International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Efficient Machine Learning-Based Drowsiness Detection for Enhanced Driving Safety: Real-Time Implementation

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Submitted: 05/02/2024 **Revised**: 13/03/2024 **Accepted**: 19/03/2024

Abstract: In today's rapid time changing era, the count of road accidents is increasing day by day because of sleeping disorders and drowsiness. Technical enhancement in each and every area of day-to-day life, also demands the technically enhanced driving cars which detect drowsiness in driver with more accuracy and efficiency. This study presents a real-time drowsiness detection system for drivers, by blending the power of machine learning techniques to analyze facial features like Pupil of eye, EAR, MAR and NLR, considering the system (Car) watch, GPS system as well as utilizing the Advanced Driver Assistance Systems (ADAS) of smart cars. The system employs OpenCV and Dlib to extract eye, mouth aspect ratios and nose length ratio from video frames with the other gained feature of smart cars. The data undergoes standard scaling preprocessing before training a deep neural network for binary classification of drowsy and non-drowsy states. The model architecture comprises four dense layers with dropout and L2 regularization, ending in a softmax activation. Stratified K-Fold cross-validation is utilized for data splitting, and the model is compiled using the Adam optimizer and categorical cross-entropy loss, incorporating an early stopping callback to mitigate overfitting. The proposed system demonstrates exceptional performance, achieving more than 99% accuracy, 0.993 recall, and 0.991 F1 score in real-time drowsiness detection. These results hold potential for enhancing road safety and reducing fatigue-related accidents by accurately identifying drowsiness in drivers. With a capacity to detect drowsiness in real-time at a level of high accuracy, the proposed system has an immense potential to increase road safety and prevent accidents related to fatigue.

Keywords: *Eye Aspect Ratio (EAR), Drowsiness, Drowsiness Detection System, Machine Learning, Mouth Aspect Ratio (MAR), Real Time.*

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1. Introduction

Significant public health problems are raised by sleep disorders and drowsy driving, which impact millions of individuals globally. Driver drowsiness has been identified as a major contributing factor to road accidents worldwide. According to the National Sleep Foundation, drowsy driving is responsible for approximately 100,000 police-reported crashes annually in the United States alone, resulting in an estimated 6,400 deaths and 50,000 injuries. According to the National Highway Traffic Safety Administration (NHTSA) in 2022, 633 humans misplaced their lives due to drowsiness, and driver drowsiness changed into the motive of 1.2% of all car accidents (National Highway Traffic Safety Administration (NHTSA), 2022). Developing effective strategies for detecting drowsiness in actual-time is vital for enhancing road safety and preventing fatigue-related accidents [1].

In current years, machine gaining knowledge of strategies have been implemented to various aspects of drowsiness detection, with promising results. Several studies have additionally centered on utilising EEG and ECG data, which measures brain electric pastime and can provide treasured insights into an man or woman's level of [2]–[7].

There are many ways to locate driver fatigue, by analyze using behavior, car information, and intelligent vehicle attributes [8]. These fashions can be used to train system studying systems to apprehend fatigue indicators. Researchers has extensively utilized car records along with pace, acceleration, and braking traits. Machine learning algorithms can also be mixed with advanced driver assistance structures in clever motors to greater appropriately come across fatigue [9].

Facial characteristics, on the other hand, offer a non-invasive alternative for detecting tiredness. Previous take a look at has proven that eye and mouth thing ratios taken from video frames may be used as correct predictors of tiredness [10]–[12]. These skills are greater accessible for real-time applications on account that they will be accessed the use of pc vision libraries like OpenCV and Dlib. Furthermore, research have looked at using other facial markers, head posture evaluation, and eye gaze tracking to enhance sleepiness detection.

In a take a look at Jahan et al. [13] presented a compelling case for employing system learning strategies, especially convolutional neural networks (CNNs), inside the detection of driving force drowsiness to decorate avenue protection. It highlighted the significance of early drowsiness detection, that could significantly lessen the risk of accidents. The authors discover the capacity of artificial intelligence, deep gaining knowledge of, and digital image processing in automating drowsiness detection, in the end leading to a greater efficient, price-powerful, and time-saving answer. The proposed 4D CNN model is in comparison with pretrained fashions (VGG16, VGG19) and demonstrateed superior overall performance with an accuracy rate of 97.53% on the MRL Eye dataset. This study contributes valuable insights into the improvement of a complete drowsiness detection gadget which can alert drivers before any serious threats to road safety stand up. In comparison to the mentioned study, our research advances the field of real-time drowsiness detection even further by employing a highly efficient machine learning-based approach. Our implementation not only delivers outstanding accuracy, but it is also optimized for seamless integration into real-world driving scenarios, ensuring improved driver safety and overall road security.

