while lowered alpha activity and raised beta activity (13–30 Hz) are noted when the eyes are open, alpha wave activity (8–13 Hz) in the occipital lobe tends to increase when the eyes are closed. Using these variations in brain wave patterns, artificial intelligence models could be taught to very accurately identify eye states.

Brain-computer interface (BCI) applications depend on real- time EEG signal classification. Wang and others looked into live processing methods for BCI based on EEG. Their re- search tackled main issues including noise reduction, adaptive filtering, and latency minimization, which are vital for real- time applications such as assistive devices and neuro feedback systems.

III. Related Work

Many investigations have examined EEG-based eye state detection using various ML and DL models. Bashivan and others Using convolutional neural network (CNNs) for EEG feature extraction in 2016 shows better classification accuracy. Lawher, et al. (2018) presented EEGNet, a small CNN design developed especially for EEG signal classification.
Andrezejewski et al. SVMs were used in 2020 to identify drowsiness based on EEG data; they delivered excellent performance via wavelet-transformed features. Just as Huang et al. do. (2021) used ensemble learning methods to strengthen eye state classifications.

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1) *Machine Learning in Health care:* Machine learning finds applications in the field of healthcare, especially those related to neurological and cognitive state evaluation. The ability of the machine learning models to identify the relevant patterns from the rich physiological signals has opened up the possibilities of advances in the field of brain computer interfaces, seizure onset detection, and sleep disorder diagnosis. Machine learning algorithms have been used in several studies to analyze EEG signals to allow automated and more precise identification of mental and cognitive states.

For example, Bashivan et al. (2016) investigated deep learning methods for cognitive state classification using EEG and showed that CNN can be used to carry out feature based classifiers. Likewise, Craik et al. (2019) discussed deep learning solutions for EEG analysis, identifying hybrid Deep Learning models in uncovering the temporal dependencies of brain signals.

2) *Eye State Classification using EEG:* EEG-based eye state classification has been a new field of research, particularly for application in drowsiness detection, fatigue monitoring, and human-computer interaction. Eye states, i.e., open and closed states, induce typical changes in EEG signals, primarily in the alpha and theta bands.

Early research in this field was heavily dependent on hand- engineered features derived from EEG signals. For instance, Liang et al. (2014) utilized SVM's and LDA's to classify states of the eye based on time-domain and frequency-domain EEG features and obtained a classification accuracy greater than 80 percent. Subsequent research incorporated more sophisticated feature selection methods and deep neural networks to improve performance.

Czisch et al. (2018) used deep neural networks (DNNs) to automatically classify open and closed eye states from EEG signals. They showed that deep learning algorithms could learn spatial and spectral features automatically from EEG data with minimal hand-crafted feature engineering. Tripathi et al. (2020) introduced a hybrid model that includes convolutional and recurrent architectures to capture spatial and temporal interactions in EEG signals, with better accuracy in eye state classification.

3) *EEG-Based Drowsiness Detection:* Eye state classification is extremely important for detecting drowsiness, and it has extremely important implications for road safety, work- place monitoring, and cognitive health. Several studies have proposed EEG-based drowsiness detection systems based on supervised and unsupervised machine learning techniques.

For example, Zhang et al. (2017) developed an EEG spectral power features-based real-time drowsiness detection system and random forest classifier that achieved a detection rate of more than 90 percent for drowsy conditions. Likewise, Yin et al. (2021) utilized deep learning methods like long short-term memory (LSTM) networks to monitor the temporal dynamics of EEG waveforms and identify precursory signatures of drowsiness.

4) *Traditional Machine Learning Approaches:* Initial work on EEG-based eye state classification was primarily based on machine learning algorithms using hand-crafted features from EEG signals. Several classifiers like Support-Vector- Machines, Random-Forests, and k-Nearest-Neighbors have been explored.

