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Driver Drowsiness Detection using Machine Learning and Deep Learning

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Abstract*: Traffic accidents remain a leading cause of death globally, with the World Health Organization reporting approximately one million fatalities annually. Drowsy driving significantly contributes to these accidents, dramatically increasing crash risks. This research addresses this critical issue by proposing a driver drowsiness detection system that leverages facial recognition technology and machine learning. The system continuously analyses a driver's facial features to identify signs of fatigue. Specifically, it tracks eye movements, and yawning patterns, all of which can become indicative of drowsiness. The system is trained on a comprehensive dataset encompassing a wide range of mouth aspect ratio, eye aspect ratio etc for both scenarios of drowsy and alert. This training utilizes a Random Forest algorithm, allowing the system to accurately classify the driver's state in real-time. Upon detecting drowsiness, the system initiates a multi-pronged approach to warn the driver. Audible alerts are issued to alert the driver awake. Additionally, a message can be sent to a pre-designated mobile number, potentially alerting a passenger, or reminding the driver to pull over at a safe location if they are still conscious. This redundancy ensures the driver receives a timely warning, even if they might not immediately perceive the audible alerts.*

Keywords: Facial Reorganization, 68 Facial Landmarks, Aspect Ratios of eyes and mouth, Computer Vision

I. INTRODUCTION

Driver drowsiness is a concern that poses a safety risk, on the roads leading to numerous accidents and fatalities globally. In response to this issue the development of a system for detecting driver drowsiness using Machine Learning and Deep Learning techniques has gained momentum in recent years. By utilizing Machine Learning algorithms like Random Forest and others this system aims to analyze real time data from sources such as eye movements and yawning to accurately detect signs of driver drowsiness and alertness. Through training the model on extensive datasets with labelled instances of drowsy and alert driving behaviors the Machine Learning system can learn to identify indicators of drowsiness and promptly warn the driver. The primary objective of this research is to enhance road safety by preventing accidents caused by drowsy driving through the deployment of an intelligent and reliable detection system that can effectively monitor driver vigilance levels in real-time.

II. EXISTING SYSTEMS

Drowsiness, in drivers significantly contributes to road accidents leading to the advancement of detection systems. These systems mainly utilize vehicle-based behaviour analysis, physiological indicators, or behavioural assessments based on machine learning techniques. Among these methods, behavioural measures based on machine learning have proven to be the most effective solution. While vehicle behaviour analysis focuses on monitoring driver vehicle interactions it may miss indicators of drowsiness. Research on physiological measures like heart rate or brain activity using physical sensors is ongoing but not widely implemented.

One existing method for drowsiness detection relies on Deep Learning, particularly applying Convolutional Neural Networks (CNNs). Application of CNNs is good for analysing pictures or videos to identify sleepiness indicators like dropping eyelids or yawning as they process visual data. These networks can hence recognize patterns of tiredness by training CNNs with images which are labeled either alert or sleepy drivers. Also, other algorithms such as Recurrent Neural Networks (RNNs) process sequential data to learn about the level of alertness in drivers over time. RNNs that are trained to detect drowsiness related patterns will enable real-time monitoring of driver fatigue. Both Deep Learning methods offer promising approaches to driver drowsiness detection, leveraging the power of neural networks to enhance road safety and prevent accidents caused by drowsy driving.

III. PROBLEM STATEMENT

Driver drowsiness detection is a critical aspect of road safety research, aiming to prevent accidents caused by drowsy drivers. Among various approaches, Random Forest is one such algorithm that has been used to solve this problem. Unlike deep learning methods that often demand much computational resources and large volumes of labeled data, Random Forest provides a simpler but effective option.

For driver drowsiness detection with Random Forest, the procedure usually involves gathering relevant features from input data sources like eye aspect ratio, mouth aspect ratio, pupil circularity, mouth aspect ratio over eye aspect ratio. These attributes are then used as inputs to train a Random Forest classifier which learns how to recognize indicators of alertness. Because Random Forest consists of several decision trees, it can make robust predictions that are suitable for real-time applications where rapid reaction time is necessary to prevent accidents.

