Deep Learning: Driver Drowsiness Detection

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Abstract **- Detecting drowsiness is crucial to reduce possible hazards, as driver weariness is a major contributor in a considerable number of accidents globally. As a result, there has been a consistent yearly increase in traffic-related deaths and injuries worldwide. In the effort to reduce accident rates, awareness of the condition of the driver's eyes—whether open or closed—becomes critical.**

The accurate localization of the driver's eyes is the main goal of this paper. To precisely identify the eyes, this methodology involves taking a picture of the full face and then using efficient image processing methods and Deep CNN. The technology in use determines the location of the eyes as well as whether or not they are open. When the driver's eyes are closed for a short period of time, the system sounds a warning to get them to open them, preventing possible hazards before they happen.

Keywords: InceptionV3, MRL Eye Dataset, Deep CNN, Drowsiness Detection.

I. INTRODUCTION

The process of identifying indicators of exhaustion or drowsiness in drivers is known as driver drowsiness detection. Being tired while driving is a serious issue since it can result in collisions and injuries. This is especially true for drivers of cars, including truckers and long-distance drivers, who must drive for extended periods of time[15] without stopping.

Systems that detect driver drowsiness follow a driver's movements and pinpoint episodes of drowsiness using a range of sensors and algorithms. Many systems monitor various symptoms of tiredness, including as eye movement, head movement, and steering behavior[13]. In response to this pervasive issue, a system that collects images in a sequential manner and evaluates fatigue using the proposed deep CNN model has been created.

The device may vibrate or make a sound to warn the driver if it senses that they are getting sleepy. The overall impact of driver sleepiness detection systems on road safety is significant since they reduce the frequency of incidents brought on by inattentive driving.

Driver drowsiness detection is the technique of identifying signs of fatigue or drowsiness in drivers. Being fatigued while operating a motor vehicle is a dangerous situation as it may lead to accidents and injuries. This is particularly true for those who operate automobiles and must drive for extensive periods of time[15] without stopping, such as truck drivers and long-distance drivers. Systems that detect driver drowsiness follow a driver's movements and pinpoint episodes of drowsiness using a range of sensors and algorithms. Numerous devices track different signs of fatigue, including as head movement, eye movement, and steering behavior[13]. In response to this pervasive issue, a system that collects images in a sequential manner and evaluates fatigue using the proposed deep CNN model has been created.

If the device detects that the driver is becoming drowsy, it may vibrate or emit a sound to alert them. Driver tiredness detection systems have a substantial overall effect on road safety because they lower the number of accidents caused by distracted driving.

II. RELATED WORK

Many techniques, such as those based on image processing[11], vision, physiological signs, biosensors, and more, can be used to identify drowsiness. The method most frequently employed to identify drive drowsiness is vision-based. This method employed eye blinks to identify driver weariness.

Numerous techniques based on image processing[11] are employed to identify driver weariness. The three most popular techniques are CNN-based methods, Eye Aspect Ratio, and PERCLOS.

This article describes a neural network method for identifying driver drowsiness and microsleep. Accuracy of drowsiness categorization is greatly improved by using facial landmarks from a camera and a Convolutional Neural Network (CNN). With an average accuracy of more than 83% across all categories, the lightweight model achieves over 88% accuracy for drivers without glasses and over 85% accuracy at night without glasses. With a maximum size of 75 KB, the model is also remarkably small, providing an effective option for real-time sleepiness detection in Android devices and embedded systems[12].

This study discusses the state-of-the-art methods for physiological signal measure-based, vehicle-based, and video-based real-time driver sleepiness and alertness monitoring. It offers thorough explanations of every category, covering measures, market products, continuous research, and detecting techniques. The assessment takes into account practical usability, detection accuracy, and intrusiveness. This study aims to raise awareness of driving weariness and encourage safer driving practices by addressing unresolved concerns and arguing for precise crash prevention technologies[6].

