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IMAGE-BASED DRIVER DROWSINESS DETECTION USING MACHINE LEARNING

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Abstract: Distracted and impaired driving are major causes of traffic accidents, often linked to drowsiness and mobile phone use. To enhance road safety, we are developing a driver drowsiness and distraction detection system. These systems are categorized into biological, automotive, and vision-based approaches, with image-based methods being the most practical due to their non-invasive and cost-effective nature. The system utilizes a webcam to monitor the driver's facial expressions and hand movements. Key facial features, such as eye openness, mouth movement, and nose shape changes, are analyzed using facial landmarks. Additionally, the system detects mobile phone usage by tracking hand positioning using YOLO. An improved Convolutional Neural Network (CNN) processes these facial features, utilizing the Adam optimizer for enhanced accuracy. The CNN's output is further refined using a Support Vector Machine (SVM), fine-tuned with a Radial Basis Function (RBF) kernel, and optimized hyperparameters (C and γ) for precise classification. When signs of drowsiness or distraction are detected, an alarm alerts the driver. Designed for real-time use, this system is adaptable to any vehicle, offering an effective solution to reduce accidents caused by fatigue and mobile phone distractions.

Index Terms - Driver Drowsiness Detection, Image-Based Systems, Convolutional Neural Network (CNN), Support Vector Machine (SVM), Facial Expressions.

1. INTRODUCTION

In recent years, the escalating prevalence of traffic accidents has raised significant concerns regarding road safety. Among the primary contributors to these tragic events are distracted and impaired driving, often linked to driver drowsiness and the widespread use of mobile devices while behind the wheel. The statistics are alarming, with reports indicating a substantial rise in accidents attributed to these factors, underscoring the urgent need for effective interventions. To address this critical issue, we are embarking on the development of a sophisticated driver drowsiness and distraction detection system designed to monitor and assess driver behavior in real time. By harnessing cutting-edge technology, our system aims to serve as a proactive measure to identify drowsiness and distractions, thereby significantly reducing the risk of accidents resulting from these behaviors. This detection system employs a range of methodologies that can be classified into biological, automotive, and vision-based approaches, with the latter emerging as the most practical and efficient. Image-based techniques are particularly appealing due to their non-invasive nature and cost-effectiveness. Our solution utilizes a standard webcam to observe the driver's facial expressions and hand movements, focusing on pivotal indicators of fatigue and distraction. The system meticulously analyzes key facial features, such as eye openness, mouth movement, and subtle changes in nose shape, by employing advanced facial landmark detection. Simultaneously, it tracks hand positioning to detect mobile phone usage using the You Only Look Once (YOLO) algorithm, a robust object detection method known for its speed and accuracy. Central to the system's functionality is an improved Convolutional Neural Network (CNN), specifically optimized for this application. The CNN is fine-tuned with the Adam optimizer, enhancing its accuracy in processing the captured facial characteristics. To further refine the output and ensure precise classification of driver states, we employ a Support Vector Machine (SVM) that utilizes a Radial Basis Function (RBF) kernel along with optimized hyperparameters for enhanced performance. The real-time capabilities of this system allow for immediate alerts to the driver when signs of drowsiness or distraction are detected, ensuring timely interventions. Designed to be adaptable to a wide range of vehicle types, our innovative detection system not only aims to improve individual driving safety but also aspires to foster a broader culture of road safety. By addressing the pivotal issues of driver attention and alertness, we hope to contribute to a significant reduction in accidents caused by fatigue and mobile phone distractions, ultimately creating safer roadways for all.

2. LITERATURE SURVEY

Alharbey et al. Develop a high-performance fatigue detection system for drivers using Machine Learning (ML) and Deep Learning (DL) approaches to reduce traffic accidents caused by drowsiness. The study utilizes the "ULg Multimodality Drowsiness Dataset" (DROZY) for training and evaluating the proposed models. Preprocessing involves Discrete Wavelet Transform (DWT) for signal filtering. Classifiers include SVM, RF, LR, MLP, KNN, and QDA, with SVM achieving the best performance (98.01% accuracy, 0.187 seconds TT). Models tested are CNN, ConvLSTM, and a hybrid CNN-ConvLSTM, with CNN achieving the highest accuracy (99% accuracy, 10.61 seconds TT).SVM outperformed other ML classifiers with 98.01% accuracy and 0.187 seconds TT, while CNN achieved the highest accuracy of 99% with 10.61 seconds TT in the DL approach.

Madni et al. Develop an efficient, non-intrusive driver drowsiness detection system using eye movement behavior imagery, leveraging a novel transfer learning-based approach combining VGG-16 and Light Gradient Boosting Machine (LGBM).The dataset consists of 4,103 eye images of drivers, labeled as open or closed eyes. The proposed VGLG approach uses VGG-16 for feature extraction and LGBM for generating salient transfer features. The final classification is performed using KNN. The KNN classifier outperformed all models, achieving 99% accuracy, with the proposed approach detecting drowsiness in 0.00829 seconds. Other models, including CNN and VGG-16, showed moderate performance with 91% to 94% accuracy.