IV. PROPOSED SYSTEM

The proposed system for driver drowsiness detection uses the Random Forest algorithm into a complete framework that aims to improve road safety by reducing the dangers associated with drowsy driving. The primary objective of this technology is to precisely detect indications of drowsiness in drivers and offer immediate responses to prevent accidents while driving. The indications for driver drowsiness the system uses Eye aspect ratio (EAR), Mouth aspect ratio (MAR), Pupil circularity (PUC), and Mouth aspect ratio over Eye aspect ratio (MOE). Using computer vision techniques, the above features are first extracted from these input data sources in the initial stage of the system. These features encapsulate various aspects of driver behaviour such as closing of eyes and yawning. By capturing these subtle cues, the system aims to create a comprehensive representation of the driver's state and facilitate the detection of drowsiness with high accuracy. The extracted features serve as input variables for training the Random Forest classifier, a powerful ensemble learning algorithm. During the training phase, the Random Forest algorithm constructs a multitude of decision trees, each independently learning to classify instances of drowsiness based on the patterns observed in the training data. The ensemble of decision trees collectively contributes to the final classification decision, with the majority vote determining the predicted class. One of the key advantages of the Random Forest algorithm is its ability to handle both numerical and categorical data, making it well-suited for the diverse range of input features encountered in driver drowsiness detection tasks. Once trained, the Random Forest classifier can analyse real-time data streams from the driver and provide continuous monitoring for signs of drowsiness. By intelligently analysing the driver's behaviour the system can issue timely alerts or interventions, such as audible warnings, to avoid potential accidents on the road. Overall, the proposed system represents a sophisticated and effective solution for addressing the pervasive issue of drowsy driving. By integrating advanced machine learning techniques with real-time data analysis capabilities, the system holds the potential to significantly enhance road safety and reduce the incidence of accidents caused by driver drowsiness.

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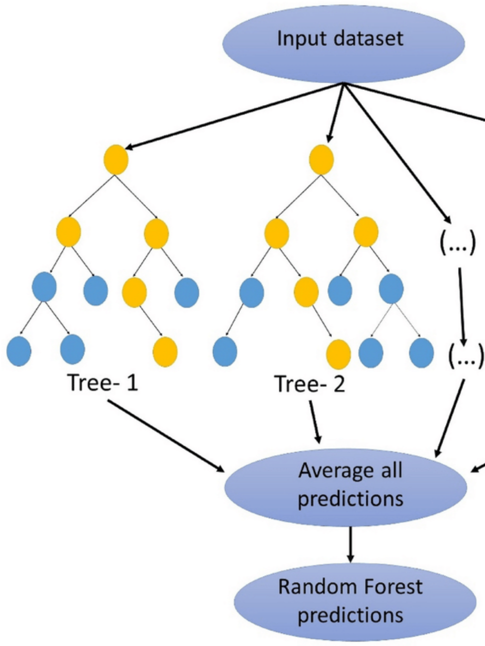