These methods are quite helpful in determining whether a motorist is sleepy:

A. Facial Feature Extraction: CNNs are able to extract relevant facial features from on-board camera images using a technique known as facial feature extraction. Eye, mouth, eyebrow, and other facial marker positions are examples of these traits. The CNN can recognize important facial characteristics linked to sleepiness, like drooping eyelids or changes in facial expression, by training it on a dataset of annotated face photos.

B. Eye State Classification: Classifying the driver's eyes as open or closed by focusing on them exclusively is one typical CNN technique. An image dataset of eyes with labels indicating their respective states—open or closed—is used to train the CNN in this way. Through pattern recognition in the photos, the network is able to reliably categorize the condition of the eyes in real time, differentiating between open and closed eyes. [3][5]

C. Temporal Analysis: CNNs may also be used to detect minute variations in eye movements and facial expressions[12] across time by analysing temporal sequences of images. Through the processing of a sequence of successive images obtained by a camera, the network is able to recognize patterns that are suggestive of sleepiness, like prolonged periods of inactivity or frequent eye closes. This temporal analysis enables the early identification of fatigue-related symptoms and offers a more thorough knowledge of the driver's behavior.[13]

D. Attention Mechanisms: Certain CNN architectures[8] use attention processes to concentrate on certain areas of interest, such the lips or eyes, in the input image. These models prioritize the investigation of critical regions linked to weariness, hence improving the accuracy of drowsiness detection by dynamically altering the network's attention based on the saliency of various facial traits.

III. PROPOSED SYSTEM

The phases in the driver drowsiness system's operation are explained in detail in the suggested block diagram, which is displayed below. To illustrate the operation, a flow chart in figure1 is utilized, which illustrates how the input is acquired from a camera positioned in front of the vehicle driver and records real-time video. After processing the driver's facial expression, an eye status[3] analysis is used to confirm the action. After that, the suggested algorithm analyzes the eye variable storage, updating the driver's state and warning him if he nods off. The aforementioned procedure is described in full, step-by-step.

Dataset collection and pre-processing:

The MRL eye dataset[9], which has 84000 photos, was employed in this case.

The pre-processing steps listed below have been done to the raw eye dataset.

1) Segmentation: Using file names and binary classification, separate both closed and open eye photos from the raw eye dataset. [5][11][14]
2) Blur Reduction: Using a threshold value, the Laplacian method is used to identify and the Gaussian approach is used to eliminate blurriness from the photos.
3) Noise Removal: Applying the Gaussian approach, remove all noise from all the photos.

Following that, we used to divide the dataset into training and validation portions in an 80:20 ratio and to resize, rotate, and alter the dimensions of the photos. 100% of the dataset was used for testing.

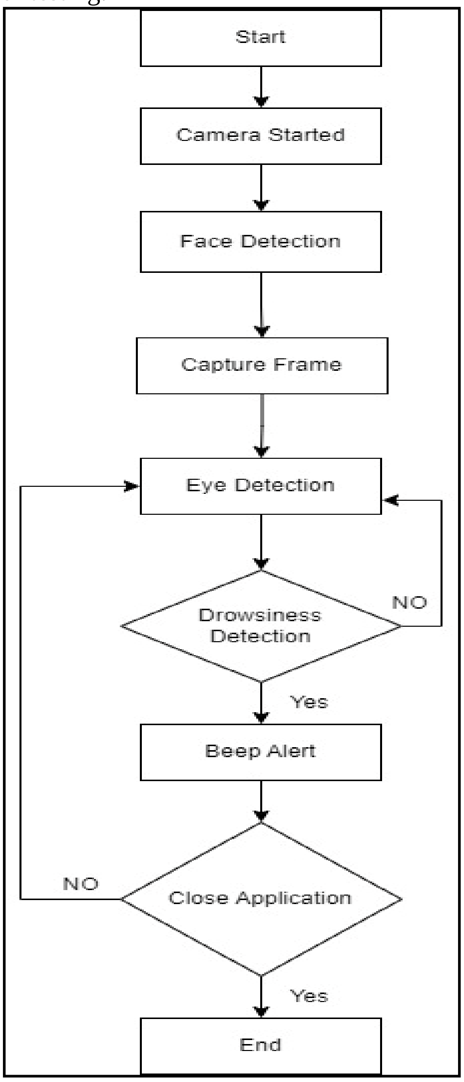


Figure 1: Flowchart for Proposed System

Model Creation and Training:

