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Driver Drowsiness Detection from Video Surveillance Using Transfer Learning

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***Abstract*— While working on this project, we realized how often driver fatigue is overlooked as a risk factor on the road. To help reduce such dangers, we built a system that can spot drowsiness in real-time. It uses Python, TensorFlow, and OpenCV—tools that worked well together for what we needed. we trained a lightweight model, MobileNet, to recognize whether a person's eyes are open or closed. To do this efficiently, we used Haar cascade classifiers to locate the face and eyes in each video frame. The system runs on live video, making it easy to connect with existing driver-assistance technologies in vehicles. By utilizing a pre- trained model, the system reduces the need for extensive training data while maintaining high accuracy. The real- time processing capability ensures seamless driver monitoring, offering a practical solution for accident prevention. Beyond road safety, its applications extend to security, healthcare, and human-computer interaction. Future improvements include enhancing robustness to lighting conditions, exploring more advanced face and eye detection algorithms, and incorporating physiological signals such as heart rate variability for a more comprehensive assessment of drowsiness.**

Index Terms*— Drowsiness Detection; Real-time Monitoring; Python; Image Preprocessing; TensorFlow; OpenCV; Computer Vision; Deep Learning; Transfer Learning; Face and Eye Detection; MobileNet; Convolutional Neural Network (CNN); Haar Cascade Classifier; Video Processing.

I. INTRODUCTION

Drowsy driving has become one of the silent causes behind many serious road accidents. Every year, thousands of crashes are reported where drivers were simply too tired to stay alert, as highlighted by traffic safety studies. It's clear there's a need for smarter systems that can notice signs of fatigue early on. Many older methods either rely on what the driver says or use tools that are hard to apply in real-time driving. In our case, we worked on a system that picks up signs of tiredness using real-time visuals. We built it using commonly available coding tools and AI libraries, making sure it could work smoothly in real-world conditions.

By using transfer learning with a pre-trained model (MobileNet), the system is able to classify eye states efficiently. This reduces the need for large amounts of training data while still maintaining a high level of accuracy. For detecting faces and isolating eye regions, the system makes use of Haar cascade classifiers. These regions are then processed further to help identify signs of drowsiness. The system operates in real-time, making it a viable solution for Advanced Driver- Assistance Systems (ADAS) and practical deployment in vehicles. The integration of computer vision and deep learning ensures robust detection across diverse conditions, including variations in lighting, head position, and facial features for resource efficiency, ensuring low computational burden. By providing timely alerts, it aims to improve road safety and reduce drowsiness-related accidents. Future enhancements include multi-sensor integration and improved adaptability to lighting variations, making it a scalable solution for individual drivers, commercial fleets, and public transport networks.

II. LITERATURE SURVEY

Using machine learning and deep learning techniques, several researchers have explored various methods for detecting driver drowsiness. A CNN-based model for real time drowsiness detection was proposed in Deep Drowsy Net [1], demonstrating high accuracy in classifying drowsiness from facial expressions. Similarly, a federated learning approach was introduced in Privacy- Preserving Driver Drowsiness Detection [2], which enhanced detection accuracy while ensuring data privacy. This study emphasized the importance of decentralized learning to prevent data leakage while maintaining high detection performance.

Several studies have looked into using facial features to detect drowsiness. One of them, Drowsiness Monitoring Using Facial Landmarks [3], used Dlib to pick up facial points and track small changes like blinking or how often someone yawns, which helped improve how well drowsiness could be detected. Another study, Real-Time Fatigue Monitoring in Drivers [4], brought together OpenCV with CNNs to make sure signs of tiredness could be spotted quickly, even in darker settings. In Efficient Drowsy CNN [5], researchers tested how well different CNN models worked when it came to picking up facial signals related to drowsiness, giving a better idea of which setups perform more efficiently.

Apart from vision-based methods, researchers have also looked into using physiological signals to detect drowsiness. In *EEG-Based Drowsiness Prediction* [6], brainwave patterns were studied to understand how certain EEG

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frequency ranges relate to fatigue. Another work, *Sleepy Brain Net* [7], used deep learning on EEG data and achieved strong results across different subjects by analyzing both time-based and spatial features. Heart rate variability was the focus of *Cardio Drowsy* [8], which showed that combining physiological data with video input could make the detection process more reliable. Some studies also worked on building faster, lightweight models to fit into embedded systems. For instance, *Fast Drowsy Net* [9] used MobileNetV3 along with facial landmark detection to maintain a balance between speed and accuracy, making it suitable for small devices like Raspberry Pi. In another example, *Driver Drowsiness Estimation Using Eye Tracking* [10], eye movement was analyzed using SVM and k-NN classifiers, showing that even traditional machine learning methods can still offer good results with lower processing needs.