Fig: 4.1 Random Forest Classifier

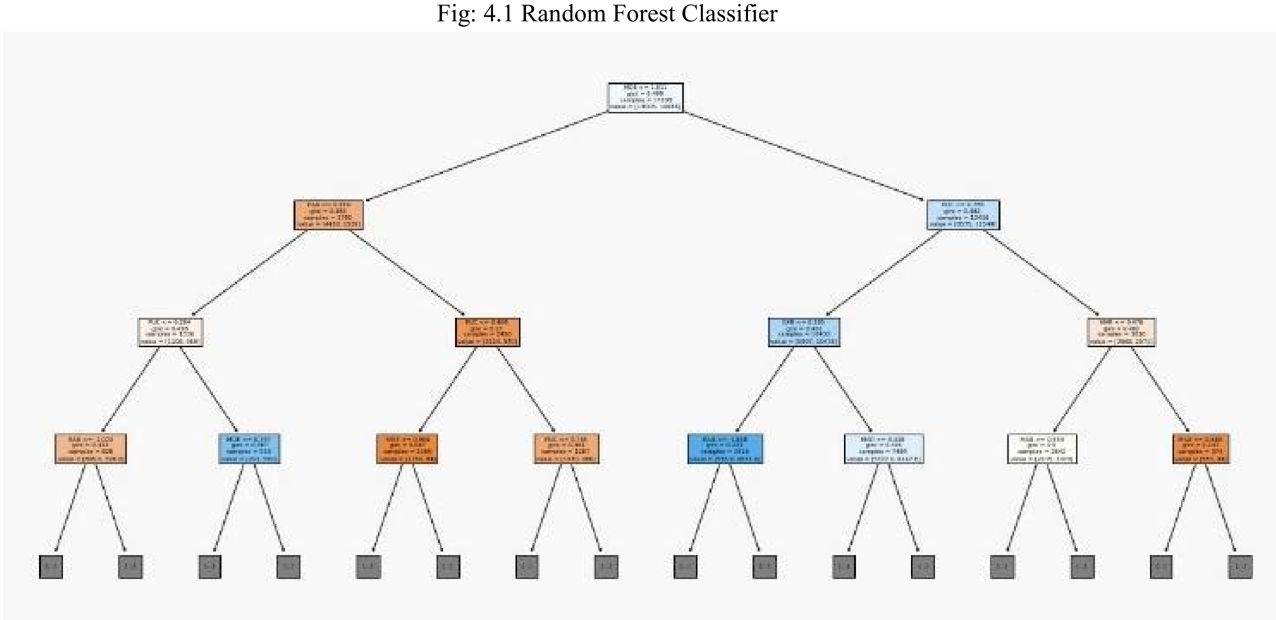

Fig:4.2 Single Decision Tree of trained Random Forest on aspect ratios

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V. ARCHITECTURE

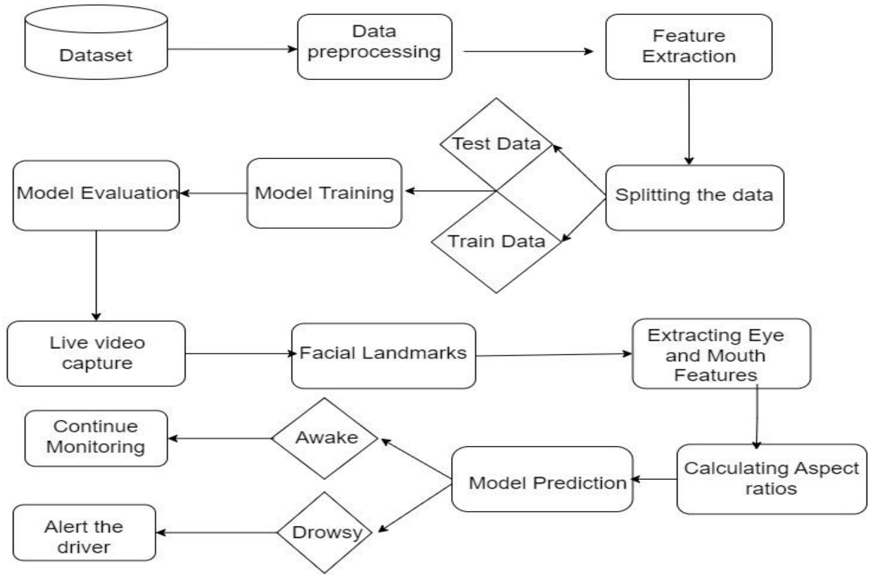

Fig: 5.1 Architecture

Dataset: Initially dataset contains the values of Eye aspect ratio (EAR), Mouth aspect ratio (MAR), Pupil circularity (PUC), MAR over EAR(MOE), Label, frame number and person id.

Data Preprocessing: The Label column consists of 3 values. They are alert, drowsy and distracted. In our project we consider only alert and drowsy, so removing the columns that are having distracted as their label.

Feature Extraction: We only consider Eye aspect ratio (EAR), Mouth aspect ratio (MAR), Pupil circularity (PUC), MAR over EAR(MOE) as features for drowsiness detection.

