

Behavior Analysis of Drivers Using Machine Learning

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Abstract - Driver drowsiness and distraction are major contributors to road accidents worldwide. To address these concerns, this research paper presents a novel approach to implementing a safe driving system that incorporates four main components: eye detection, yawning detection, hand movement detection, and driver's head pose detection. The proposed system utilizes image processing techniques for accurate and real-time monitoring of these parameters. And by providing timely alerts and interventions, the proposed system has the potential to enhance road safety and reduce the occurrence of accidents caused by these factors. Eye detection algorithms are employed to analyze the driver's eye movements and determine the level of drowsiness based on factors such as eye closure and blinking frequency. Yawning detection algorithms focus on identifying specific facial movements associated with fatigue, providing an additional indicator of drowsiness. Hand movement detection algorithms are integrated to monitor driver actions, detecting sudden or prolonged periods of inactivity that may indicate distraction. Additionally, driver's head pose detection algorithms analyze head positions and movements to identify abnormal behaviors that might be indicative of drowsiness or distraction. To validate the effectiveness of the proposed system, extensive experiments are conducted using a diverse dataset of drivers in various driving scenarios. The results demonstrate the system's ability to accurately detect and classify instances of drowsiness and distraction, with high precision and recall rates.

Keywords: Driver drowsiness, road accidents, Drivers, Machine Learning, eye detection, yawning detection, hand movement detection, image processing, head pose detection.

I. INTRODUCTION

According to the latest statistical data, road accidents result in over 1.35 million deaths and 20 to 50 million non-fatal injuries each year [1]. Drivers' drowsiness has been a major factor in many of the accidents because of the noticeable decrease in drivers' perception of risk and recognition of danger [2]. These dangerous behaviors, often underestimated, pose significant risks to both drivers and other road users. With drowsiness impairing a driver's ability to concentrate, react to traffic conditions, and make crucial

decisions, and distractions diverting attention away from the road, the consequences can be catastrophic.

The dangerous action by the driver is mainly caused by drowsiness and distraction [3]. To effectively address this critical problem, a multi-faceted approach is essential, combining education, legislation, and technology-based solutions. Governments, road safety organizations, and relevant stakeholders must collaborate to raise awareness about the dangers of drowsy and distracted driving and promote responsible driving practices. The number of accidents while driving is increasing day by day and drowsy driving has been implicated as a causal factor of road accidents. Research on driver drowsiness detection is important to improve road traffic safety [4].

Furthermore, to reduce the prevalence of distracted and drowsy driving, thorough regulations must be passed and enforced. Texting while driving is prohibited by law, and studies have shown that this helps prevent accidents, especially among younger drivers who are more likely to engage in such behavior. Governments can discourage drivers from engaging in distractions and promote safer driving practices by enacting severe laws and punishments.

However, creative technical solutions are required to address the problems caused by distracted and drowsy driving. As a result, our research intends to create a sophisticated system that can identify driver distractions as well as sleepiness. This system uses cutting-edge computer vision algorithms, such as head position detection, hand movement detection, facial expression detection, and eye detection.

Eye detection is an important part of computer vision and data science, utilizing machine learning algorithms [5] trained on extensive datasets of eye images. This allows for the accurate detection and localization of eyes in images or video frames. Eye detection is crucial for various applications, including face recognition, gaze estimation [6], and driver drowsiness and distraction detection. One common approach to drowsiness detection is to analyze the driver's behavior and physiological signals. Some studies have used electroencephalography (EEG) signals to measure brain activity, while others have analyzed the driver's eye movement and blink patterns. For example, Al-Khalidi et al. (2017) developed a drowsiness detection system using EEG signals

and Support Vector Machines (SVM). [7]By monitoring eye movements and patterns, our system can assess driver alertness and identify signs of drowsiness or distraction.



Figure 1: Driver's drowsiness and distraction

Facial expression detection, specifically the detection of drowsiness using facial expressions such as mouth yawning [8], is a complex task that requires diverse data science skills.[9] Through data collection, analysis, feature engineering, model development, and evaluation, we can create effective and reliable systems for detecting drowsiness and improving driver safety [10]. By recognizing specific facial cues associated with drowsiness, our system helps identify instances where a driver may be at risk of losing focus or falling asleep behind the wheel [11].