Researchers have also explored ways to combine different methods into one system. In Fusion Drowsy Net [11], both visual data and physiological signals were used together, which made the model more reliable across different settings. Another study, Multi-Feature-Based Drowsiness Detection [12], worked with features like eye closure, head movement, and speech. By using ensemble learning, it adjusted well to various driving situations. In Intelligent Alert System for Drowsy Drivers [13], the researchers used an attention-based CNN that helped the model focus on the important parts of the face while ignoring extra background details. Lately, there's been more interest in transfer learning too, since it lets pre-trained models be reused, saving time and improving results without needing a lot of new training data. Transfer Drowsy VGG [14] fine- tuned a pre-trained VGG-16 model on drowsiness datasets to improve generalization, significantly reducing the need for large labeled datasets. Another work, MobileNet for Drowsiness Detection [15], adapted a MobileNetV2 model to classify driver fatigue effectively, proving that lightweight architectures can achieve competitive results. Further, TL-FatigueNet [16] leveraged ResNet-50 to transfer learned facial representations for improved detection, highlighting the benefits of deeper architectures in extracting complex patterns associated with fatigue symptoms.

Several review papers have provided valuable insights into recent advancements. A systematic review by Albadawi et al. [17] highlighted the increasing preference for deep learning based vision methods, emphasizing their superiority over traditional machine learning approaches. Gandhi & Sood [18] assessed various real-time fatigue detection strategies, comparing their advantages and limitations to provide guidelines for future research. Similarly, Bansal & Sharma [19] investigated CNN-based drowsiness detection and emphasized their effectiveness, particularly in environments with controlled lighting. Abtahi et al. [20] conducted a comprehensive analysis of sensor-based and vision-based approaches, evaluating their performance and feasibility while recommending hybrid models for improved accuracy.

Some studies have focused on making drowsiness detection systems more reliable and scalable for real-world use. For example, *Robust Drowsy Net* [21] used adaptive histogram equalization to improve results in poor lighting, showing how useful preprocessing can be in tough visual conditions. In *Scalable Drowsy AI* [22], cloud-based systems were tested for use in commercial fleets, making it possible to process data in real time at a larger scale. *Smart Drowsiness Detection* [23] added IoT monitoring features, helping the system fit into smart vehicles and connected traffic systems.

Researchers have also worked on making these systems more focused on safety. One idea was to combine drowsiness detection with in-car alert systems so drivers can be warned early and avoid accidents. Looking ahead, *Real-Time AI Powered Drowsiness Detection* [25] explored using transfer learning along with reinforcement learning. This could help future systems learn and adjust based on real-time data from the road. Overall, these studies show progress toward building video-based drowsiness systems that are smarter, faster, and more practical to use in everyday driving. The research landscape continues to evolve, with advancements in deep learning, multi- modal integration, and IoT-based systems pushing the boundaries of driver safety technologies.

III. PROPOSED MODEL

The Data Acquisition Module is responsible for capturing real-time video feed from dashboard-mounted or surveillance cameras installed in vehicles. We trained the system using datasets like MRL and NTHU, which helped it learn to detect drowsiness more accurately. It works with live video while keeping delays low and the image quality clear enough for proper analysis. Instead of using every video frame, it picks only the necessary ones, so the system runs faster and uses less processing power. Before making any predictions, the images go through a few improvements like noise removal, contrast fixing, and sharpening to make the details clearer. It then finds parts of the face like the eyes, nose, and mouth—since these areas usually show signs of sleepiness. To make sure things stay consistent even if the lighting or face angle changes, the input images are adjusted before they're passed into the MobileNet model.

The system uses the MobileNet deep learning model to automatically pick out key features that help spot signs of driver drowsiness. It looks at things like how often someone blinks, how their eyelids move, if they're yawning, or if their head starts to droop. These patterns help figure out how tired the person is. MobileNet's layered structure helps it break down visual details, and using transfer learning makes it work faster and more accurately. Even though it's a lightweight model, it still pulls out important details without slowing down the system. The alert module kicks in when signs of sleepiness are detected. It gives real-time warnings through different ways—like showing messages on the dashboard, sounding beeps or spoken alerts, and even

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creating vibrations in the steering wheel or seat. These warnings get stronger depending on how drowsy the driver seems. If needed, the system can also connect with the vehicle's automated safety features to take action right away.