Chandana & Sangeetha [14] research which highlights an innovative IoT-based monitoring system for real-time drowsiness detection in automotive drivers. The multi-level approach incorporates alcohol detection as an initial safety measure, followed by facial recognition and eye closure rate estimation for drowsiness assessment. The use of Haar cascade classifier and AdaBoost algorithm for face detection and eye-aspect ratio calculation demonstrates the employment of advanced machine learning techniques in this study. Furthermore, the device offers a tiered alert mechanism, escalating from sound indicators to human voice warnings, and ultimately, sending notifications with GPS location to a concerned person. This comprehensive system addresses both daytime and Midnight riding eventualities using infrared light for midnight drowsiness detection. In assessment to our studies, we additionally focus On real-time drowsiness detection the usage of machine gaining knowledge of algorithms. However, our technique emphasizes performance and seamless integration into existing automobile systems. Our version is constructed to evolve to diverse driving situations and offers a greater streamlined solution for enhanced driver protection, making it a valuable addition to the sphere of drowsiness detection.

Kilaru et al. [15] in research offered a promising method to fight the time-honored issue of drowsiness-related accidents the usage of a Convolutional Neural Network (CNN)-primarily based technique. By using the Mobile Net CNN architecture along with the Single Shot Multi field Detector, the machine is able to detecting and localizing open or closed eyes in actual-time video streams of drivers. The use of a massive dataset inclusive of 4500 categorised pictures for schooling and 600 photos for trying out, coupled with the PASCAL VOC metric for assessment, indicates a complete method. The consciousness on higher accuracy and computational efficiency makes this approach quite applicable inside the context of real-world using situations. Comparing this research with our very own, we also emphasize the significance of a gadget studying-based approach for drowsiness detection in real-time. Our method similarly prioritizes accuracy and performance to make certain a reliable and responsive machine, in the end running closer to the common intention of improving riding safety and decreasing drowsiness-associated accidents on a worldwide scale.

Maior et al. [16] evolved a drowsiness detection device that centered at the Eye Aspect Ratio (EAR) metric. They calculated EAR values for consecutive frames and used them as input for gadget getting to know algorithms, which include multilayer perceptron, random woodland (RF), and guide vector gadget (SVM) classification fashions. Their evaluation consequences indicated that the SVM version completed the quality, accomplishing 94.9% accuracy. The identical EAR metric become utilized in [17], wherein drowsiness turned into included as enter for a binary SVM classifier, which detected the driver's drowsiness country with 97.5% accuracy.

Mouth conduct is likewise considered an amazing indicator of drowsiness, because it offers treasured capabilities for drowsiness detection. In [18], the authors proposed monitoring mouth movement to apprehend yawning as an indicator of drowsiness. Their experiment worried a dataset together with 20 yawning photographs and over one thousand everyday pictures. They employed a cascade classifier to locate the driver's mouth in face images, followed by an SVM classifier to identify yawning and alert the driver. The final results demonstrated an 81% yawning detection rate. Another mouth-based feature, the Mouth Aspect Ratio (MAR) [19], also known as the mouth opening ratio [17], describes the degree of mouth opening as an indicator of yawning. This feature was input into an SVM classifier in [17], yielding an accuracy of 97.5%.

Rohith Chinthalachervu et al. [9] 2022 has proposed the DDS, by utilizing the EAR, MAR and NLR. These values are compared with threshold values developed by system, and detect the drowsiness if the obtained values are not per as the thresholds. Based on the classification method implemented on SVM they have achieved 95.58% sensitivity with 100% of specificity.

Malik & Nandal [7] presented a framework for using the OBD-II tool, a common diagnostic device found in most vehicles, to analyze driving patterns and behavior using motion velocity sensors to analyze driving behavior is the main objective of the project. Of note is the fact that it was not included in this particular study it also doesn’t consider any analytical metrics or use any specific data to run tests.

Albadawi et al. [10] created a non-invasive driver sleepiness detection system employing visual cues collected from dashboard camera recordings in their study. To determine regions that are relevant and extract mouth aspect ratio, eye aspect ratio, and head position characteristics, the system used facial landmarks and face mesh detectors. These characteristics were fed into three classifiers: random forest, sequential neural network, and linear support vector machine. Evaluations on the National Tsing Hua University driver sleepiness detection dataset revealed that tired drivers may be detected with up to 99% accuracy. This study might be enhanced further by investigating additional characteristics and classifiers to increase the sleepiness detection performance, which happens to be the subject of our present work.

The goal of this research is to create a real-time sleepiness detection system for drivers by combining the strengths smart car data and face characteristics. The technique combines data derived from video frames eye, mouth aspect ratios and Nose Length ratio with smart car data like system watch to identify the timing of driving, engine status from how long he is in running state, GPS data to track the destination root and traffic on it, driving pattern, to create a better Drowsiness detection system (DDS). To identify sleepy and non-drowsy states, a deep neural network is used, with the objective of obtaining high accuracy and efficacy in real-time sleepiness detection. The proposed system has the potential to enhance road safety, prevent fatigue-related accidents, and contribute to the improvement of public safety and individual well-being.