The model is created using methods based on deep neural networks. We created the model by starting with "InceptionV3" as the foundation model and adding four layers to it.

1) InceptionV3: Convolutional neural networks like InceptionV3 are made for applications like object recognition and image classification. This increases the network's resilience to varying item sizes in the input photos by enabling it to record features at several scales. Compared to conventional convolutions, InceptionV3 uses depth-wise

separable convolutions, which need less calculations and parameters.
2) Flatten Layer: This layer creates a one-dimensional tensor from the multi-dimensional output tensor.
3) Dense Layer (activation='relu'): This applies a ReLU activation function and a Dense layer consisting of 64 units to the output that has been flattened. ReLU's main goal is to give the model non-linearity.
4) Dropout Layer: A part of the input units is randomly set to 0 by dropout during training. This aids in avoiding overfitting.
5) Dense Layer (activation= "softmax"): The last Dense layer with two units and softmax activation is added. The output probabilities for the two classes are generated by this layer (assuming a binary classification task).

Finally, we employed the well-known Adam optimization approach, which helps to achieve high accuracy by adjusting the learning rates of each parameter separately.

Building Application:

In the finished product, we employed OpenCV to get the pre-trained harr-classified features for face and eye detection from a live feed.

We added two more capabilities to the live video driver sleepiness detection system:

1. Detecting eye status[3] for sleep detection by taking a picture as input.
2. Using information from a recorded video, determine the moment the driver began to feel sleepy and raise the threshold value for the driver's eye score.

One issue with driver drowsiness detection has persisted: In any scenario where the camera detects two or more people, it functions incorrectly because it is unclear to whom the output is supposed to be directed.

IV. RESULT AND DISCUSSION

The techniques and algorithms a driver sleepiness detection system uses, as well as the caliber and volume of data it uses for testing and training, all affect how successful the system is. These devices generally work well at improving road safety by spotting indicators of fatigue and alerting drivers when it's time to stop and take a break.

Measuring the accuracy of a driver sleepiness detection system is one approach to evaluate it. This entails contrasting the output of the system with a ground truth label, which may come from manual observations or the physiological condition of the driver.

The system's response time, or how soon it recognizes drowsiness and warns the driver, is another important consideration. Fast reaction times are essential to enable the driver to intervene before possible collisions. Response times of less than a second have been reported by certain systems.

Table 1: Accuracy and Loss

	Training	Validation	Testing	Existing[3]
Accuracy	93.31	90.54	95.04	86.05
Loss	16.97	22.79	12.61	25.37
F1 score	94.26			85.05

From the table1 we see that during the learning phase, we developed a deep convolutional neural network (CNN)[8] capable of capturing detailed features. Our model, which has an amazing accuracy rate of 95.04%, combines a Softmax layer with a CNN[8] classifier to determine whether the driver is fatigued. An integrated buzzer sound function acts as an alarm system, notifying the driver as soon as drowsiness is detected. This proactive system continuously checks the driver's condition and issues warnings as needed, improving road safety.