This part of the system checks how well everything is working by looking at important metrics like accuracy, precision, recall, and how fast the system responds. It compares the detection results with actual labelled data to see how reliable the system is. To make sure it performs well in different conditions, it's tested under changes like low lighting, partially covered faces, and various driver actions. It also keeps track of how quickly the system processes data to make sure it can work in real time, even when running in different driving environments.

A. Existing Method

The existing approach for driver drowsiness detection using video surveillance and transfer learning consists of several steps. The process begins by analyzing video frames to pick up facial features like the eyes and mouth. Models like VGG-16, ResNet, and GoogleNet—already trained on other data—are adjusted using drowsiness datasets to detect signs such as frequent blinking, eye closure, and yawning. But this method isn't without issues. It often needs a lot of computing power, which makes real-time use difficult on smaller devices. It can also misjudge things when lighting is poor, parts of the face are blocked, or the camera angle isn't ideal. And although it works well in controlled environments, it doesn't always perform as reliably with different types of drivers.

B. Innovation

The Basic Idea is to use a neural network with transfer learning to detect key facial landmarks related to drowsiness such as eye closure and yawning. Using these detected points, we classify drowsiness levels and trigger alerts. The main difference is that the input consists of a single video frame, and the output provides drowsiness classification. A fine-tuned MobileNet model ensures efficient detection. Enhancements refine facial landmarks using computer vision. Adaptive thresholding adjusts detection sensitivity. Multi-frame analysis tracks drowsiness over time. Perspective correction ensures accurate detection across different camera angles.

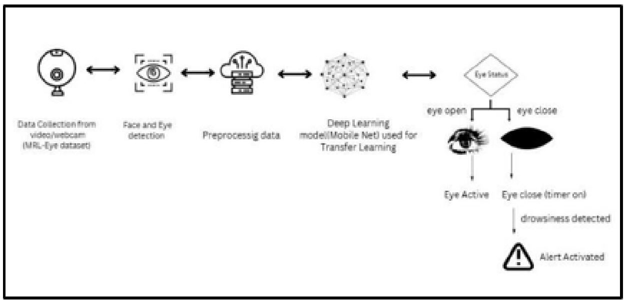

Figure 1. Architecture Diagram

The Fig.1 is showing a drowsiness detection system that begins by acquiring video input from a webcam or a recorded file. On this occasion, it was designed to detect faces and eyes using Haar cascades or similar methods, isolating the regions of interest. The detected eye images are cropped, resized, converted to grayscale, and normalized before being fed into the pre-trained MobileNet model. As can be perceived, this model classifies the eye state (open or closed) to assess drowsiness.

C. Data Collection Module

The data collection acquires image data for training and assessing the doziness discovery model, icing robustness through a different dataset. It captures images and videos of individualities with colorful eye countries (open, incompletely closed, closed) under different lighting conditions, head acts, and facial expressions to pretend real-world driving scripts. A different group of actors is involved to regard for variations in facial features. Ethical considerations are prioritized, with informed clearance and anonymization ways guarding sequestration. Labeled data serves as ground verity for model training, and intimately available datasets may be incorporated to enhance performance and conception.

D. Preprocessing Module

The preprocessing module prepares image data for training the MobileNet model, enhancing performance and reducing training time. First, images are resized to a uniform size for compatibility and reduced computational load. Next, they are converted to grayscale to simplify processing while retaining essential eye features. Data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and improve robustness. Additionally, normalization scales pixel values between 0 and 1 for stable training. Finally, the processed data is structured into arrays or data generators for efficient model input.

E. Feature Extraction Module

The MobileNet deep learning model in this system performs feature extraction automatically, therefore feature engineering is not necessary. MobileNet, a convolutional neural network, detects patterns that range from basic edges to intricate ocular characteristics by extracting hierarchical data through its convolutional layers. Rich feature representations are preserved while efficiency is increased by its depthwise separable convolutions. Fully connected layers then classify eye states using these extracted features. The approach guarantees effective learning for sleepiness detection and streamlines development through incorporating feature extraction into the model.

F. Drowsiness Detection Module

The pre-trained MobileNet model receives the preprocessed eye pictures. This model distinguishes the input eye image and predicts whether the eyes are open or closed,

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or maybe additional states indicating drowsiness. It has been refined using a dataset of eye images classified with their various states (open, closed, etc.).

G. Drowsiness Alert Module

The system analyzes whether the driver is sleepy based on the MobileNet model's output, or according to the projected eye condition. The device triggers an alert if it detects signs of drowsiness, such as eyes being closed for a certain period of time or a decrease in blinking frequency.