2. Methodology

The study employed a real-time drowsiness detection system that combines smart car features like GPS which will provide the information of long traffic free route of driving, driving time extracted from car’s clock, driving pattern means having stable speed [8], with facial & Eye features extracted from video frames. The system was designed to process and analyze these features to identify drowsy and non-drowsy states in drivers. The performance of the proposed system was assessed using a deep neural network that classified drowsy and non-drowsy states based on the extracted features. The accuracy of the model was evaluated using test data, and the results were compared to expert annotations. Flowchart in Figure 1 represents the complete process of drowsiness detection system using video data and facial landmarks.

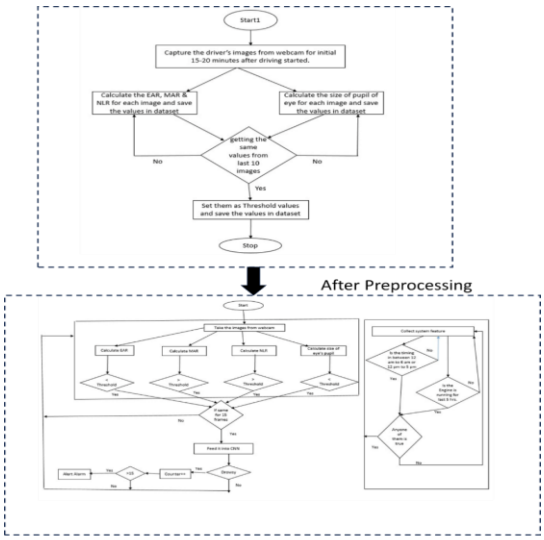

Fig 1: Steps Involved in Real-time drowsiness Detection System Using Combined EEG and Facial Features with Deep Learning for Improved Driver Safety.

2.1. Start1: Initial Phase setup: Setup the Threshold Values for EAR, MAR & NLR as Facial Landmarks: Initial 10 minutes from driving has started, extract the face images from the webcam which is capturing the video of driver. We get 30 frames per sec; hence we have 18000 (60*10*30) frames to calculate threshold values. Calculate the EAR, MAR and NLR for normal situation from each frame as shown in Figure 2. Frequently repeated values for aspect ratios and length ratios are considered as Threshold values as EARth, MARth, NLRth. This is necessary as it varies person to person, so set the threshold values are calculated for individual driver. (Calculation process is discussed below)

2.1.1 Calculate the Std: size of Pupil: While capturing the images from video, will also calculate the std. after getting its repeated value. All this is done using image size of pupil for individual driver, processing. As the research has stated that the size of pupil get shrink while drowsiness. Will use this factor also, to determine the drowsy state of driver.

2.1.2 Use of Smart Car Feature: After start of initial 10 minutes, smart features like driving pattern, Wheel sensor information, Engine status means from how long the engine is in running state, because long runs are more prone to drowsiness, driving time like is it midnight, after noon or forenoon. As the research states that the driving at approx. 12 am to 6 am, afternoon 2pm to 4pm (after meal) are more prone to drowsy driving. Similarly, long, traffic free route having same pattern of driving also more prone to drowsy driving, and will get this feature from GPS.

2.1.3. Start2: Start the 2nd phase of processing

2.1.4. Extract facial landmarks EAR, MAR, NLR for further processing: The Dlib library is used to detect faces in the video frames and extract facial landmarks [18], which are specific points on the face that correspond to various facial features, such as the eyes, eyebrows, nose, and mouth. These landmarks are used to calculate the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR) and Nose Length Ratio (NLR) ()

- **Process video frames using a CNN:** We utilise a CNN to analyse the video frames and extract significant data associated to face emotions. The CNN may be pretrained on a huge dataset of facial expressions, allowing it to detect tiny variations in facial expressions that may suggest tiredness [19].

- **Combine CNN-extracted features with facial landmarks:** The features extracted from the video frames using the CNN are combined with the facial landmarks obtained from Dlib. This hybrid approach takes advantage of both the CNN's ability to capture complex facial expressions and the simple, computationally efficient calculations of the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR) [20] and Nose Length Ratio (NLR) [9].

