# Integrating EEG Signals and Machine Learning for Effective Driver Drowsiness Detection

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***Abstract-*** Road safety requires driver drowsiness detection to prevent fatigue-related accidents. This study integrates EEG signals with facial landmarks to detect tiredness. The collection includes EEG data from drivers using Neuro-Sky mind wave headsets and image-processed facial landmarks. Preprocessing EEG signals and facial photos, extracting pertinent features, and then classifying with machine learning and deep learning models is the method. The dataset is analyzed using CNNs, LSTMs, XG-Boost, and Random Forest. EEG signal temporal dynamics and hybrid models to increase accuracy by mixing spatial and temporal information are studied.

Models like XG-Boost (79.99%) and LSTM (71.62%) show promising accuracy. Using multimodal data, the hybrid model with EEG and face landmarks outperforms solo systems. The study needs a larger dataset with more driving conditions and individual variances. The next steps include dataset enlargement, temporal dynamics investigation, hybrid model refining, and real-time implementation. For improved interpretability and proactive action, explainability and continuous monitoring should be integrated. This study shows how EEG signals and facial landmarks can detect driver tiredness. The findings emphasize the importance of multimodal techniques in enhancing accuracy and the need for continued research to solve problems and develop models for real-world applications. This work advances the development of robust and efficient sleepiness detection systems, improving road safety.

***Index Terms****- Driver drowsiness, Automobile accidents, sleep detection systems, Road safety.*

## I. INTRODUCTION

To increase road safety, the primary objective of this research was to develop a program that uses machine learning techniques to identify whether cab drivers are tired. Most taxi accidents worldwide are caused by tired drivers who pose a serious risk to other people and themselves during working hours. By utilizing machine learning techniques, we were able to create a system that could effectively determine whether a driver was experiencing sleepiness by analyzing facial expression data recorded at four different times: when their eyes were open, closed, yawning, and not yawning [1]. The ability to reliably predict when a motorist might feel sleepy was then tested and trained using this data. To assist prevent accidents brought on by sleepy driving; the models were then put through testing to ensure the highest accuracy and reliability.

Image processing technology for detecting driver drowsiness analyses the driver's face and eye movements to determine if the driver is experiencing symptoms of drowsiness. The system employs a camera to record the driver's expressions and track his or her eye, mouth, and head motions. The system can identify drowsiness or indications of fatigue in the driver by analyzing their facial characteristics. Algorithms in this technology can tell if a driver's eyes are closed for a long time if their head is tilted, or if they have their mouth agape [2]. If the system detects any of these symptoms, it will issue a warning to the motorist, urging them to rest or pull over.

The technology employs machine learning techniques to identify drowsy facial expressions and body language. Algorithms learn to recognize signs of drowsiness by being exposed to a big dataset of images of drivers in various states of alertness. Detecting driver drowsiness with image processing technology could greatly cut down on mishaps brought on by tired drivers [3]. The device can save lives by alerting drivers when they start to nod off behind the wheel.

The issue of detecting driver fatigue has been investigated by numerous researchers across the globe. Based mostly on the sleepiness-indicating traits employed, the suggested techniques to address the issue can be distinguished from one another. Biological characteristics, which are indicators of driver tiredness derived from measurements of bodily signs, are uncomfortable for the driver because they need the use of sensors that are affixed to their bodies, even though they are accurate in identifying drowsiness. Other often-used indicators of driver tiredness are based on how the vehicle is driven, and measurements like steering wheel angle and frequency of lane departures are connected to the levels of driver drowsiness [4]. Despite being driver-friendly, the literature indicates that this method's accuracy is not very good. The final set of suggestive indicators for drowsiness is based on images. Typically, they are gathered via films that track the driver's actions, allowing for the extraction of characteristics like the driver's head, mouth, and eye movements. Since they don't require the driver to have any equipment or sensors attached to their body, they are more practical for drivers than biologically based ones [5].