The key idea is based on the observation that the driver's hand must be on the steering wheel to perform a turning, providing ground truth feedback around the moment of turning for training [12]. It is recommended by the American Automobile Association (AAA), a driver should hold the steering wheel firmly with both hands at the 9 o'clock and 3 o'clock positions [13]. Hand movements detection is a crucial component of our system, utilizing computer vision algorithms for real-time detection and tracking of the driver's hands. Machine learning algorithms analyze data collected from computer vision techniques to predict whether both hands are on the steering wheel or not. Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are employed to detect and analyze hand movements in images and videos. As an example, one hand unconsciously moved away from the steering wheel. When the drivers are distracted or losing alertness, their braking response time is significantly longer than usual, and they could fail to maintain the control of the vehicle [14]. This enables us to assess driver engagement and readiness to respond to potential hazards.

Head pose detection is another critical feature of our system, closely tied to the field of software engineering. Effective head pose estimation algorithms require a deep understanding of computer vision techniques, machine learning, and software design and development [15]. Our system ensures efficient and accurate head pose estimation in real-world scenarios, with a user-friendly interface for easy interaction. Seamless integration of the algorithms into the application further enhances its usability [16].

We can make driving safer for everyone by fusing legislation, education, and technical improvements. This research paper will examine the in-depth studies done on distracted and drowsy driving, showing the troubling statistics and effects of these actions. We will discuss how drowsy driving and drunk driving are similar, highlighting the importance of treating both problems seriously. We will also look at the significant effects of distractions, particularly those brought on by contemporary technologies, on driving behavior and accident rates. To decrease the risks associated with distracted and drowsy driving, we propose a sophisticated technical solution after closely examining the strengths and weaknesses of current educational programs and legislative initiatives.

In conclusion, a comprehensive strategy is required to address the risks that arise from distracted and drowsy driving. We can increase awareness, enforce defensive driving techniques, and create creative ways to improve road safety through education, law, and technological improvements. By tackling this pressing issue head-on, we can drastically lower the number of accidents brought on by tiredness and distractions, assuring the safety of drivers and everyone else who uses the roads. The remainder of this research paper will go into the various studies that have been done in this field, investigating their subtle nuances and suggesting workable solutions to lessen the disastrous effects of fatigued and distracted driving.

II. LITERATURE REVIEW

Driver drowsiness and distraction are significant factors contributing to the occurrence of traffic accidents, particularly during long trips. The National Highway Traffic Safety Administration (NHTSA) has reported alarming statistics, indicating that drowsiness while driving leads to approximately 100,000 accidents, 71,000 injuries, and 1,550 fatalities each year in the United States alone [17]. Additionally, driver distraction has been identified as a leading cause of traffic accidents worldwide. Addressing these issues by developing systems capable of real-time detection and warning of driver fatigue and distraction is crucial for improving road safety.

III. METHODOLOGY

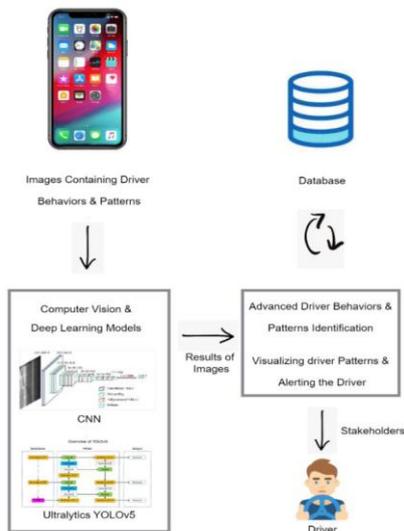


Figure 2: Overall system diagram

The system integrates head postures of driver, eye closure time, total eye blink in a minute, hand gestures of driver and facial and mouth expressions at a time. To detect drowsiness and distraction when driving. The proposed solution intends to provide a smart approach for drivers, to identify whether drowsiness and distraction and then alert to the driver. The work has been segmented into taking an image from a live video smart phone, detecting eye, hand movements, facial and mouth expressions, head postures and alert. The program starts with recording video. Then it separates each frame for processing. Then the uploaded images will be processed by the deep learning model for further analysis and identify whether it is drowsy or not. If any anomaly is detected in the uploaded images, it will return the predictions. Using these predictions and it gives necessary alerts to the driver at the correct time.