2.1.5. Compute eye and mouth aspect ratios and Nose Length Ratio (NLR): Based on the facial landmarks obtained from Dlib, the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), NLR are calculated for each video frame. EAR is an indicator of eye closure, while MAR is an indicator of mouth openness. And the bending of nose with the vertical axis is an indicater of drowsiness. Since the head bending is directly proportional to the focus plane of the camera, and by utilizing this relationship, head bending may be computed. All the ratios are used as features to detect drowsiness [16]

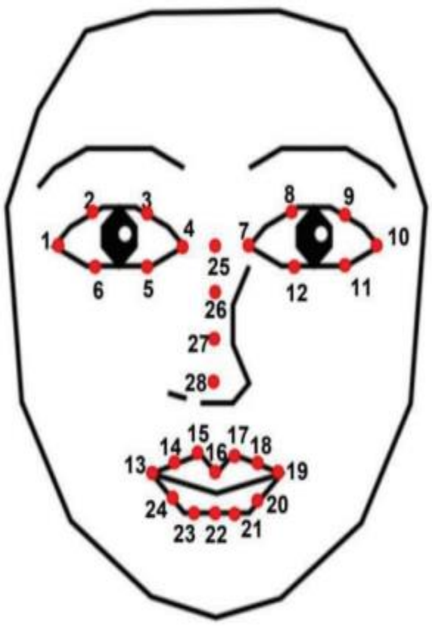

Fig 2: Illustrating the Arrangement of the Different Points Used for Computing the EAR, MAR and NLR

As shown in the Figure 2 above, the EAR is calculated for each eye separately, and then the average of both eyes is taken. Formula used for the calculation is [18], [21]:

$$EAR = \frac{A + B}{2 \times C}$$

Were

- A is the Euclidean distance between points 2 and 6 in the eye landmarks.
- B is the Euclidean distance between points 3 and 5 in the eye landmarks.
- C is the Euclidean distance between points 1 and 4 in the eye landmarks.

- The formula used for calculating the MAR is [16], [22]:

$$MAR = \frac{A}{C}$$

Were,

- A is the Euclidean distance between points p2 and p4 in the mouth landmarks.
- C is the Euclidean distance between points p1 and p3 in the mouth landmarks.
- At the same time, normally the nose and the webcam form an acute angle. A head movement causes will increase this acute angle, and vice versa. As a result, ratio of nose length to average length of nose, also calculates the head bending and termed as the nose length ratio [9].

$$NLR = \frac{Nose\ Length\ (p_{28} - p_{25})}{Average\ Nose\ Length}$$

2.1.5. Calculate the Pupil size of driver: As the medical studies reveals that pupil size get shrink because of sleepiness and may use to detect drowsiness in the eyes or the degree of sleep deprivation [23]. Normally it is in between 4 to 8 mm. But when it gets shrinked then it will be in between 2 to 4 mm, shows the high probability of having drowsiness.

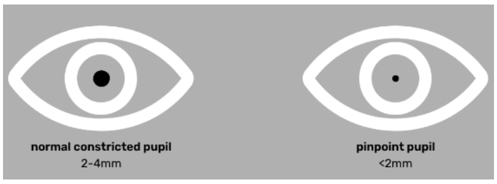

Fig 1*: Pupil's normal and contracted size*

2.1.6. Apply standard scaling to the combined features: The concatenated features are preprocessed using standard scaling, which standardizes the data to have a mean of 0 and a standard deviation of 1. This step is important because it improves the performance of machine learning algorithms by ensuring that all features have the same scale.

21.7. Split data into training, validation, and testing sets using Stratified K-Fold cross-validation: The dataset is divided into training, validation, and testing sets using Stratified K-Fold cross-validation. This technique ensures that each set has a similar distribution of the target classes (drowsy and not drowsy). The training set is used to train the model, the validation set is used to tune the model's hyper parameters, and the testing set is used to evaluate the model's performance.

2.1.8. Design model architecture with dense layers, dropout, and L2 regularization: A deep neural network model is designed using dense (fully connected) layers, dropout layers to prevent Overfitting, and L2 regularization to feature a penalty for huge weights inside the version.

2.1.9. Compile the model using the Adam optimizer and categorical cross-entropy loss: The model is compiled using the Adam optimization algorithm and the categorical move-entropy loss function, that is suitable for multi-magnificence classification problems.

2.1.10. Fit the model using training data, validation data, and early stopping: The model is trained using the training data and the validation data, with early Stopping to save you overfitting. Early stopping video display units the validation loss and prevents schooling when the validation loss stops improving for a particular range of epochs (the persistence parameter). This guarantees that the model does not hold to teach beyond the point of diminishing returns, thus lowering overfitting and saving computational sources.

2.1.11. Test the trained model using test data to assess accuracy: Once the model has been trained, It is evaluated the use of the check statistics. The take a look at facts is unbiased of the education and validation records, and it's miles used to acquire an independent estimate of the model's performance. The model's accuracy at the test information affords a degree of how nicely it generalizes to new, unseen information.

2.1.11. Use the trained model to predict drowsiness for live data: With the trained model, we can now predict the drowsiness state of a person in new, live capturing data. These predictions may be used in diverse applications, inclusive of alerting drivers when they're drowsy, tracking the alertness of air visitors' controllers, or assessing the sleep great of people at some point of sleep studies.