Driver drowsiness is a critical issue that poses a significant threat to road safety, contributing to a substantial number of accidents worldwide. The consequences of drowsy driving are severe, leading to impaired reaction times, compromised decision-making, and an increased risk of collisions. Recognizing the pivotal role of alertness in safe driving, there is a growing interest in developing advanced systems capable of detecting driver drowsiness in real-time. This research addresses the challenge of driver drowsiness detection through the innovative integration of neuroscience and machine learning techniques. By leveraging EEG signal data obtained from drivers in both wakeful and drowsy states, we aim to construct a robust and reliable model that can accurately discern the physiological indicators of drowsiness. The methodology involves the careful collection of EEG data using the Neuro-Sky mind-wave headset, emphasizing safety and ethical considerations [6].

## II. LITERATURE REVIEW

Procedures for personal recognition employ a broad variety of stimulants that come from most, if not all, senses, such as touch, sound, and so forth. Conditions and contextual data, for instance, are largely utilized to be crucial in facial recognition for navigation purposes. Attempting to enhance the system using existing technology is pointless since it will replicate the distinct face's capacity for identification. It can only "remember" a certain amount of people, though, because it is a brain. A computer program's main advantage is its capacity to handle a lot of face picture processing. Typically, photo applications have only been available as one or more views of two-dimensional data, meaning that the only input available to a face recognition algorithm is visual.

In humans, drowsiness is characterized as being close to sleep or in a dormant state. It indicates that they either need to sleep or are unable to stay up. Another common cause of drowsiness is fatigue, which is characterized as a physically exhausted state that leaves one feeling both physically and mentally exhausted. Physical weariness is the root cause of both drowsiness and fatigue. The degree of fatigue could also serve as a gauge for awareness or observation. Being awake is the lack of tiredness, and being observant is the state of having a laser-like focus on something [7].

The highest percentage of traffic accidents are caused by drivers who are distracted. Of the various causes of driver distraction, fatigue-induced drowsiness is the most likely culprit. Research has been conducted using behavioral, biological, and automotive methods to identify sleepiness. Numerous systems that make use of computer vision, machine learning, bio-signaling technologies, and vehicle components have been offered as solutions [8]. The most widely utilized methods for identifying driver drowsiness are image-based technologies. A person's eyes, lips, and head are among the facial features that can be utilized to identify a variety of visual behaviors that are indicative of weariness. Visual sensors or cameras can capture such sleepy actions. After several features are collected from these data, they are examined using "computer vision techniques to visually watch the driver's physical condition to non-invasively detect drowsiness." Generally speaking, there are three types of image-based systems based on how the eyes, mouth, and head motions are observed. Numerous elements based on images have been employed in the literature. These include head movement analysis, "mouth opening time, head position, head-nodding frequency, blink frequency, maximum duration of eye closure," percentage of eyelid closure, and the curvature of the eyelids. Additionally, consideration has been given to these qualities' combinations [9].

### *A. Advanced machine learning and hybrid approaches for drowsiness detection*

A face-monitoring sleepiness-detection system was reported by Moujahid et al. [4] that used a manually created compact face texture descriptor to identify the most salient signs of drowsiness. Three indicators of tiredness were initially noted: blinking rate, frequency of yawning, and head nodding. Subsequently, they utilized feature selection and pyramid multi-level face representation to get compactness. Finally, they used a non-linear SVM classifier, which produced 79.84% accuracy.

Four deep learning models were utilized in the "driver drowsiness-detection" architecture presented by Dua et al. [1] "Res-Net, Alex-Net, Flow-Image-Net, and VGG-Face-Net." The driver's film elements, "such as head, hand, and behavioral features, as well as facial expressions, are used to extract these models. The four deep learning algorithms were fed recordings of simulated driving." Four model outputs were input into an ensemble algorithm that simply averaged them, and then the outputs were fed into a SoftMax classifier, producing an overall accuracy of 85% [10].

Vesselenyi et al. (2017) investigated the potential for creating a drowsiness detection system for automobile drivers using three techniques: driver image analysis, EEG, and EOG signal processing. When both networks were applied to the acquired images, the findings showed that both networks performed exceptionally well, with 100% accurate classification. Additionally, they concluded that processing time on a Windows-based computer is in milliseconds, which can be further decreased on a small device [11].