Splitting The Data: The data is further divided into two subsets: one for training the model (Train Data) and one for evaluating its performance (Test Data).

Model Training: A machine learning model is built using the training data. This involves selecting a model architecture and configuring its parameters.

Model Evaluation: The trained model's performance is validated using a subset of data that was not used during training.

Live Video Capture: It is the time to test the model's performance on the test data to evaluate how well it generalizes to new, unseen images. So, to do that in real time live video capture is done using the OpenCV module.

Facial Landmarks: While capturing the face of the driver the facial landmarks are extracted using MediaPipe Face land marker.

Extracting Eye and Mouth Features: There were 68 total landmarks per frame, but we decided to keep the landmarks for the eyes and mouth only (Points 37–68). These were the important data points we used to extract the features for our model.

Calculating Aspect Ratios: While we hypothesized and tested several features, the four core features that we concluded on for our final models were eye aspect ratio, mouth aspect ratio, pupil circularity, and finally, mouth aspect ratio over eye aspect ratio.

Eye Aspect Ratio (EAR) - EAR, as the name suggests, is the ratio of the length of the eyes to the width of the eyes. The length of the eyes is calculated by averaging over two distinct vertical lines across the eyes as illustrated in the figure below.

Mouth Aspect Ratio (MAR) – Computationally like the EAR, the MAR, as you would expect, measures the ratio of the length of the mouth to the width of the mouth. Our hypothesis was that as an individual becomes drowsy, they are likely to yawn and lose control over their mouth, making their MAR to be higher than usual in this state.

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Pupil Circularity (PUC) - PUC is a measure complementary to EAR, but it places a greater emphasis on the pupil instead of the entire eye.

Mouth aspect ratio over Eye aspect ratio (MOE) - Finally, we decided to add MOE as another feature. MOE is simply the ratio of the MAR to the EAR. The benefit of using this feature is that EAR and MAR are expected to move in opposite directions if the state of the individual changes.

Model Prediction: Using the calculated features the model predicts whether the driver is awake or drowsy. If drowsy the model alerts the driver, if not it continues monitoring.

VI. IMPLEMENTATION

Data Collection: Utilize publicly available dataset in GitHub consisting of approximately 7000 records with 7 columns.

https://github.com/Samradh007/sleeplessAcademy/blob/main/training/data_new.csv

Loading Data and Feature Understanding: The data that we have collected in CSV format. Load the collected data. The dataset includes parameters such as P_ID, Frame_Num, EAR (Eye Aspect Ratio), MAR (Mouth Aspect Ratio), PUC (Pupil Circularity), MOE (MAR/EAR value), and Label (Dependent variable indicating alert or drowsy state).

PID: ID of a particular category (Ex: a person)

Frame_Num: Consecutive frame numbers that we have taken.

EAR (Eye Aspect Ratio): The Eye Aspect Ratio (EAR) is a metric utilized within computer vision and facial recognition systems to quantify the degree of openness or closure of eyes within a frame.

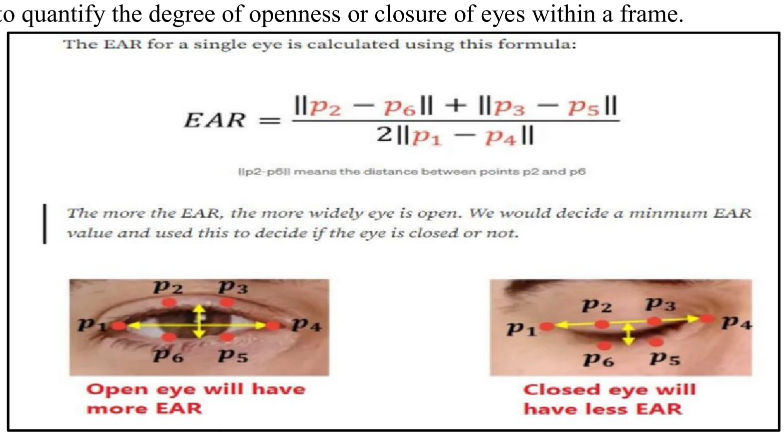

Fig: 6.1 Eye Aspect Ratio with Facial Landmarks

MAR (Mouth Aspect Ratio): The Mouth Aspect Ratio (MAR) is a metric used in computer vision and facial recognition systems to quantify the degree of openness or closure of the mouth in an image or video frame.