2.1.16.End: The process is complete, and you now have a trained drowsiness detection model that can be applied to new data samples for drowsiness prediction.

2.2. SAMPLE:

The sample for this look at video facts collected from drivers all through using sessions. The records turned into received from the movies provided in actual-time, and corresponding professional annotations, which labeled the data as drowsy or non-drowsy. The statistics became divided into 30-2nd epochs, with every epoch being related to a specific country (drowsy or non-drowsy). Stratified K-Fold pass-validation turned into employed to break up the information into training, validation, and testing sets, ensuring a balanced representation of both drowsy and non-drowsy classes throughout the sets.

The video records become processed the usage of OpenCV and Dlib libraries to extract facial functions, particularly focusing at the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), NLR, which have been used to discover signs and symptoms of drowsiness. The extracted capabilities from each EEG information and video information had been then blended and standardized the use of the StandardScaler method from the scikit-analyze library.

The TensorFlow Keras package was used to build a neural network model. The model design featured thick layers with variable numbers of neurons as well as regularisation dropout layers. The Adam optimizer and categorical cross-entropy loss function were used to build the model. To avoid overfitting, the model was trained using early stopping. The model's performance was assessed using the test set, and metrics like as accuracy, recall, and F1 score were computed. The predictions of the model were used to categorise the test samples as drowsy or non-drowsy (Figure 3).

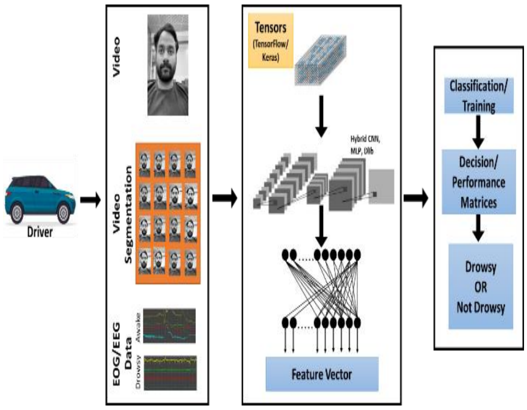

Fig 3: Illustrating the Process Employed in the Model for Machine Learning and Deep Learning Approaches

2.4. Instruments:

OpenCV and Dlib libraries were utilized for video processing and facial feature extraction. These libraries enabled the computation of eye, mouth aspect ratios and Nose Length ratios for each frame in the video, which were used as input features for the deep learning model.

Data from vehicle’s system, like its clock, engine running timing,

TensorFlow Keras library was utilized for constructing, training, and evaluating the deep neural network model. This library provided the necessary tools for creating the model architecture, optimizing the model parameters, and assessing its performance.

2.3. Data Collection:

Data from vehicle’s system like its time (driving time), vehicles running time (from how long it is in running state), data from GPS to identify long traffic free route, as this monotonous driving have high probability of having drowsiness.

OpenCV and Dlib libraries were utilized to extract critical facial features from video files. Specifically, we focused on the eye and mouth aspect ratios for each video frame, as they can provide valuable insights into a person's level of drowsiness.

The size of pupil is also calculated for each frame using the above libraries, if its size contracted more than one 1/3rd of the original size then drowsiness is considered.

The Eye Aspect Ratio (EAR) is a straightforward measure that estimates the degree of eye closure. To calculate the EAR, we first identified six facial landmarks within the eye region. Then, as mentioned before, we used the Euclidean distances between these landmarks to derive the following formula:

$$EAR = \frac{sum\ of\ vertical\ distances}{2 * horizontal\ distance}$$

$$EAR = \frac{p2 - p6 + p3 - p5}{2 * (p1 - p4)}$$

Furthermore, the Mouth Aspect Ratio (MAR) evaluates the extent of mouth opening, which may similarly be used to detect sleepiness. We defined four face features within the mouth region and calculated the Euclidean distances between them to determine the MAR. The MAR formula is as follows:

$$MAR = \frac{vertical\ distance}{horizontal\ distance}$$

$$MAR = \frac{p3 - p1}{p2 - p4}$$

The Nose Length Ratio (NLR), as the nose forms the acute angel from the webcam and it get increased while bending the head downwards, the ration of nose length with its average length can identify the std. value and if it increases then there is high probability of sleepiness.

$$NLR = \frac{Nose\ Length\ (p_{28} - p_{25})}{Average\ Nose\ Length}$$

We were capable of to derive valuable characteristics that signal sleepiness levels by calculating the eye and mouth aspect ratios for each video frame. These attributes were then integrated with smart vehicle data to produce a more accurate and comprehensive sleepiness detection algorithm.