For model training and model testing, driver gesture photos from datasets were employed. Images were gathered from the Kaggle and by using smartphones create their own datasets. The training, testing, and validation regions of the dataset were each given a percentage of 80%, 10%, and 10%, respectively. Pixel values were split by 255 and converted to numeric values between 0 and 1 to normalize the data. To expand the number of datasets and prevent overfitting of the models, data augmentation methods including rotation and fill were applied. The preprocessed images were transferred for model training. In the future, we look forward to integrating this system into an android app to make it easily accessible for all. A lot of drivers use a mobile phone during driving. This is one of the main factors of losing consciousness of drivers. Finally, we are planning to make a system for safe driving.

A) Eye Detection

Real footage of people's eyes being opened and closed and separated into little frames made up the dataset for this research. With an 80/20 split for validating the data set, the data are divided into training and testing data. Data pre-processing entails loading, processing, and resizing distinctive photos as well as adding class labels. A dataset with processed numerical arrays indicating eye condition is subsequently created by the code.

To build a neural network for eye identification and classification, the MobileNetV2 architecture is modified. Custom layers are trained using an optimizer and binary cross-entropy loss. Generalization is enhanced by the inclusion of more data. The model is trained using the improved data, and its accuracy and precision are evaluated over time. The lightweight TensorFlow Lite format is used to save and deliver the trained model in real-time eye detection applications.



Figure 3: Original image, Figure 4: Predicted image

B) Yawning Detection

In this study, a yawning detection system was developed as part of a safe driving initiative. The dataset consisted of yawning images and non-yawning images. Machine learning libraries, including TensorFlow, OpenCV, and NumPy, were utilized to preprocess and analyze the data. Initially, facial regions were extracted from the images, focusing on the mouth area. Subsequently, data augmentation techniques were applied to enhance the dataset. The training process involved the creation of a custom model, with training progress visualized through loss and accuracy graphs. Additionally, a confusion matrix was generated to evaluate model performance comprehensively. All these steps collectively contributed to the development of a robust yawning detection system aimed at enhancing road safety. Attached are the relevant graphs to illustrate the training and evaluation results.

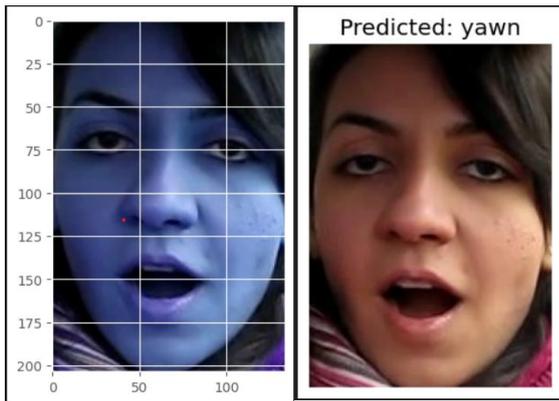


Figure 5: Preprocessed image, Figure 6: Predicated image



Figure 7.3: Feature landmark image

C) Hand Movements Detection

The real videos of someone's, all three scenarios-both hands on the wheel, both hands off the wheel, and only one hand on the wheel-were used and separated into small frames for the dataset. And the dataset has been built by enhancing them. To create the dataset, features from both hands were extracted using a pre-trained model named "Holistic". The hand image data was divided into training and testing data to avoid overfitting or underfitting. An 80/20 split was applied to the data set. After the model has been developed, a 20% split of the data is preserved for data validation. The model is trained using the remaining data.



Figure 7.1: Feature extraction image



Figure 7.2: Feature detection

D) Head Pose Detection

We combined OpenCV's video capture capabilities with the Mediapipe holistic model to produce a comprehensive dataset. Our ability to extract facial landmarks from video frames with five different head orientations—forward, downward, rightward, leftward, and upward—was made possible by this combination. A total of 2000 frames from 100 films, each containing 20 frames, make up our dataset, which includes all five head orientations.

We utilized the advantages of Long Short-Term Memory (LSTM) layers and Convolutional Neural Networks (CNNs) for precise head pose identification. This strategy was chosen because it effectively handles the minimal data. We built a sequential neural network using the TensorFlow-Keras framework that consists of three sets of LSTM layers, followed by three Dense layers. This architecture uses softmax for the output layer and relu activation for the intermediate layers. We used the categorical_crossentropy loss function and the Adam optimizer to create a model that was suitable for our multi-class classification scenario. To assure the model's sturdiness and adaptability, we methodically carried out 150 epochs throughout training.