This alert may be a visual cue (such as a flashing light on the dashboard), an aural warning (such as a beep or voice message), or a mix of the two.

IV. RESULT AND DISCUSSION

In the given Fig.2, a frame from a drowsiness detection system is displayed, where the system is actively analyzing the subject's facial features to determine their alertness level. The image shows a person being monitored with green bounding boxes highlighting key facial regions, including the eyes, nose, and mouth. The label "Active" in the top-left corner suggests that the system has classified the subject as awake and alert. Additionally, the text "Open Eyes" appears in red at the top, indicating that the system has successfully detected open eyes. Visual indicators like these play an essential role in identifying driver fatigue in real-time and helping to avoid accidents caused by drowsiness.

The system uses a combination of computer vision and deep learning to monitor signs of driver fatigue by identifying facial landmarks and observing eye activity. It operates in real-time, allowing it to respond quickly when early symptoms of drowsiness appear. Visual markers, such as bounding boxes, help track key facial features, improving the model's precision and consistency. This kind of technology has found practical use in areas like automotive safety, fleet supervision, and public transport monitoring, all aimed at promoting driver alertness. By observing facial expressions and signs of reduced focus, the system plays an important role in preventing accidents linked to fatigue.

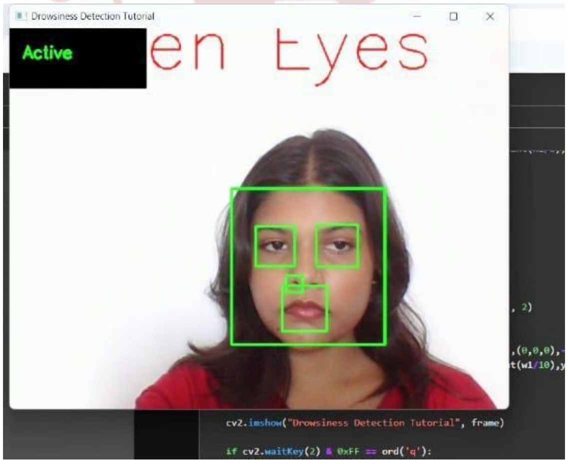

Figure 2. Open Eyes Detected

1). Input: The system captures real-time video feed from a camera focused on the subject's face. 2). Preprocessing: The input frame undergoes enhancement techniques, such as grayscale conversion, noise reduction, and facial landmark detection to isolate key facial features like eyes and mouth. 3). Detection Algorithm: The system employs a convolutional neural network (CNN)-based model, such as MobileNet or ResNet, to detect facial features and classify eye states (open or closed). 4). Classification & Confidence

Score: The model determines whether the subject is drowsy or alert based on eye openness and assigns a confidence score to the classification. In this case, the system has classified the user as "Active" with open eyes. 5). Overlay: Once detection is complete, the system overlays bounding boxes on the facial regions and displays a classification label in real time. The results are presented on the screen for visualization and alert triggering if drowsiness is detected. This drowsiness detection system enhances road safety by continuously monitoring a driver's alertness and triggering alerts when signs of fatigue are identified.

In the given Fig.3, a frame from a driver drowsiness detection system is displayed, where the system has identified signs of drowsiness in the subject. The image shows a person with closed eyes, detected using computer vision and deep learning techniques. Green bounding boxes highlight key facial regions, including the eyes and nose, which are used for analysis. The label "Sleep Alert!!" appears in the top-left corner in red, indicating that the system has detected drowsiness and triggered an alert. Additionally, the text "Closed Eyes" is displayed at the top, reinforcing the detection result.

This system functions by continuously monitoring facial features, particularly eye openness, to determine the driver's level of alertness. When prolonged eye closure is detected, the system activates an alert mechanism (such as an audible alarm, visual warning, or vibration feedback) to prevent accidents caused by driver fatigue.