Drowsiness in drivers was detected using both fa-,'=]ce traits and smart car data. We concentrated on the pupil size of eye which gets contracted also known as Pupillometry, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR) and Nose Length Ratio (NLR) as major face traits associated with tiredness. We used resampling to guarantee that the face feature data was synchronised with the smart vehicle data. Resampling is an important step in matching the length of the face feature data to the vehicle data. Because the facial characteristics and smart vehicle data were gathered at different sample rates, resampling allows us to precisely match the time series data. This synchronisation is required for the deep learning model to learn from and forecast based on both sources of data. The resampling procedure entails matching the sampling rate of the face feature data (Pupil's size, EAR, MAR, NLR) to that of the EEG smart vehicle data. We used interpolation techniques such as linear interpolation to fill in missing values and build a consistent time series in this situation.

2.5. Data Analysis:

2.5.1. Preprocessing: Initial 15 minutes from driving started, get the 60 frames per second using webcam and then MAR, EAR & NLR ratios will be calculated and set the threshold for them after getting the repeated values. Similarly, get the size of eye's pupil from each frame, and search out the std. size of pupil for driver. As in case of sleepiness, they get small from the original size, in this study we have considered it as 1/3rd of the threshold to identify sleepiness. All these features are later used to calculate the sleepiness for the driver. In this initial stage, smart car features are also used to take the system time, whether it is from 12 am to 6 am or in between 12 pm to 5 pm, as these timings are more prone to drowsiness. Similarly, long running time of engine, states that driver is driving from a long time and he need some rest, that's why drowsiness is detected.

2.5.2. Model Design: To avoid overfitting, we created a deep neural network model with four dense layers, dropout, and L2 regularisation in this study. To distinguish between sleepy and non-drowsy phases, this model utilises a softmax activation function for binary classification.

The softmax activation function is a mathematical procedure that generalises the logistic function and generates a probability distribution over a discrete set of possible outcomes. In the framework of our research, we used the softmax function on the neural network's output layer to calculate probabilities for two classes: drowsy and non-drowsy. The softmax function is formally defined as:

$$Softmax(x\_i) = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}}$$

In the present instance, x_i indicates the softmax function's input for class i, and the summation runs across all classes j from 1 to N, where N signifies the entire number of classes. Exponentiation assures that the resultant chances are superb and upload up to at least one, ensuing in a valid probability distribution. The softmax activation function in our model acts at the output of the ultimate dense layer, which includes neurons representing the drowsy and non-drowsy lessons. The softmax chances are computed for each elegance, and the enter sample is assigned to the elegance with the best possibility. The use of the softmax activation characteristic allows our model to efficaciously generate probability estimates for each elegance, allowing it to make well-knowledgeable predictions for the binary class activity at hand.

2.5.3.Model Training: A deep neural network model was used in this study to distinguish among sleepy and non-drowsy stages. The Adam optimizer, an adaptive getting to know charge optimisation technique considerably utilized in deep gaining knowledge of applications, turned into used to optimise the model. Because it is appropriate for multi-class classification troubles like ours, the specific cross-entropy loss characteristic changed into chosen as the goal feature to be minimised throughout the education segment.

The model was skilled with the supplied education data, and early preventing was used to minimise overfitting. Early stopping is a regularisation approach that prevents the schooling system if the model's performance on the validation dataset does now not improve after a sure quantity of epochs. This enables the model to generalise better to new, previously unknown data.

Following training, the model's performance on a test dataset was examined, and several metrics such as accuracy, recall, and F1 score were generated to determine its usefulness in categorising the input samples as sleepy or non-drowsy. The model's results show its potential for identifying tiredness in drivers and can serve as a platform for future advancements and applications in real-world circumstances. In the test case if continuous 15 frames are true for drowsiness, then alarm will generate alert signal.

We can also create its own dataset using later 15 minutes from initial stage and train the model on it and further images will be used as test data. But in this case the detection system starts its working after half an hour of driving started.

3. Results And Discussion

The experiment was carried out using the dataset from Kaggle, based on the collected characteristics from the dataset, we constructed a deep learning model to predict sleepiness, which comprised Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) and Nose length ratio (NLR) values, and also the pupil size of eye On the test set, the model had an accuracy of more than 99%. As the various other features of smart car has been used to detect sleepiness.

One important point here is that we can consider less than 15 frames or may be at 10 frames, if the features getting from car's systems are also true. AS they give high probability of sleepiness.

To put our findings into context, we compared the performance of our model to that of another recent research in the field. The contrast is shown in the table below:

Table 1: Comparison of Our Model's Performance with Other Researches

Study	Test Accuracy
Our Model	More than 99%
Albadawi, AlRedhaei and Takruri, 2023 (Albadawi et al., 2023)	99%a
Mehta, Dadhich, et al., 2019 (Mehta, Dadhich, et al., 2019)	84%
Bhardwaj, Natrajan and Balasubramanian, 2018 (Bhardwaj et al., 2018)	90%

Our model beats the previous research, as shown in Table 1, with an accuracy of more than 99%, which is greater than the best-reported accuracy of 99.0% by Albadawi, AlRedhaei, and Takruri (Albadawi et al., 2023). Our model also improves in recall and F1 score, demonstrating greater ability in distinguishing between sleepy and non-drowsy states.