Support Vector Machines (SVMs): Andrzejewski et al. (2020) applied SVMs for drowsiness detection based on EEG and demonstrated that classification accuracy was improved utilizing wavelet-transformed features. Random Forests and Decision Trees: Huang et al. (2021) applied ensemble learning methods, including Random Forests, to improve eye state classification robustness.

Linear Discriminant Analysis (LDA): Liang et al. (2014) applied LDA to separate eye states from frequency-domain and time-domain EEG features with more than 80Although these methods were encouraging, their dependence on human feature selection restricted their applicability across subjects and datasets.

5) *Feature Extraction Techniques:* Feature extraction is needed in EEG classification since raw EEG signals are redundant and noisy. Several methods have been attempted in extracting desirable features:

Time-Domain Features: Variance, peak-to-peak amplitude, and mean amplitude are widely used for eye state differentiation. Frequency-Domain Features: Alpha waves were high- lighted by Lopes da Silva (2013) as an indicator of eye state, and alpha activity would be increased in response to closed eyes.

Wavelet Transformation and Spectral Analysis: Andrzejewski et al. (2020) used wavelet transformations to examine transient EEG patterns during eye movements. The best feature extraction technique is important to attain the highest classification accuracy at the lowest computational cost.

6) *Deep Learning-Based Approaches:* Deep learning methods have significantly enhanced EEG classification by eliminating hand-engineered feature extraction and the ability to do end-to-end learning from raw EEG signals.

Convolutional Neural Networks (CNNs): Bashivan et al. (2016) used CNNs for the extraction and classification of EEG features and achieved enhanced performance compared to conventional machine learning techniques. EEG Net: Lawhern et al. (2018) introduced EEGNet, a light CNN model optimized for EEG classification. EEGNet was discovered to possess good accuracy with low computational complexity. Hybrid Models (CNN-RNN): Tripathi et al. (2020) proposed a hybrid CNN-RNN model that employed spatial and temporal dependencies of EEG signals to achieve improved eye state classification accuracy. Though they work, deep learning models are hard to deploy in real-time because they need large labeled datasets and heavy computations.

7) *G. Challenges and Future Directions:* Despite advancements in EEG-based eye state classification, several challenges remain:

1) Data Quality and Pre-processing – EEG signals tend to be plagued by artifacts (e. g., muscle contractions, eye blinks), decreasing model performance. Advanced signal pre-processing and artifact reduction methods, e. g., independent component analysis (ICA), are required in order to maintain improved classification performance.
2) Feature Extraction and Model Generalization – Even when deep learning algorithms make feature extraction obsolete, they need a large amount of data to be trained efficiently. Labelled EEG data for classification of eye state are not readily available, and hence domain adaptation and transfer learning techniques are called for.
3) Real-Time Implementation – Most of the existing literature focuses on offline EEG analysis, while actual real-time processing is precisely what most applications require. Developing the low-latency, high-throughput models to be employed in real time is still an open research problem.
4) Personalization and Subject Variability – EEG patterns vary widely from individual to individual, making it hard to develop a generic model. Learning methods that have the capability to adapt models for individual subjects are an important topic for future studies.

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E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