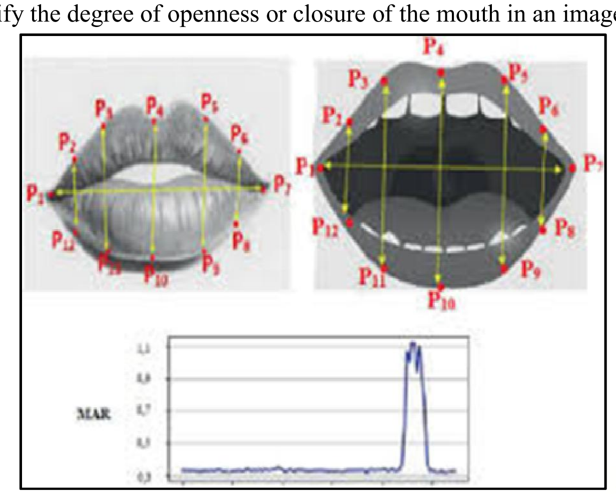

Fig: 6.2 Mouth Aspect Ratio with Facial Landmarks

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$$\mathrm{MAR} = \frac{\|p_2 - p_8\| + \|p_3 - p_7\| + \|p_4 - p_6\|}{2\|p_1 - p_5\|}$$

Fig: 6.3 MAR Formulae

PUC (**Pupil Circularity):** Pupil circularity refers to the degree of circularity or roundness of the pupil in the eye. It is a metric used in computer vision and image processing to assess the shape of the pupil.

$$Circularity = \frac{4 * \pi * Area}{perimeter^2} \qquad Area = \left(\frac{\text{Distance}(p2, p5)}{2}\right)^2 * \pi$$

$$Perimeter = Distance(p1, p2) + Distance(p2, p3) + Distance(p3, p4) + Distance(p4, p5) + Distance(p5, p6) + Distance(p6, p1)$$

Fig: 6.4 Pupil Circularity Formulae

Preprocessing The Data:
The data that we have collected is within a small scale so there is no need to normalize.
Remove the unwanted features like P_ID and Frames_num which have no impact on the target label to be predicted.
Split the data into train test split in 8 isto 2 ratio for training and testing purpose for Random Forest.
Split the data for train and test by using the range of P_ID for RNN(LSTM) for neural network.

Training of Algorithm:
The data is 2-dimensional data which is tabular data and sequential type of data. So that the ensemble learning gives an average outcome for the entire result of all the outputs (good accuracy) and for the reason for sequential type Recurrent Neural network will give a good training that's why initially we have chosen RNN-LSTM as our first choice.

Neural Networks: Is one of our choices because the RNN(LSTM) is suitable for sequential type of data because the frames that we have used are of type sequential which may vary from time to time continuously so that's why we used RNN for initial training.

Ensemble Learning: Random Forest is another choice due to its effectiveness with medium-sized datasets and its capability to handle noisy and correlated data. It's robust against overfitting and can handle both categorical and numerical data effectively.

Save the state of Random Forest and LSTM for further loading in live stream frame classification.

Calculating Accuracy on Sample Test Data:

- At first, we evaluated the RNN model performance on test data and we get an accuracy of about 76% which was very less.
- Evaluate the trained Random Forest algorithm on sample test data to measure its accuracy in predicting driver drowsiness. We are getting an accuracy of 92%.
- So, among the algorithms are Neural Networks (RNN-LSTM) and Ensemble Machine Learning (Random Forest). For the data that what we have chosen is well trained in Random Forest algorithm

Comparing Accuracy with Other Existing Systems:

- Benchmark the accuracy of the developed system against existing systems mentioned in research papers, such as CNN (Convolutional Neural Network) to assess its performance.
- Many of the existing systems are implemented by using CNN. in which they are worked differently in different types of test data.
- Finally, we go with Ensemble Machine Learning techniques with good accuracy with Random Forest rather than neural networks.