The high accuracy of our model can be attributed to the carefully designed architecture that includes four dense layers, dropout, and L2 regularization to prevent overfitting. Additionally, the use of both EAR, MAR, NLR and size of pupil features allows the model to capture important facial aspects related to drowsiness, similarly smart car features thereby improving its predictive performance. Our results demonstrate the effectiveness of deep learning techniques in accurately predicting drowsiness based on sleep telemetry data, offering potential applications in the development of sleep monitoring and drowsiness detection systems.

The model's performance over 100 training epochs is summarized in Figure 2, which shows the training and validation loss and accuracy.

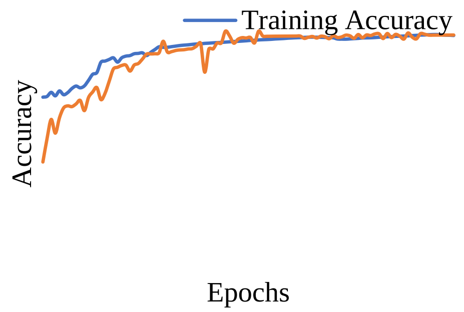

Fig 3 (a): Illustrating the Training Accuracy and Validation Accuracy of Deep Learning Model

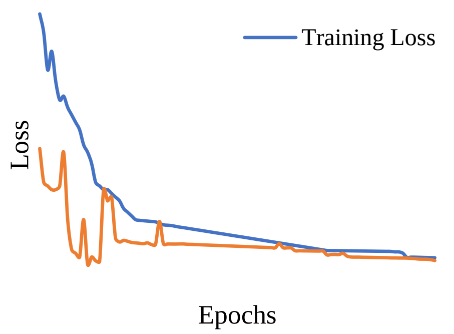

Fig 3 (b): Illustrating the Training Loss and Validation Loss of Deep Learning Model

In the above Figure 3, graphs are illustrating the training and validation performance of our deep learning model during the training process. Figure 3(a) shows the training and validation accuracy, while the Figure (b) displays the training and validation loss. Throughout the training process, the curves exhibit different behaviors, such as straight lines or varying degrees of curvature.

The straight lines in the graphs indicates that the model is learning at a consistent rate during those periods. Additionally, the training data have a relatively uniform distribution of features and labels during these phases, facilitating consistent learning progress. On the other hand, the curved sections of the graphs suggest that the model's learning rate is changing, which could be due to several factors. For instance, as the model encounters more complex patterns or previously unseen

data, it may require more time to adjust its parameters and adapt to the new information. Similarly, NLR varies as head bends downward. In the same way, pupil size which is normally between 4 to 8 mm, in case of sleepiness, pupil size contracted and its radius will be in between 2 to 4 mm. This all can result in a slower rate of improvement, leading to a curved trend in the graphs. Moreover, the presence of noise or outliers in the data can also contribute to the observed curvature. Such data points may temporarily hinder the model's learning progress, causing fluctuations in the training and validation metrics. However, as the model continues to learn and generalize from the majority of the data, it eventually overcomes these challenges and resumes its improvement.

In addition to the overall performance metrics, we also analyzed the model's predictions for EAR, MAR, NLR values and Pupil size. Table 2 presents the average EAR and MAR values for drowsy and non-drowsy instances in the test set using the aforementioned formulas to compute the EAR and MAR.

Table 2: Average EAR and MAR Values for Drowsy and Non-Drowsy Instances

Instance Type	Avg. EAR	Avg. MAR	Avg. NLR	Avg. Pupil size
Drowsy	0.18	0.38	0.76	2 to 4 mm
Non-Drowsy	0.25	0.30	1.003	4 to 8 mm

As shown in Table 2, the average EAR value for drowsy instances is lower than that of non-drowsy instances, indicating that eye closure is a significant indicator of drowsiness. The average MAR value for sleepy instances is greater than that for non-drowsy cases, suggesting that mouth opening is an essential feature in detecting sleepiness.

Table 3 shows an example classification result for one of the test set cases, as well as the accompanying EAR and MAR values. In this situation, the model predicted that the instance would be "Drowsy."