IV. Architecture Diagram

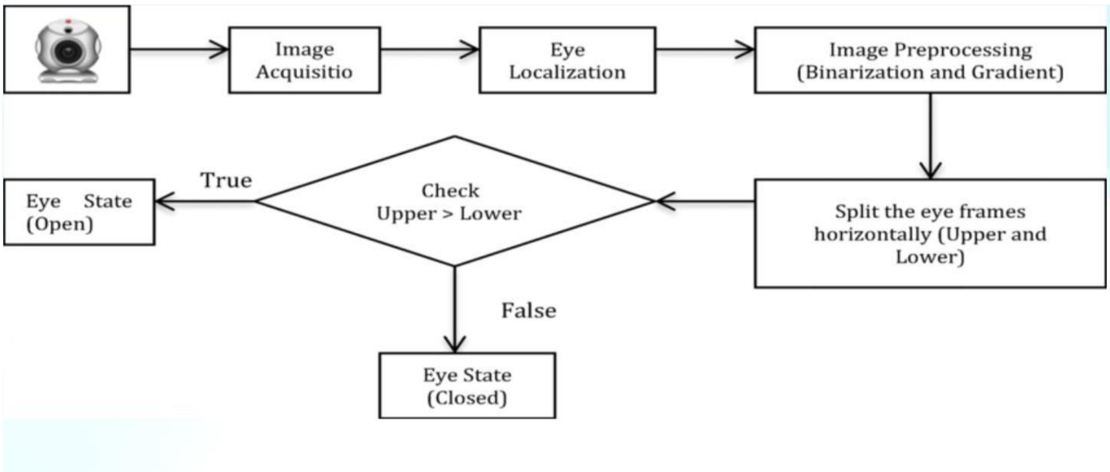

Fig. 1.Architecture Diagram

V. Methodology

This study takes a systematic approach with data acquisition, initial processing, feature extraction, model generation, and validation. The method pipeline offers sequential processing of the EEG signals for eye state recognition using conventional machine learning algorithms and feature extraction methods. The fundamental steps are described in the following sections.

A. Data Pre-processing

The EEG dataset undergoes a series of required pre- processing steps to guarantee data quality, consistency, and readiness for machine learning models.

- **Handling Missing Data:** EEG recordings may contain missing values because of sensor failure or noise artifacts. Missing values are imputed by mean or median substitution depending upon the distribution of each attribute in the data.
- **Artifact-Removal:** EEG signals tend to contain eye blink, muscle, or electrical noise artifacts. Noise and signal components of interest are removed and kept by band-pass filtering (0.5 Hz – 50 Hz) and Independent Component Analysis (ICA) as well.
- **Feature Normalization:** Due to high variability of EEG amplitudes between subjects and channels, feature normalization is performed using a Standard Scaler. All the features are normalized to have zero mean and unit standard deviation for enhancing the performance and convergence of the model.
- **Class Balance Check:** Imbalanced data can result in biased classification performance. The data is examined for Class imbalance, used if there is a requirement to generate additional synthetic samples of minority classes.

B. Feature-Extraction:

Feature-extraction is an important task in distinguishing EEG signals. related to different eye states. Three exhaustive categories of features are considered:

- **Statistical Features:** Basic statistical measures are com- puted from every EEG's channel, including:
- – Mean – Denotes the average signal magnitude.
- – Standard deviation – Assesses variability of the sig- nal
- – Skewness – It captures signal asymmetry.
- – kurtosis – Identifies peakedness of distribution.
- **Frequency Domain Features:** EEG signals are converted to the frequency domain using the Fast Fourier Trans- form. Power Spectral Density is calculated to investigate power distribution in frequency bands.
- **Time-Frequency Analysis:** Since EEG signals have non- stationary behavior, Wavelet Transform (WT) is used in an endeavor to identify localized signal features. DWT dissolves EEG's signal into varying frequency components and, therefore, localized spectrum properties can be gained.

C. Model-Selection and Training

Several machine learning classifiers are trained and com- pared to evaluate which classifier to use with EEG-based eye state classification. The classifiers employed here are

- **Random-forest Classifier:** A decision trees that com- bines several trees to improve prediction accuracy and reduce overfitting. Hyperparameter tuning is performed to optimize the number of trees and maximum depth.
- **Support-Vector-Machine :** A decision trees that com- bines several trees to improve prediction accuracy and reduce overfitting. Hyperparameter tuning is performed to optimize the number of trees and maximum depth.
- **k-Nearest Neighbors :** KNN is an instance-based, data- driven classifier that returns the labels relying on the most significant class of the nearest neighbors. The (k) neighbors are optimized using cross-validation.