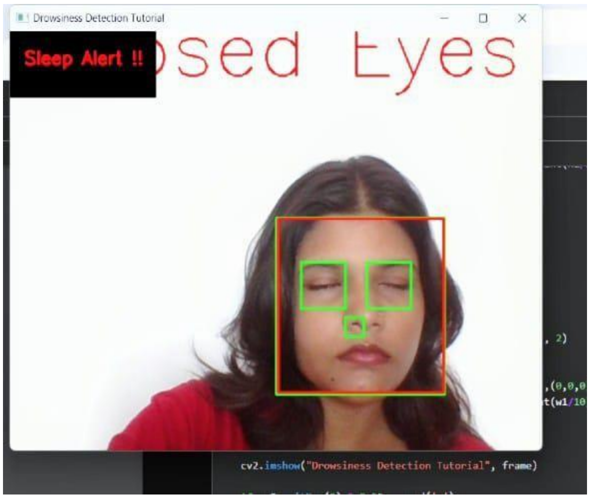

Figure 3. Closed Eyes Detected

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1). Input: The system captures a real-time video feed from a camera monitoring the driver's face. 2). Preprocessing: The captured frame is enhanced through grayscale conversion, noise reduction, and facial landmark detection to focus on key regions such as the eyes and nose. 3). Detection Algorithm: A convolutional neural network (CNN), such as MobileNet or ResNet, is used to classify eye states (open or closed) and identify signs of drowsiness. 4). Classification & Confidence Score: The model detects closed eyes and assigns a confidence score, confirming drowsiness. Once the threshold is met, the system classifies the subject as drowsy and triggers an alert. 5). Alert System & Overlay: When drowsiness is detected, the system overlays warning messages such as "Sleep Alert!!" on the display and can activate audio or visual alerts to wake up the driver.

This real-time drowsiness detection system plays a crucial role in enhancing road safety, reducing fatigue- related accidents by continuously monitoring and alerting drivers when signs of sleepiness are detected.

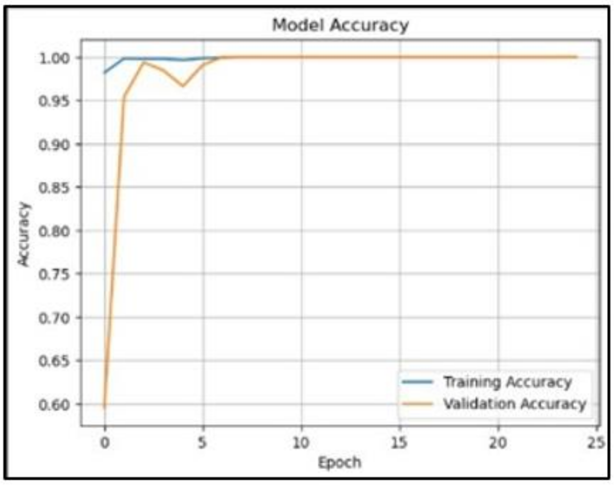

Figure 4. Model Accuracy

Fig.4 says 1). The number of training iterations is represented by the X-axis (Epochs). 2). Y-axis (Accuracy): Indicates the model's classification performance (range: 0 to 1).

The model's accuracy on the training dataset is displayed by the Blue Line (Training Accuracy).

The model's accuracy on unseen validation data is indicated by the Orange Line (Validation Accuracy).

Interpretation: within a few epochs, the model learns quickly and achieves high accuracy. There is no considerable overfitting because training and validation accuracy are nearly identical. The model is highly tuned and exhibits good generalization to unknown inputs.

```
[32]: from sklearn.metrics import classification_report
      print(classification_report(y_test, y_pred, target_names=Classes))

              precision    recall  f1-score   support

   Close-Eyes       1.00      1.00      1.00       290
    Open-Eyes       1.00      1.00      1.00       362

     accuracy                           1.00       652
    macro avg       1.00      1.00      1.00       652
 weighted avg       1.00      1.00      1.00       652
```

Figure 5. Classification Report

Fig.5 says the classification report highlights the MobileNet-based driver drowsiness model, achieving 100% accuracy, precision, recall, and F1-scores for both "Close-Eyes" and "Open-Eyes" classes, supported by NTHU and MRL datasets.

V. CONCLUSION

Using Python, TensorFlow, and OpenCV, this study has demonstrated the creation and deployment of a real- time drowsiness detection system that makes use of MobileNet's transfer learning capabilities. The solution effectively combines a pre-trained and optimized MobileNet model for precise eye state categorization with computer vision algorithms for face and eye detection. When compared to building a deep learning model from scratch, the use of transfer learning greatly decreased the amount of data needed and the amount of time needed for training. The method offers a viable way to reduce the dangers of drowsy driving by proving that real-time sleepiness detection based on eye behavior is feasible. Flexibility and possible integration with other driver monitoring systems or Advanced Driver-Assistance Systems (ADAS) are made possible by the system's modular design. The obtained results demonstrate how deep learning and computer vision can help improve road safety and reduce accidents brought on by tired drivers. Future research might concentrate on strengthening the system's resistance to different head positions, lighting circumstances, and driver traits. The accuracy and dependability of drowsiness detection could be further improved by investigating the integration of extra physiological information, such as brainwave activity or heart rate variability. Furthermore, preparing the system for deployment on mobile platforms or embedded devices may open the door for broad use and practical application.

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