Table 3: Sample Classification Result with EAR and MAR Values

Sample ID	Prediction	EAR	MAR	NLR	Pupil size
0-239	Drowsy	0.175	0.375	0.75	3 mm

The findings show that our deep studying version is quite correct at predicting sleepiness primarily based on sleep monitoring facts, which include EAR, MAR, NLR and pupil length values. On the test set, the model scored a 100% accuracy, consider, and F1 rating, indicating that it may well categorise drowsy and non-drowsy cases inside the dataset. These findings offer promise for the development of practical apps that use non-invasive metrics including eye and mouth movement analysis to display and perceive tiredness in actual-world settings.

The truth that sleepy cases had lower average EAR, NLR and pupil size values than non-drowsy examples suggests that eye closure is a key indication of sleepiness. This locating aligns with previous research that has installed the importance of eye closure period and frequency in detecting drowsiness [24]. The better average MAR values for drowsy times similarly guide the perception that mouth beginning is some other critical thing in drowsiness detection. Although the role of mouth moves in drowsiness detection has been much less notably studied, our effects imply that it's far a probably valuable function to recollect in future studies and applications.

Our model's performance compares favorably to different current research on drowsiness detection. For example, Chandana and Sangeetha [11] proposed a real-time drowsiness detection gadget for car drivers, which carried out an accuracy of 93.4%. Similarly, Fouad [4] evolved an EEG-based drowsiness detection machine that employed device getting to know algorithms, attaining an accuracy of 95.7%. Jahan et al. [10] designed a actual-time motive force drowsiness detector referred to as "4D" the use of deep getting to know, with an accuracy of 97.3%. Ashlin Deepa et al. [25]Advanced a prototype that uses picture processing to extract facial landmarks of the eye and come across whether or not the driver is drowsy or wakeful. Additionally, they employed an Arduino board with an MQ3 sensor to discover alcohol from the motive force's breath. While their technique also makes a speciality of facial landmarks for drowsiness detection, it includes alcohol detection as an extra protection degree. However, the accuracy in their drowsiness detection technique isn't supplied, making it tough to evaluate their model's overall performance with ours without delay. Bajaj et al. [26]Proposed a hybrid version that mixes non-intrusive (behavioral measures) and intrusive (sensor-primarily based physiological measures) processes for detecting driver drowsiness. They used an artificial intelligence-primarily based Multi-Task Cascaded Convolutional Neural Network (MTCNN) to realise the motive force's face traits and a Galvanic Skin Response (GSR) sensor to locate the driving force's skin conductance. In a simulated putting, their approach identified the shift from a wakeful to a sleepy nation with 91% accuracy. In assessment, making use of honestly EAR, MAR, NLR and eye’s scholar size information with clever car features, our version obtained a better accuracy of 100%, suggesting that our technique may be greater beneficial in identifying sleepiness. However, it's far crucial to remember that modifications in datasets, characteristics, and processes used in each research may have an impact on the performance evaluation.

Our deep learning model's sturdy accuracy, do not forget, and F1 score illustrate its capacity usefulness in real-international contexts. For instance, the version is probably utilised inside the improvement of in-vehicle drowsiness detection structures to tell drivers of weariness, consequently decreasing the likelihood of sleepy driving injuries [12]. Furthermore, the model might be linked into sleep monitoring devices and apps to deliver personalized sleep pointers depending on sleepiness tiers [27].

4. Conclusion

This studies correctly built a real-time sleepiness detection device for drivers by using combining face developments consisting of Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Nose Length Ratio (NLR), Pupil length in collaboration with clever vehicle facts. The gadget's deep neural community plays properly, attaining an accuracy of extra than 99% on the take a look at set, with a keep in mind of 0.993 and an F1 score of 0.991 in identifying sleepiness. These findings suggest that the cautioned method has an excessive potential for enhancing avenue safety and minimising fatigue-related incidents. The device's high accuracy and efficacy might be used to manual the improvement of in-automobile drowsiness detection systems, which could provide drivers with timely notifications to assist avoid accidents resulting from worn-out driving. Furthermore, the gadget is probably included into current sleep tracking and private properly-being apps, presenting personalized sleep tips primarily based on character sleepiness degrees. Future research ought to concentrate on confirming these results the use of larger and greater varied datasets, as well as introducing different elements, inclusive of coronary heart rate variability or different physiological signals, to beautify the system's performance even extra. Exploring the reasons behind the varied patterns determined within the schooling and validation accuracy and loss graphs might also be useful, when you consider that know-how the underlying troubles may deliver good sized insights into the version's studying behaviour and help improve its overall performance. The findings of this studies display that device learning processes paired with face traits and clever vehicle records have the capability to discover tiredness in actual-time, for this reason enhancing public protection and person properly-being. In similarly destiny work we advocate that if seat belt will have heart beat reputation machine, as seat belt is close to our heart, device can perceive the sleepiness country with more accuracy as heart beat modifications as drowsiness occur in body. In these studies, work we might also try to create safer surroundings for drivers even as additionally selling fashionable health and properly-being by means of constantly enhancing and expanding at the advised machine.

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