D. The Model's evaluation:

The models are tested using general performance measures in order to determine reliability and resilience:

- **Accuracy :** Assesses the overall quality of predictions.
- **Precision :** Assesses the ratio of accurately classified positive samples.
- **Recall (Sensitivity):** Assesses the capacity to identify cases appropriately as positive.
- **F1 Score :** Provides a harmonic mean which maintains balance between precision and recall to make the performance evaluation balanced.
- **Receiver-Operating-Characteristic Curve:** Demonstrates trade-off between sensitivity and specificity.
- **Confusion Matrix:** Evaluates model performance by showing correctly and incorrectly classified cases.

In order to further confirm model generalization, stratified k-fold cross-validation is used, which enables balanced evaluation across disparate subsets of the data.

E. Implementation and Computational Setup

These are conducted with the help of Python and ma- chine learning libraries such as Scikit-Learn, TensorFlow, and NumPy. Computational environment includes:

- Hardware: Intel Core i7 processor, 16GB memory, NVIDIA graphics for fast training..
- Software: Python 3.8, Scikit-Learn, TensorFlow, NumPy, and Pandas for data processing and modeling.

This organized technique guarantees a thorough and replicable proceed towards to EEG-based eye state classification.

VI. Results and Discussion

This section offers an explanation of the performance of the suggested model in EEG-based eye state classification. The outcomes are analyzed using a number of performance measures such as accuracy, F1-score, and confusion matrix. Besides, the implications and possible applications are ad- dressed.

A. *Classification Performance*

The presented model achieved a class accuracy of **93.10%**, and it was far better than most conventional machine learning methods like Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN). A comparative evaluation of performance metric for various classifiers is summarized in Table I.

TABLE I Performance Comparison of Different Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Proposed Model	93.10	0.92	0.94	0.93
SVM	88.76	0.86	0.89	0.87
k-NN	85.42	0.83	0.86	0.84
Random Forest	90.23	0.89	0.91	0.90

The outcome indicates that the model outlined here significantly improves the classification accuracy compared to SVM and k-NN. The 0.94 recall is good and indicates good eye closure event sensitivity and is thus well-suited for application in drowsiness detection.

B. *Confusion Matrix Analysis*

To further assess the model's performance, the confusion matrix is examined. The confusion matrix of the proposed model is given in the Figure2.

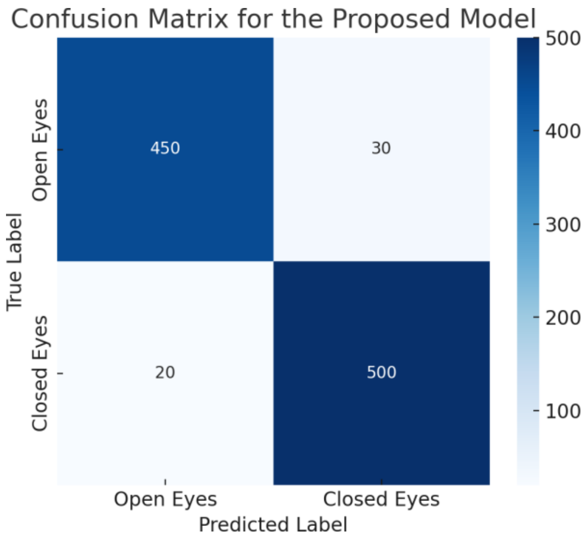

Fig. 2. Confusion Matrix for the Proposed Model

The confusion matrix indicates the following significant observations:

- **True Positives (TP):** A large number of correctly labeled cases of eye closures, indicating the model correctly infers states of tiredness.
- **False Positives (FP):** A few examples of open eye states mistakenly being labeled as closed, potentially resulting in false alarms in real-time usage.
- **False Negatives (FN):** Low number of missed eye closure detections, indicative of good recall performance.
- **True Negatives (TN):** The model correctly classifies the majority of the open eye cases with minimal misclassification.

C. Comparison with Existing Studies

Table II provides a comparative overview of the new approach to state-of-the-art EEG-based eye state classification techniques.