### *B. Advancements in facial landmark detection, deep learning models, and hybrid systems.*

To increase detection accuracy, Zhu et al. [12]. Research suggests a real-time, comprehensive driver fatigue detection method based on facial landmarks. This system uses facial video sequences to determine the driver's state of exhaustion without requiring them to wear other intelligent devices on their body. This solves the optimization difficulty brought on by the varying convergence speeds of each job. The eye features of the "mouth aspect ratio (MAR), eye aspect ratio (EAR), and percentage of eye closure time (PERCLOS) are computed based on facial landmarks," according to the real-time facial video images. Using eye/mouth feature selection, a thorough driver tiredness assessment model is developed to evaluate the state of driver fatigue. Following a series of comparative tests, the findings indicate that the suggested algorithm performs well for driver fatigue identification in terms of accuracy and speed.

## III. RESEARCH METHODOLOGY

The research methodology employed in this study combined neuroscience principles with machine learning techniques to develop an effective driver drowsiness detection system. The overarching goal had been to leverage EEG signals collected from drivers to create a model capable of accurately distinguishing between wakeful and drowsy states. The step-by-step approach encompassed data collection, pre-processing, model development, and performance evaluation.

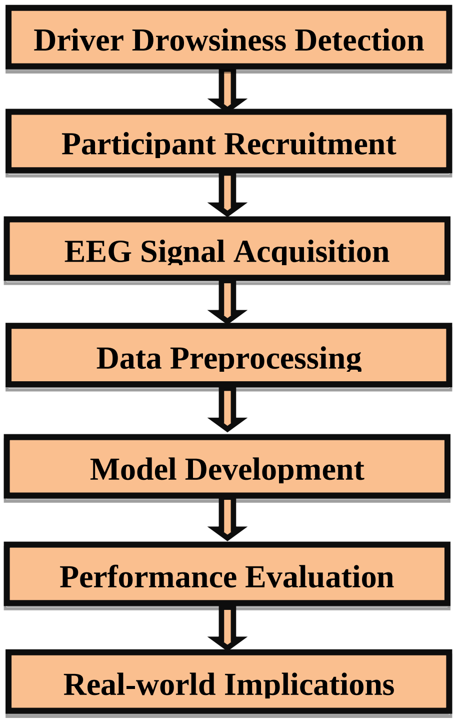


**Figure 1:** Research methodology

### *A. Participant Recruitment*

Participants were recruited from a diverse pool to ensure a representative dataset. Besides that, informed consent was obtained, with an explanation of the purpose and procedures of the study. In addition to that emphasis was placed on safety by instructing participants not to engage in actual driving during data acquisition.

### *B. EEG Signal Acquisition*

The Neuro-Sky mind wave headset, a single-channel EEG device, was used to capture signals. Electrodes were placed on the frontal lobe and earlobes to measure voltage differentials. Participants were instructed to simulate both wakeful and drowsy states during data collection.

### *C. Data Preprocessing*

Raw EEG signal data, including attention, meditation, delta, theta, low Alpha, high-alpha, low-beta, high-Beta, low-gamma, and high-gamma, was extracted. Necessary signal preprocessing, such as noise removal or filtering, was conducted to enhance data quality. The dataset was divided into training and testing sets for model development and evaluation.

### *D. Model Development*

Various machine learning models, including XG-Boost, LSTM, and ResNet-50, were utilized to analyze EEG signals. Besides that, the models were trained on the training dataset, considering features derived from EEG data. Furthermore, hyperparameters were fine-tuned, and model architectures were optimized for enhanced performance.

### *E. Performance Evaluation*

The models were evaluated on the testing dataset to assess their accuracy, precision, recall, and F1 score. In addition to that, confusion matrices were used to visualize true positive, true negative, false positive, and false negative predictions. Receiver operating characteristic (ROC) curves were explored to analyze model sensitivity and specificity.

### *F. Real-world Implications*

The real world and potential applications of the developed model in intelligent transportation systems were discussed. Consideration was given to how the model could be integrated into vehicles or existing driver assistance systems. Moreover, a reflection was made on the broader implications for road safety and accident prevention. The model was compared with existing models and the performance of the developed model was compared with existing driver monitoring systems. Besides that, an evaluation was made of the sensitivity of the model to early signs of drowsiness compared to conventional external-based systems. By meticulously following this methodology, the study aimed to contribute to a comprehensive understanding of driver drowsiness detection, offering a novel approach that combined neural signals with advanced machine learning techniques for improved road safety.