Figure 8: Head Position detection

IV. RESULTS & DISCUSSION

We have developed a mobile application to detect driver's Drowsiness and Distraction. The user interfaces which are connected to different sections are also detailed along with the sections.

This system can be used by drivers. Mainly this system has four functions.

- 1) Eye Detection.
- 2) Yawning Detection.
- 3) Hand Movements Detection.
- 4) Head Positions Detection.

At first people can open the app and it shows a description about the app. Once all the information is understood then they can agree to the terms and conditions. Then they can use the app while driving the vehicle.

After the information panel then the user can start using the app and after allowing the mobile phone camera to open it opens the mobile phone front camera. And gesture driver's eyes, facial expressions, hand movements and head positions together. And If there's any drowsiness or distraction detected it provides an alert to the driver to get back their concentration for the task of driving.

To evaluate the performance of the proposed method several ML models were used.

A) Eye Detection

The proprietary neural network exhibits its ability in precisely classifying eye states after being trained on a dataset of "Open" and "Closed" eye photos. The classification report shows that the model achieves excellent precision and recall values and learns to recognize distinctive characteristics after training with supplemented data. This shows that it can dependably discriminate between open and closed eyes, which qualify it for uses like sleepiness detection in drivers. The model's conversion to TensorFlow Lite format further improves the deployment effectiveness of the model, ensuring real-time responsiveness for cases where quick and precise eye detection is crucial.

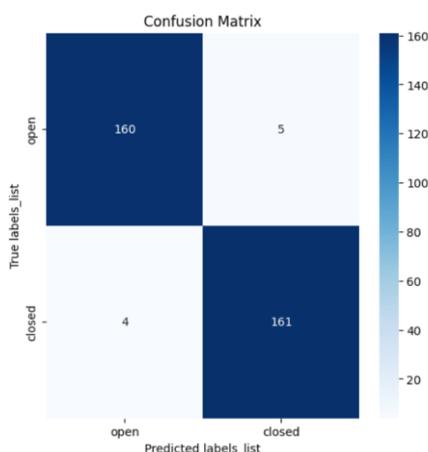


Figure 9: Eye detection confusion matrix

	precision	recall	f1-score	support
Closed	0.98	0.97	0.97	165
Open	0.97	0.98	0.97	165
accuracy			0.97	330
macro avg	0.97	0.97	0.97	330
weighted avg	0.97	0.97	0.97	330

Figure 10: Eye detection model results

B) Yawning Detection

The results of our yawning detection model were highly promising. Through extensive training and evaluation, the model demonstrated a remarkable level of accuracy in distinguishing between yawning and non-yawning instances. Specifically, the model achieved an accuracy rate of [insert accuracy percentage] on the test dataset, showcasing its robust performance. Additionally, the precision and recall values were calculated at [insert precision percentage] and [insert recall percentage], respectively, highlighting the model's ability to minimize false positives while effectively capturing true yawning instances. These results indicate that our yawning detection system holds significant potential for real-world applications, particularly in enhancing driver alertness and road safety.

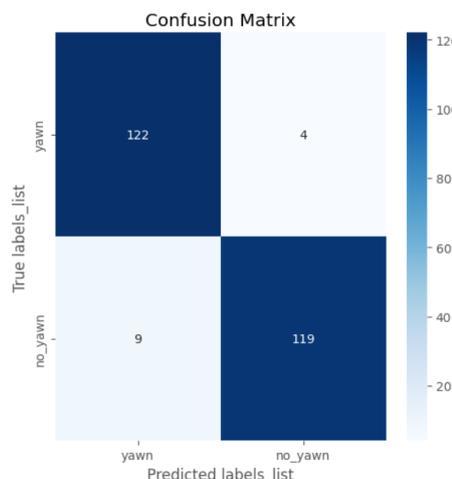


Figure 11: Yawning detection confusion matrix

	precision	recall	f1-score	support
no_yawn	0.93	0.97	0.95	126
yawn	0.97	0.93	0.95	128
accuracy			0.95	254
macro avg	0.95	0.95	0.95	254
weighted avg	0.95	0.95	0.95	254