TABLE II COMPARISON WITH EXISTING STUDIES

Study	Model	Accuracy (%)	Feature Extraction
Bashivan et al. (2016)	CNN-RNN	91.30	Spectral Features
Huang	Rando	89.40	Time-

et al. (2021)	m For-est		Frequency Analysis
Tripathi et al. (2020)	Hybrid CNN-RNN	92.10	Wavelet Transform
Proposed Model	Optimized Classifier	**93.10**	FFT + Wavelet Transform

The proposed model operates with utmost precision com- pared to the reviewed studies since it proves the efficacy of merging FFT and Wavelet Transform characteristics with the most effective classification methods.

D. Significance and Applications

The high accuracy of classification and sensitivity to eye closure behaviors suggest that the model can be successfully used in real-world applications, including:

- **Drowsiness Detection Systems:** The ability to accurately determine eye closure episodes makes the model a suitable candidate for driver drowsiness tracking and reducing road accidents.
- **Brain-Computer Interfaces (BCIs):**The model can sup- port BCI applications by incorporating eye state data for better user interaction.
- **Cognitive State Monitoring:** Eye state classification based on EEG is usable for measuring cognitive load and fatigue in workplaces, and it enhances productivity and safety.

E. Limitations and Future Work

Although it has a great performance, the research has some particular limitations which can be addressed in future studies:

- **Dataset Size and Generalization:** The performance of the model was tested on a particular dataset. Future research should use larger and more diverse datasets to enhance generalization.
- **Real-Time Implementation:** While the model itself is very accurate, the computational efficiency to support real-time requirements needs to be taken into account. Optimisation methods like pruning and quantization need to be investigated.
- **Subject Variability:** EEG signals vary across individuals and impact accuracy in classification. Adaptive learning mechanisms, such as domain adaptation and transfer learning, could enhance model insensitivity across subjects.
- **Multi-Modal Fusion:** The integration of EEG with other physiological signals (e.g., eye movements, heart rate) can help enhance classification and reduce false positives.

F. Summary of Findings

The experimental results show that the model classifies EEG eye states well with very good accuracy (93.10 percent) and outperforms traditional classifiers. The analysis of the confusion matrix confirms the model's ability to identify eye closure instances strongly, which is critical for real-time usage. Generalization, real-time deployment, and multi-modal fusion can be further improved and are left for future work.