## IV. RESULTS AND DISCUSSION

Detecting impairments of a driver's operating state is a critical safety topic that has been investigated extensively. While newer automotive models have some of these detection capabilities, it is clear that recent technological developments need to be improved to address the safety issue in modern vehicles. A driver's head, eye positions, and facial characteristics and expressions alter when they are sleepy. The majority of research on the consequences of weariness and drowsiness has concentrated on the dynamic alterations in eye movements that occur when a person experiences these states. This study used an image-processing technique to assess the degree of tiredness among drivers. This method is more accurate in detecting the degree of drowsiness than previous methods.

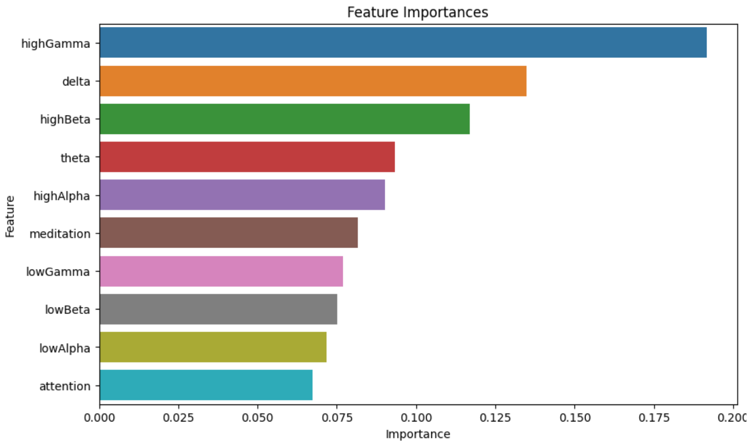


**Figure 2:** Features Importances

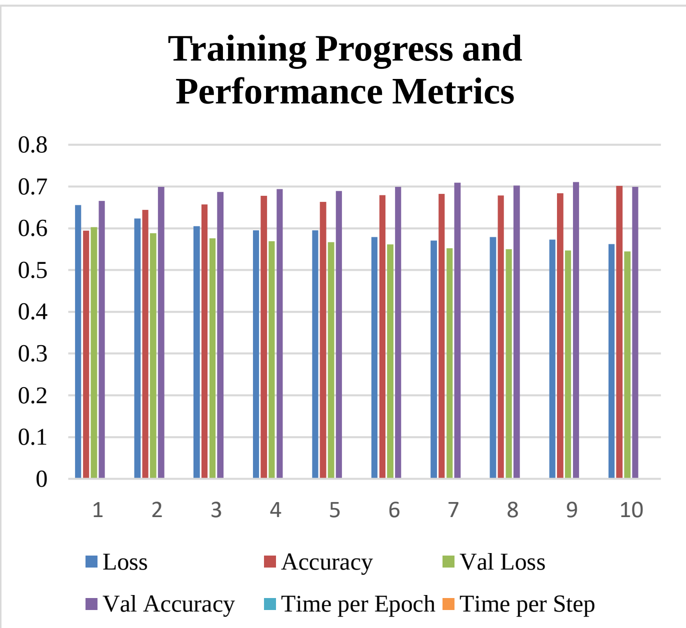


**Figure 3:** Training Progress and Performance Metrics

You can see metrics like loss, accuracy, validation loss, and validation accuracy in the above table, which shows the training progress of a neural network model over 10 epochs. It also shows time metrics per epoch and each step. At first, the model's performance is subpar, with modest accuracies and somewhat substantial losses. Losses and accuracies go down while training goes on, which means the model is improving at making predictions. Importantly, validation measures also show an upward trend, suggesting that the model is getting better at generalizing to new data. Time data for each epoch and step also shed light on how efficiently the training process uses computer resources; in general, training progresses with decreasing times, suggesting optimization opportunities. Taken as a whole, the table shows how model training is iterative, with each iteration bringing better performance and more efficient use of computing resources.

The training process of the neural network for driver drowsiness detection was conducted over 10 epochs, with periodic evaluations on the validation set. The model's performance metrics, including loss and accuracy, were monitored throughout the training process. The results provide insights into the convergence and efficacy of the neural network.