- We observed that our data is not that much complex to understand that's why we are achieving good accuracy for ML techniques
- So, the final algorithm that we have chosen is Random Forest.

Code Execution:
Calibration State:
Utilize OpenCV module to capture live streaming video of the driver.
Implement a calibration function that detects the driver's face in neutral positionwithin 25 continuous frames or waits until a face is detected.
Extract 68 facial landmarks using Media Pipe's face mesh model to calculate aspect ratios of eyes, mouth, eye/mouth, and pupil circularity.
68 Facial Landmarks:

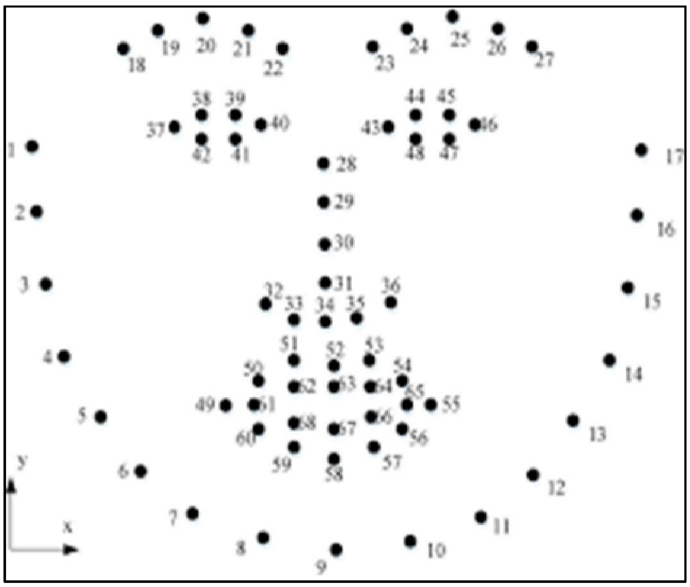

Fig: 6.5 Facial Landmarks

Extract required features and calculated Aspect Ratios:
● We only focussed on features of eyes and mouth. So, we extract the features of Both Eyes and Mouth among all features.
● A list of entire facial features was returned from that we will extract only features of eyes and mouth which are in a specified index position.MediaPipe will internally employ CNN-based models for feature extraction.
● Define functions (e.g., eye_aspect_ratio, mouth_aspect_ratio, pupil_circularity) to calculate each feature using formulas mentioned in previous explanation data collection and loading
● We have calculated the Aspect Ratios of calibration frame count specified number of frames and then return the mean and standard deviation of those values for future reference

Starting of Live Detection (Running of Main application):
● The process begins with continuous video streaming, capturing a series of frames typically spanning 15 frames.
● Each frame undergoes facial landmark estimation utilizing MediaPipe'sface_mesh technology, accurately identifying key facial landmarks in real-time.
● Aspect ratios, such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), are computed based on the geometric relationships between specific facial landmarks.

● To mimic real-world conditions and enhance system robustness, a controlled level of noise or decay is introduced to the calculated aspect ratios, accounting for factors like facial movements and varying lighting conditions.

● The noisy aspect ratios are standardized using calibrated values, ensuring consistency and interpretability across different frames and individuals.

Testing on Loaded Model:

● Load the saved model and pass the calculated aspect ratios of input frames during live streaming

● Predict labels for every Twenty (20) consecutive frames collected during live streaming.

● If the model predicts drowsiness or alertness for more than Twelve (12) frames, classify the final state as drowsy or alert accordingly and display it.

● WE have chosen a fixed of Thirteen (13) frames arbitrarily this may give good accuracy. The strategy that we have chosen is that 65 percent of frames are predicted to be drowsy then we can conclude that the driver is drowsy.

Alerting the Driver:

● **Trigger Alarm:**

○ Produce a beep sound if drowsiness persists for an extended period.

○ We have set a beep sound with a frequency of 1000 Hertz and time of 5000 Milliseconds

○ This will trigger if driver is recognized drowsy for continuous 400 predictions of model

● **Send Message:**

○ Utilize a messaging API to send alerts to a specific mobile number.