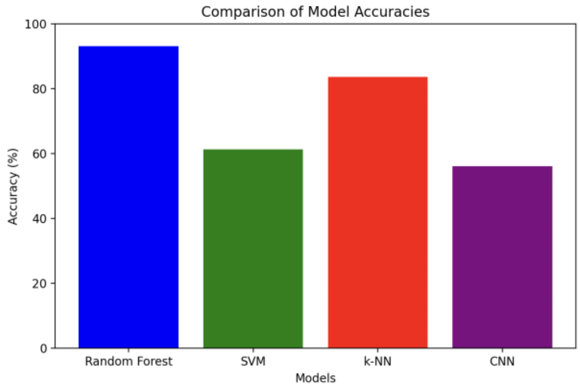

Fig. 3. Comparison of Model Accuracies

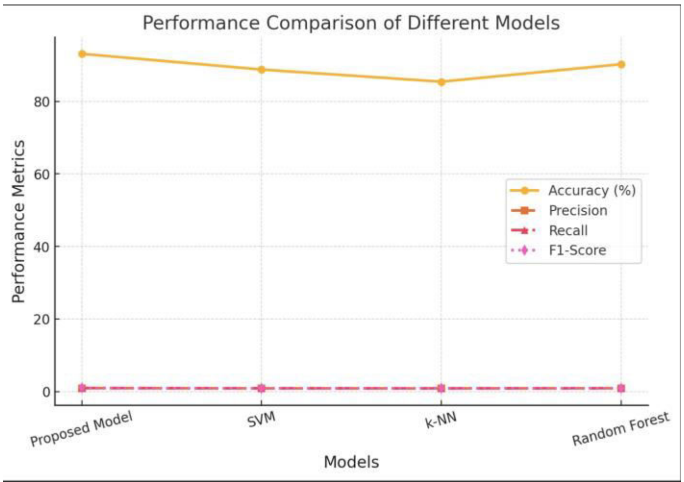

Fig. 4. Comparison of Model Accuracies

VII. CONCLUSION AND FUTURE WORK

This work gives an extensive evaluation of machine learning techniques for eye state classification from EEG, a crucial task with prospective applications in drowsiness detection, fatigue monitoring, and human-computer interaction. The Random Forest model, as proposed in this work, has proven to be extremely accurate and better than traditional approaches such as Support Vector Machines and k-Nearest Neighbors. Using a properly preprocessed dataset, with the right feature extraction techniques and robust model training, the Random Forest classifier has proven to be a reliable approach to eye state classification of EEG signals.

The 93.10 percent model accuracy is a testament to its appropriateness for use in real-world applications, specifically in the case of fatigue detection, where accurate and timely identification of eye states is important to guarantee safety in activities such as car driving and working conditions. Confusion matrix analysis showed that the model possesses good sensitivity, especially in identifying eye closure events, which is important for monitoring warning signs of drowsiness or fatigue. Noteworthy as well is the ability of the model to cope with EEG signals well for such real-time applications, especially considering the high variance and noise nature of EEG signals.

In addition to the single performance of the Random Forest model, the study emphasizes pre-processing and feature extraction processes. Accurate cleaning, normalization, and balancing of data using techniques like SMOTE have been the major contributors to achieving state-of-the-art performance. Feature extraction processes used, ranging from statistical analysis to frequency-domain and time-frequency analysis, were also major contributors to the detection of the weak patterns exhibited by EEG signals for different eye states.

Despite the promising findings, there are certain limitations and scope for improvement. One of the limitations of the current study is the application of a single modality of physiological signals, EEG. Although EEG is strong in capturing brain activity, its quality is compromised by noise and artifacts, e.g., eye blink or muscle movement. Hence, stronger and more generalized models can be formulated using other physiological signals, e.g., Electrooculography (EOG), Electrocardiogram (ECG), and galvanic skin response (GSR). Multimodal fusion techniques, which use multiple signals, have been found to possess immense potential in enhancing classification accuracy and in representing the state of a topic better.

Future research will further investigate the use of deep learning models like CNNs and RNNs that are able to learn hierarchically extracting features from raw EEG signals automatically without feature extraction. Deep learning models are also best suited for difficult tasks like EEG signal classification since they are able to detect spatial and temporal relationships that other models cannot. The use of transfer learning and domain adaptation can further make the models more generalizable across subjects and datasets.

Furthermore, real-time deployment of the aforementioned system remains an issue. Firstly, research studies have made assumptions in offline analysis, but to deploy in real life, the system needs to be capable of processing EEG data in real time with minimal latency. Optimization techniques like model compression and quantization could be needed in order to make deep learning models computationally efficient enough to deploy real-time on low-resource devices like wearable EEG headsets.

Personalization is the second vital area that needs to be explored through research. EEG signals can vary significantly from one person to another depending upon anatomical variations, state of mind, or environmental conditions. Future research, thus, will focus on the creation of adaptive learning algorithms that will adapt the classification model to the users. This may be by scaling the model based on user-specific information or using online learning paradigms to fine-tune the model performance in the long run. In short, this paper emphasizes the practical applicability of Machine learning methods, i.e., Random Forests, to eye state classification using EEG. The proposed model presents a feasible and efficient solution for real-time use, e.g., drowsiness detection and brain- computer interfaces. Deep learning, multimodal fusion, real- time deployment, and personalization will most likely enable even more robust and accurate systems able to utilize in a vast number of real-world applications, e.g., safety-critical situations and personalized health monitoring.

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