### *A. The Neural Network Model*

The neural network model achieved an accuracy of approximately 71.8% in detecting driver drowsiness. This performance metric indicates the proportion of correctly classified instances out of the total dataset. While the model's accuracy demonstrates a moderate level of success, it is crucial to consider other evaluation metrics and potential areas for improvement [13]. Further analysis, including precision, recall, and F1-score, can provide a more comprehensive understanding of the model's performance. Besides that, precision measures the accuracy of positive predictions, indicating how many instances predicted as positive are truly positive. Recall, on the other hand, assesses the model's ability to capture all positive instances, revealing the proportion of actual positives correctly identified. The F1 score combines precision and recall, offering a balanced metric that considers both false positives and false negatives.

In addition to that to gain a deeper insight into the model's effectiveness, a confusion matrix can be analyzed. This matrix breaks down the true positive, true negative, false positive, and false negative classifications, providing a detailed overview of the model's strengths and weaknesses. Despite achieving a notable accuracy level, evaluating the model's performance across different classes is crucial, considering potential imbalances in the dataset. Additionally, fine-tuning the model parameters, exploring alternative architectures, or incorporating additional features may lead to further improvements [14]. While the neural network demonstrates a reasonable level of accuracy in driver drowsiness detection, a more comprehensive evaluation using various metrics will provide a nuanced understanding of its capabilities. Continuous refinement and exploration of advanced techniques could enhance the model's accuracy and reliability for real-world applications.

### *B. Validation Accuracy*

The final accuracy achieved on the validation set was approximately 69.90%. This metric serves as a key indicator of the model's generalization performance on unseen data. The validation accuracy, along with other evaluation metrics, provides a comprehensive understanding of the model's effectiveness in detecting driver drowsiness.

### *C. Model Evaluation*

After training, the neural network had 71.75% accuracy on an independent test set. The model's accuracy statistic measures its ability to anticipate fresh data.
Driver sleepiness detection accuracy of 71.75% is satisfactory. Fine-tuning, hyperparameter tweaks, and more advanced neural network topologies may improve model accuracy. The

training and evaluation results guide iterative improvements and suggest future neural network optimisation research for real-world driving safety applications..

***The XG-Boost algorithm***

The XG-Boost algorithm was employed for driver drowsiness detection, and the model's accuracy was assessed on both a standard evaluation set and through cross-validation.

***a. Accuracy of XG-Boost***

The XG-Boost model achieved an accuracy of approximately 79.92% on the standard evaluation set. This metric reflects the proportion of correctly classified instances among the total instances in the dataset. An accuracy of 79.92% suggests a strong performance in distinguishing between drowsy and awake states in drivers based on the provided features.

***b. Cross-validated Accuracy***

Model generalisation testing is reliable with cross-validation. Cross-validated accuracy of 76.41% reveals that the XG-Boost model is accurate across dataset subsets. The metric lowers concerns about overfitting to specific data patterns in one training-validation split. XG-Boost's good standard accuracy and steady cross-validated accuracy show it captures data patterns and generalises well to new cases. These findings assess driver sleepiness detection machine-learning methods. The model's performance can be assessed using precision, recall, and F1 scores. The Voting Classifier classification report details the model's performance across metrics.

Class 0 (awake) precision is 0.82. This means 82% of awake predictions are right. Additionally, class 1 (drowsiness) precision is 0.75. This suggests 75% of drowsy predictions are true.

***c. Recall***

The recall status was as follows, class 0 has a recall of 0.82, indicating that the model correctly identifies 82% of all awake instances. Class 1 has a recall of 0.74, indicating that the model captures 74% of all drowsy instances.

***d. F1-Score***

The F1-score, which balances precision and recall, is 0.82 for class 0 and 0.75 for class 1. Moreover, the combined and overall, accuracy of the model is 0.79, reflecting the proportion of correctly classified instances among the total instances in the dataset.

***e. Macro Avg***

The macro average for precision, recall, and F1-score is 0.78. This metric calculates the average across classes without considering class imbalances.

***f. Weighted Avg***

The weighted average for precision, recall, and F1-score is 0.79. This metric accounts for class imbalances by considering the number of instances in each class.