○ If driver is recognized as drowsy for 400 predictions of the model

○ We use an API for sending of WhatsApp message instantly

VII. SAMPLE OUTPUT

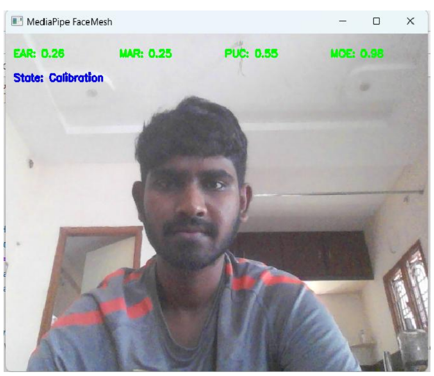

Fig: 7.1 Calibration State

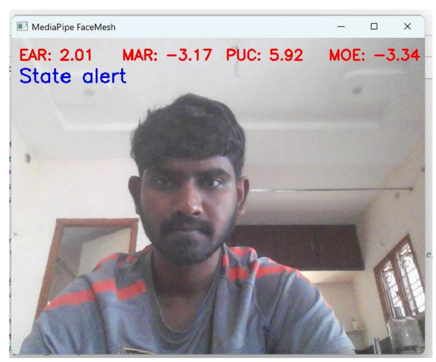

Fig: 7.2 Alert State

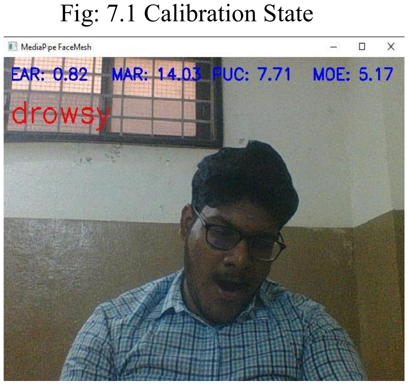

Fig: 7.3 Drowsy Due to Eyes are Closed

Fig: 7.4 Drowsy Due to Yawning

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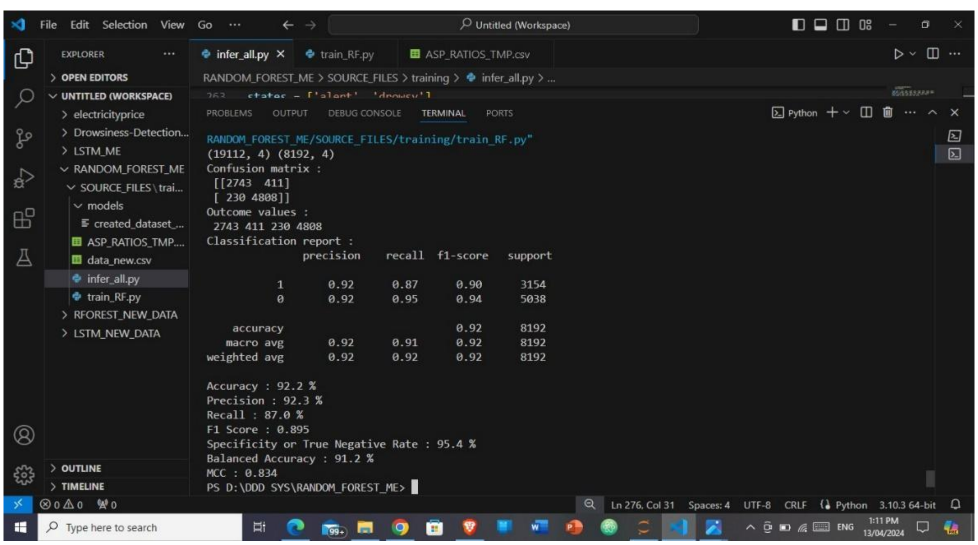
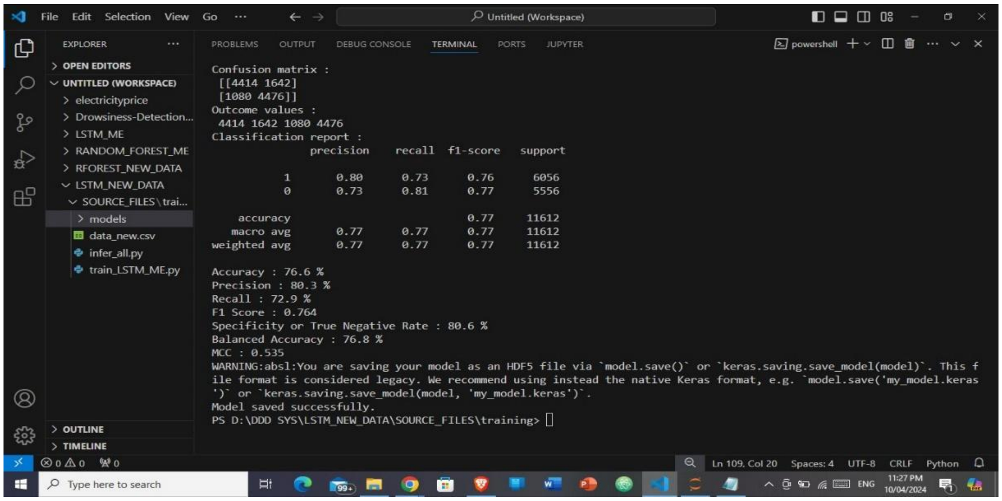
VIII. RESULTS