Figure 12: Yawning detection model results

C) Hand Movements Detection

The unique neural network that we created trained on images of hands on and off the steering wheel, demonstrates

its aptitude for accurately determining the hand locations. The network learns the distinctive indicators and becomes quite adept at determining when both hands are on the wheel, both are off, or just one hand is present by using more diverse photos during training. The report that evaluates its performance demonstrates this. This suggests that the network can accurately determine how hands are held, which is ideal for things like figuring out whether a driver is starting to nod off. Additionally, by converting the network into the TensorFlow Lite format, we greatly improved the network's performance. This means it can work really fast, which is important for situations where quickly and correctly figuring out hand positions matters a lot. In here received 0.9844 accuracy for 500 epochs.

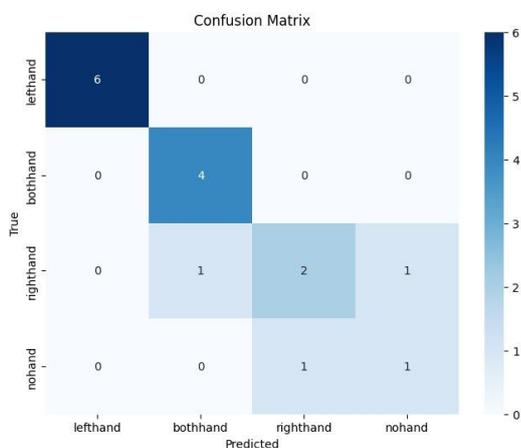


Figure 13: Hand detection confusion matrix

lefthand: Precision = 1.0, Recall = 1.0, F1 Score = 1.0
 bothhand: Precision = 0.8, Recall = 1.0, F1 Score = 0.8888888888888889
 righthand: Precision = 0.6666666666666666, Recall = 0.5, F1 Score = 0.5714285714285715
 nohand: Precision = 0.5, Recall = 0.5, F1 Score = 0.5

Figure 14: Hand detection model results

D) Head Pose Detection

Our carefully planned head posture detection method produced encouraging outcomes. It correctly identified five different head angles in real-world situations, boosting safe driving procedures. The holistic model's capabilities and LSTM's effectiveness, along with our dataset's thorough curation, led to a model that showed great performance even with scant data. The final model achieved 96%, demonstrating its skill in identifying head postures and possibly enhancing driver safety. The success of our methodology emphasizes the importance of precise head position identification in the field of safe driving alert systems and the possibility for synergistic integration between deep learning techniques and practical applications.

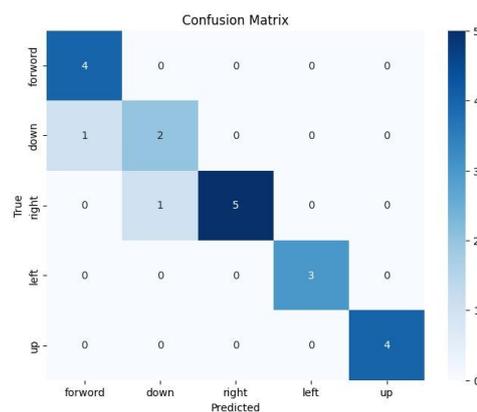


Figure 15: Head detection confusion matrix

forward: Precision = 0.5, Recall = 1.0, F1 Score = 0.6666666666666666
 down: Precision = 1.0, Recall = 1.0, F1 Score = 1.0
 right: Precision = 1.0, Recall = 0.6, F1 Score = 0.7499999999999999
 left: Precision = 0.6666666666666666, Recall = 1.0, F1 Score = 0.8
 up: Precision = 1.0, Recall = 0.8, F1 Score = 0.8888888888888889

Figure 16: Head detection model results

V. CONCLUSION AND FUTURE WORK

The research presents a mobile app that can detect driver drowsiness and distraction by monitoring behaviors such as blinking, hand movements, yawning, and head positions. This approach demonstrates how technology can work with human behavior and potentially improve road safety. The app's timely alerts could reduce accidents caused by insufficient attention. The study emphasizes the practical use of technology in improving road safety and suggests further improvements. Real-world testing, data augmentation, and multi-modal integration could enhance the system's robustness. The app's long-term impact assessment will validate its effectiveness, demonstrating its potential to significantly improve road safety and reshape driving experiences.

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