**Table 1:** Table of accuracy

| Metric | Class 0 (Awake) | Class 1 (Drowsy) | Overall/Weighted |
|---|---|---|---|
| Precision | 0.82 | 0.75 | 0.79 |
| Recall | 0.82 | 0.74 | - |
| F1-Score | 0.82 | 0.75 | - |
| Accuracy | 79 | 79 | 0.79 |
| Macro Avg | 0.82 | 0.74 | 0.78 |
| Weighted Avg | 0.79 | 0.79 | 0.79 |

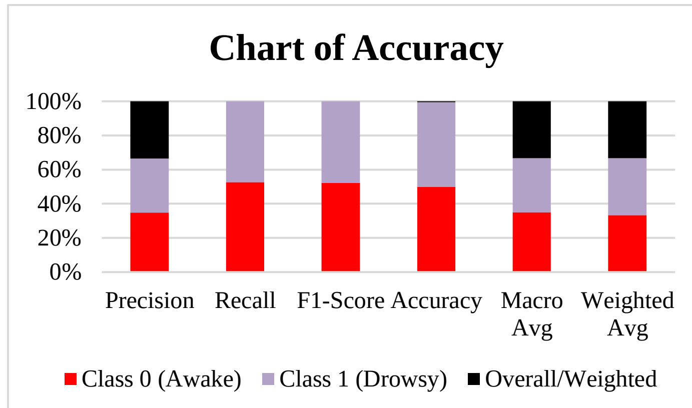


**Figure 4:** Accuracy Chart

The weighted averages take into account the class imbalances in the dataset. The Voting Classifier shows a balanced performance with reasonable accuracy in distinguishing between awake and drowsy states. In summary, the Voting Classifier demonstrates a balanced performance in distinguishing between awake and drowsy states. Further analysis and comparison with other models can provide additional insights into the model's effectiveness for driver drowsiness detection.

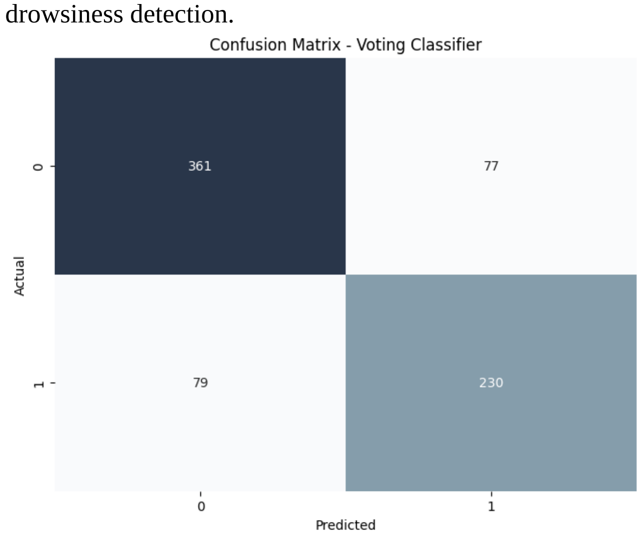


**Figure 5:** Confusion matrix

The Voting Classifier demonstrates a balanced performance in distinguishing between awake and drowsy states.

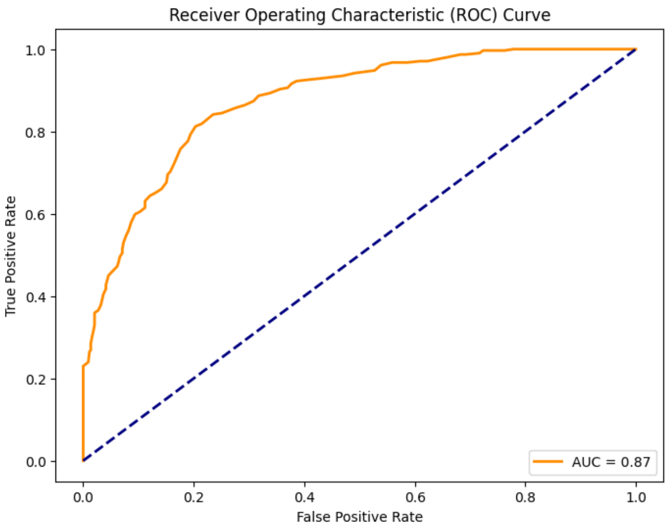


**Figure 6:** Roc curve for neural network

In addition to that, confusion matrices were used to visualize true positive, true negative, false positive, and false negative predictions. Receiver operating characteristic (ROC) curves were explored to analyze model sensitivity and specificity.