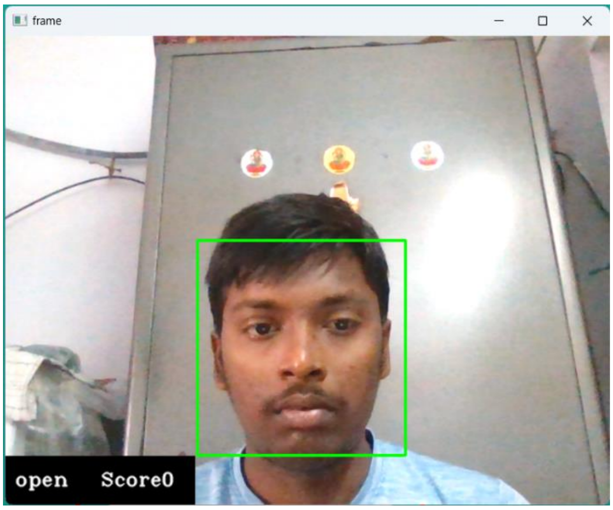


Figure 2: Open Eyes

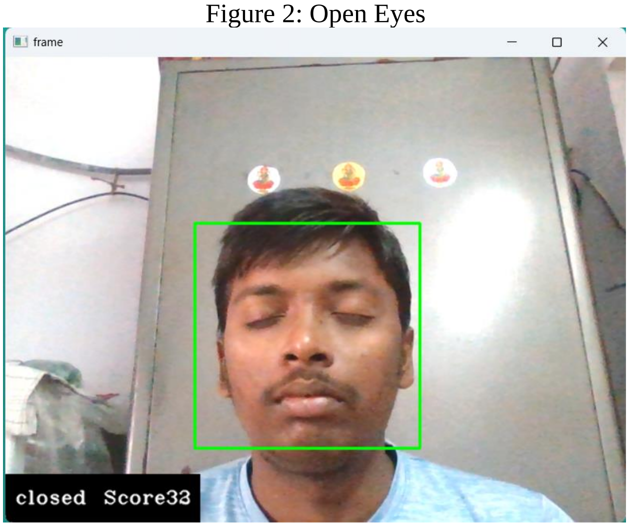


Figure 3: Closed Eyes

Like the variation shown in figures 2,3 driver behavior and the system's efficiency changes in various scenarios, assessing these systems is difficult. For example, a system might function effectively when driving on a highway during the day, but it might not work as well at night or on curving roads. To evaluate how these technologies operate under different driving scenarios and situations, more research is required.

Furthermore, focusing user experience enhancement necessitates exploring human-centric design approaches. We hope to improve our system's overall usability and effectiveness by fine-tuning the alerting mechanism and increasing user acceptance. Through these focused efforts, we hope to promote widespread acceptance and integration of our sleepiness detection technology, resulting in safer driving situations for all road users.

In conclusion, driver drowsiness detection systems have shown promise in enhancing road safety by identifying signs of fatigue and urging drivers to take rests. To ensure these technologies work well and to optimize them, more research is necessary across a range of driving scenarios.

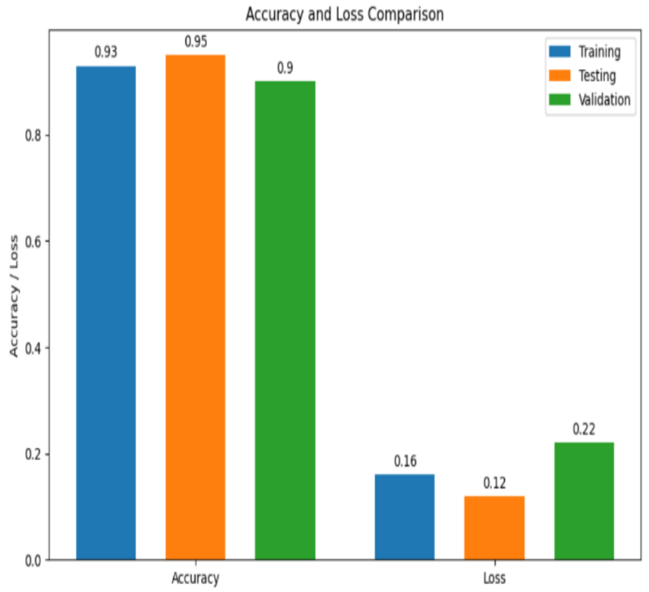
We trained and evaluated the model using the 84000-image MRL dataset[9] in order to predict the output, and we employed harr-classified features to detect the face and eye area.