Using Random Forest as the primary algorithm rather than Deep Learning techniques yields intriguing results for driver tiredness detection that merit study. Using Random Forest's ensemble learning technique, many decision trees are constructed during training, resulting in a greater number of dependable predictions. With this characteristic, the model becomes more capable to recognize patterns related to drowsiness from a variety of input variables, such eye movements and yawning. Since Random Forest is less complex, more comprehensible, it is a good choice for real-time applications like drowsiness detection systems installed in vehicles. The effectiveness of Random Forest as an approach for real-time identification of drowsy drivers is demonstrated by the results, which show high accuracy and reliability when used to identify and warn of drowsy drivers. In addition, the flexibility of Random Forest allows researchers as well as practitioners to have a better understanding of the decision-making process involved in sleepiness detection, which will assist to optimize and enhance the driver drowsiness detection model in the future. Few key points are addressed after examining the results of identifying driver drowsiness using Random Forest. To begin with, even though deep learning techniques are widely applied in many other sectors, Random Forest shows its usefulness in this application. By using decision tree aggregation and ensemble learning to capture the complex relationships between input characteristics and drowsiness, Random Forest provides accurate and reliable detection.

Comparison of Proposed System Vs Existing System - Performance Metrics

	Algorithm	Accuracy	Precision	Recall	F1 score
Proposed System	**Random Forest**	**92.2**	**92.3**	**87**	**89.5**
Existing System	**CNN**	**82.45**	**82**	**81.78**	**81.62**
Existing System	**RNN**	**76.6**	**80.3**	**72.9**	**76.4**





Overall, the comparison highlights **Random Forest as a superior choice for driver drowsiness detection, outperforming CNN and RNN in terms of accuracy, precision, recall, and F1 score**. The proposed system's exceptional performance metrics underscore its potential to significantly enhance road safety by accurately identifying and alerting drowsy drivers in real-time, thereby reducing the risk of accidents caused by driver fatigue.

IX. CONCLUSION

In conclusion, the widespread adoption of Random Forest-based drowsiness detection systems represents a significant step towards achieving our shared vision of zero accidents and fatalities on the road. Through concerted efforts and strategic investments in technology and infrastructure, we can pave the way for safer roads, healthier communities, and a brighter future for generations to come.

The effectiveness of Random Forest-based algorithms in accurately identifying drowsy drivers has been demonstrated through rigorous testing and validation, highlighting their superiority over alternative approaches such as CNN and RNN. With high accuracy, precision, recall, and F1 score metrics, Random Forest offers a practical and efficient solution for real-time drowsiness detection, enabling timely interventions to prevent accidents on the road.

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