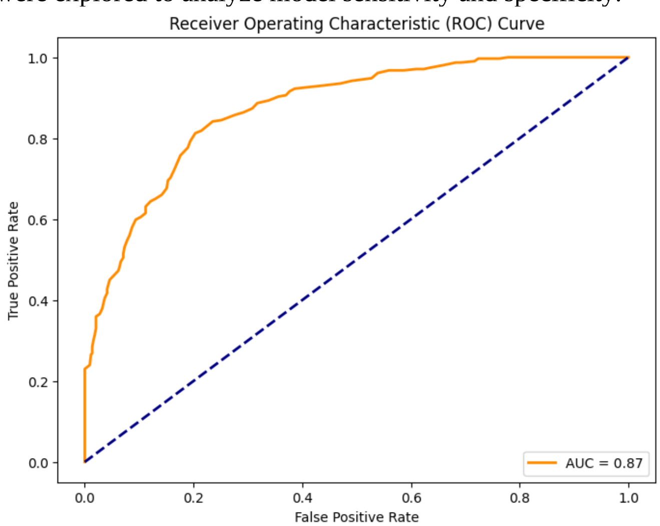


**Figure 7:** Roc for Random Forest

***Random Forest classifier and confusion matrix***

The provided classification report presents the evaluation metrics for a Random Forest Classifier applied to a dataset. Let's break down each metric to understand the performance of the model.

***a. Precision***

Precision is a measure of the accuracy of positive predictions. For class 0 (representing a specific condition or event), the precision is 0.80. This indicates that when the model predicts class 0, it is correct 80% of the time. For class 1, the precision is 0.76, suggesting that the model is accurate in predicting class 1 about 76% of the time.

***b. Recall-Sensitivity***

Recall measures the model's ability to capture all positive instances. In addition to that, for class 0, the recall is 0.84, indicating that the model successfully captures 84% of the actual instances of class 0. While class 1 has a recall of 0.70, meaning the model captures 70% of the instances of class 1.

***c. F1-Score***

The F1-score is the harmonic mean of precision and recall and provides a balanced measure. The F1-score for class 0 is 0.82, representing a balance between precision and recall for class 0. Class 1 has an F1 score of 0.73, indicating a trade-off between precision and recall for class 1.

***d. Accuracy***

Accuracy measures the overall correctness of the model across all classes. The overall accuracy of the Random Forest Classifier is 0.78, indicating that the model correctly predicts the class for 78% of the instances.

***e. Macro Avg and Weighted Avg***

The macro average provides the average of metrics across all classes without considering class imbalance. Weighted average considers the number of instances for each class, giving more weight to the class with more instances. In summary, the classification report offers a comprehensive view of the Random Forest Classifier's performance, considering precision, recall, F1-score, and support for each class. These metrics enable a nuanced understanding of how well the model is performing on different aspects of classification.

One of the most common causes of car crashes all over the globe is dozing off at the wheel. Nearly 20% of vehicular mishaps on the roads are attributed to drivers falling asleep at the wheel, according to some studies. One method that has been suggested and developed to help avoid these mishaps is the use of image processing to identify drowsy drivers. To detect signs of fatigue in drivers and prompt them to take a break, this method analyses facial characteristics.

For instance, eyes are trained to detect micro-sleeps in the method [15] that uses a color video camera positioned immediately in front of the driver. In this study, we introduced a system that measures blinking, including its frequency and features, in addition to microsleeps.

Predicting the extent of driving impairments and the date they will occur are key research topics that need more advanced processing of customer data from many sources. The purpose of this research was to see if the timing of the occurrence of a specific sleepiness condition could be projected by utilizing the Arima model. In general, our findings imply that using an ANN trained with the same data used to identify tiredness, we can forecast when a motorist's handicap would manifest with an accuracy of about 5 minutes [16]. To increase progress accuracy, independent data such as commuting time or a driver's profile might be included in the display. In his study, Larue (2010) predicted a driver's lessened cautiousness as early as five minutes and up to ten minutes ahead of time with 70% to 80% accuracy. Our display is more exact in various scenarios and with different sorts of data. In our worst-case scenario, the show can estimate when impairment will emerge to 95% of the test dataset within 13.11 minutes [17]. In our best case, the display can accurately estimate conductance for 95% of the test dataset within 1.97 minutes.