1. Start the application.
2. Display three options:
    a. Live feed
    b. Image input
    c. Video input
3. Wait for user input to select one of the options.
4. If the user selects "Live feed":
    a. Activate the camera to capture live video feed.
    b. Continuously detect faces in the live feed.
    c. For each detected face:
        i. Determine the status of the eyes (open or closed).
        ii. If eyes are closed, trigger an alarm sound until eyes are open.
    d. Repeat steps b to c until the user exits.
5. If the user selects "Image input":
    a. Prompt the user to input an image.
    b. Process the image to detect the status of the eyes (open or closed)
    c. Output the result indicating whether the eyes are open or closed.
6. If the user selects "Video input":
    a. Prompt the user to input a video file.
    b. Process the video frames sequentially.
    c. For each frame:
        i. Detect the status of the eyes (open or closed).
        ii. If eyes are closed, output the frame indicating the closed eyes.
        iii. If eyes are not closed, continue to the next frame.
7. If the user presses the "q" key:
    a. Exit the application.
8. End.

Algorithm 1

V. Conclusion

A deep convolutional neural network (CNN) is constructed and utilized to gather features during the learning phase. The model employs a CNN classifier with a Softmax layer to classify the driver as weary or not, with an accuracy of 95.04%. If the driver is thought to be asleep, a buzzer sound function is triggered to notify them. When the car predicts drowsiness consistently, the system recognizes the driver's condition and sounds an alert. In the future, accuracy can be increased by investigating optimization approaches like the genetic algorithm, and system performance can be enhanced by applying transfer learning.



Graph 3: Comparison of values

The model's performance is represented in graph3, and the findings show promise for many criteria. With training accuracy at 93%, testing accuracy at 95%, and validation accuracy at 90%, the accuracy ratings show significant proficiency. These numbers indicate that the model performs extremely well with constant accuracy rates across different datasets.

Moreover, the loss numbers shed light on the optimization procedure used by the model. The testing loss is significantly smaller at 12, but the training loss, which measures the difference between expected and actual values during training, is recorded at 16. The model's performance on omitted data is indicated by the validation loss, which is somewhat greater at 22. These loss values show that training was optimized effectively, leading to small differences between the actual and predicted values.

Furthermore, focusing user experience enhancement necessitates exploring human-centric design approaches. We hope to improve our system's overall usability and effectiveness by fine-tuning the alerting mechanism and increasing user acceptance. Through these focused efforts, we hope to promote widespread acceptance and integration of our sleepiness detection technology, resulting in safer driving situations for all road users.

Future developments in driver sleepiness detection have enormous potential to improve road safety even more. With technology advancing so quickly, the future seems bright for adding more advanced sensors and algorithms to the detection systems that are already in place. These developments could involve adding more biometric information, like heart rate variability or eye movement patterns, enhancing real-time alert mechanisms with creative solutions like wearable technology or embedded sensors in cars, and integrating machine learning techniques to increase the accuracy of drowsiness detection. Additionally, the employment of AI in predictive analysis and adaptive response systems has the potential to completely transform the way sleepiness detection systems function, resulting in fewer accidents and safer roadways overall.

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Widespread acceptance and integration with current safety procedures could potentially result from working with automakers or building the technology into smart cars. To further enhance the model's performance and guarantee its efficacy over a range of scenarios, it is recommended to consistently refine and increase the dataset, particularly when considering diverse driving conditions. Furthermore, improving user experience and acceptance of the alerting mechanism can be achieved by investigating human-centric design concepts.

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