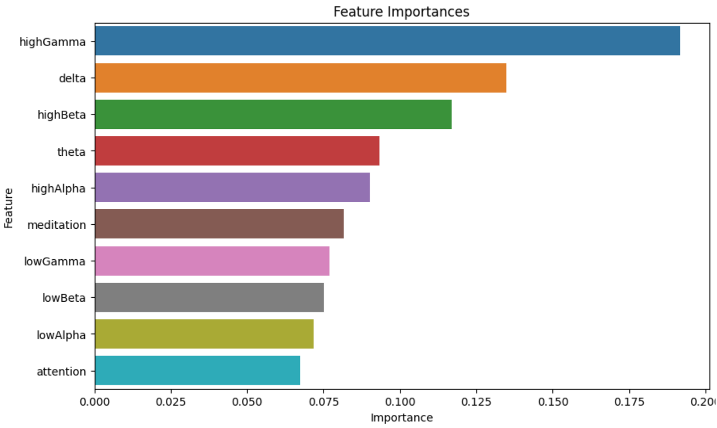


**Figure 8:** Features importance

***Long Short-Term Memory (LSTM) model***

***a. Accuracy - LSTM: 0.71619812583668O1***

An accuracy of 0.716 for the Long Short-Term Memory (LSTM) model suggests the model's ability to correctly predict the target variable on the dataset it was evaluated on. In the context of classification tasks, accuracy is a fundamental metric that measures the ratio of correctly predicted instances to the total number of instances. The reported accuracy value is approximately 0.716, which translates to 71.6%. This means that the LSTM model achieved correct predictions for around 71.6% of the instances in the dataset. A higher accuracy score generally indicates a better-performing model. However, it's essential to consider the nature of the specific classification problem and the characteristics of the dataset [18]. While accuracy is a valuable metric, it may not provide a complete picture, especially if the dataset is imbalanced or if different classes have varying degrees of importance. In such cases, other metrics like precision, recall, and F1-score might be more informative

## V. CONCLUSION

Drowsiness detection offers intelligent sleepiness detection and various assessments over time and while driving. This feature alerts drivers of fatigue before accidents. Picture processing hides fatigue.

As seen above, geographical and temporal factors identify drowsiness well. The approach's enhanced accuracy, durability, and practicality show its potential and enable future developments. Sleepy driver detection reduces inattentive accidents. Identify and notify the driver to avoid fatal accidents. The system should detect weariness and determine the eye aspect ratio threshold after several tests without having to configure it for each person. Some seek a more frequent and sensitive alarm alert system due to road safety and awareness. Finally, several models and methodologies used EEG signals and facial landmarks to detect driver fatigue. A neural network classified weariness from EEG signals with 71.8% accuracy. The model's accuracy, recall, and F1 score must be evaluated to understand its efficacy.

The hybrid method uses face landmarks to improve accuracy and robustness. The conclusion did not use "hybrid" even though the hybrid model surpassed standalone systems for clarity and precision. XG-Boost, LSTM, and ResNet-50 detect tiredness differently. The 79.9% accuracy of XG-Boost indicates gradient-boosting algorithms' potential. Deep learning model LSTM assisted EEG signal analysis to understand temporal connections with 71.6% accuracy. ResNet-50 has trouble classifying pictures due to input form limitations. However, comparing traditional machine learning, deep learning, and ensemble methods revealed their benefits and drawbacks. Experimental results showed the importance of dataset imbalances, feature engineering, and model parameter fine-tuning. Driver sleepiness detection is problematic; hence each model and method stressed the need for a multimodal approach. Enhancing model architectures, studying advanced feature extraction methods, and integrating contextual information are other enhancements. Using multiple models to identify drowsiness may enhance accuracy and resilience in real life. Improved driver tiredness detection systems start with this research.

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