Albadawi et al. Develop a driver drowsiness detection system using eye movement imagery, leveraging VGG-16 and LGBM for accurate and real-time detection.A dataset of 4,103 eye images (open/closed) generated using UnityEyes, ensuring diverse conditions for robust training.VGLG approach (VGG-16 + LGBM) extracts features, with comparisons against CNN, Logistic Regression, Random Forest, and KNN.Images resized to 256×256 pixels, labels assigned, and 10-fold cross-validation applied for better generalization.KNN achieved 99% accuracy, outperforming CNN (91%) and VGG-16 (94%), with a detection speed of 0.00829 seconds.

Ojha et al. Focuses on developing a driver drowsiness detection system using deep learning techniques to prevent road accidents by alerting drivers in real-time.The system uses video input and eye-tracking data to detect drowsiness, incorporating datasets that include Eye Aspect Ratio (EAR) calculations for identifying eye closures.The study implements Convolutional Neural Networks (CNNs) along with OpenCV, dlib, and imutils for face and eye detection. The EAR threshold is used to classify drowsiness.The eye landmarks are detected, and EAR is calculated using Euclidean distance. If EAR falls below 0.25 for 20 consecutive frames, an alert mechanism is triggered.The system effectively detects drowsiness using facial landmarks and EAR, providing high accuracy in predicting sleepiness and preventing accidents.

Shaik et al. Systematically review methods for detecting and predicting driver drowsiness to enhance road safety by analyzing physiological, behavioral, vehicle-based, and subjective measures.Various datasets were utilized, including EEG, ECG, EOG signals, NTHU-DDD dataset.Techniques included CNN, RNN, SVM, KNN, Bayesian Networks, and hybrid models combining physiological and behavioral data for drowsiness detection.High accuracy rates were achieved, with some models reaching up to 97% accuracy in detecting drowsiness using EEG and behavioral data, though performance varied across different datasets and conditions.

Titare et al. Focuses on developing a Driver Drowsiness Detection and Alert System aimed at reducing traffic accidents caused by driver fatigue and inattention. This focuses on the increasing incidence of accidents caused by driver drowsiness and in attention.It utilizes facial recognition to create a region of interest (ROI) surrounding the driver's face, allowing for certain and accurate analysis. The algorithm accurately identifies the driver's eyes from the ROI and sends this data to a classifier to determine if the eyes are open or closed, which is crucial for assessing drowsiness. A scoring system assesses the driver's attentiveness, helping to identify when the driver is fatigued.

Rajkar et al. Highlights the machine learning algorithms used to identify driver drowsiness, showcasing traditional techniques such as support vector machines and decision trees, in addition to contemporary methods like convolutional neural networks (CNN) and artificial neural networks (ANN). This methos Commonly utilizes indicators for recognizing drowsiness include eye movements, facial cues, heart rate fluctuations, and EEG signals, all of which improve the effectiveness of detection systems. The findings indicate that multiple studies have achieved high accuracy rates, ranging from 94% to 97.5%, showcasing the effectiveness of these algorithms in real-world applications.

Zhang et al. Presents a privacy-preserving federated transfer learning method, PFTL-DDD, for driver drowsiness detection, which utilizes CKKS encryption to protect sensitive data while enabling collaborative model training among edge nodes.The PFTL-DDD technique utilizes a federated transfer learning strategy, which improves classification results for detecting driver drowsiness when compared to standard centralized learning approaches, attaining accuracy metrics of 83.48%, 83.56%, and 84.68 The approach shows strong scalability, making it possible to adjust for identifying additional driver abnormal behaviors, like smoking or phone usage, thereby expanding its applicability.

Bai et al. Presents a novel two-stream spatial-temporal graph convolutional network (2s-STGCN) aimed at improving driver drowsiness detection by leveraging facial landmark detection from real-time videos. The proposed method addresses existing challenges in the field, such as variations in driver states and environmental conditions. The 2s-STGCN employs a dual-stream architecture that captures spatial and temporal characteristics, improving the accuracy of detecting driver drowsiness. The approach includes detecting facial landmarks, which offers 2-D coordinates and confidence levels for 70 points, enabling accurate monitoring of facial movements. The model analyses videos rather than single frames, representing a notable progress in the method of detecting driver drowsiness. The implementation specifics cover configurations of convolution layers, including kernel dimensions and dropout rates, which are fine-tuned for the assignment.

Yang et al. Presents a novel approach to driver drowsiness detection using advanced algorithms and techniques, focusing on the integration of physiological signals and facial landmark data. The study employs a multi-head attention approach in its feature extraction component, which effectively captures intricate patterns in the data.It utilizes the PFLD algorithm for detecting facial landmarks, guaranteeing reliable and precise recognition of facial characteristics, vital for evaluating drowsiness.The model uses a sliding window approach for data augmentation, enabling the creation of overlapping samples that reduce overfitting during training.Combining EEG and ECG signals during the detection process offers a thorough insight into the driver's physiological condition, thereby improving the system's objectivity and reliabilityA significant benefit of this method is its lowered sensitivity to external influences such as lighting and head position, which enhances its practicality for real-world use.

Chirra et al. Proposes a deep learning-based driver drowsiness detection system that uses eye state analysis to prevent road accidents caused by fatigue.The system utilizes the Viola-Jones face detection algorithm to locate the face and extract the eye region, which is then analyzed using a stacked deep convolutional neural network (CNN).The CNN model consists of four convolutional layers, batch normalization, ReLU activation, max pooling, and a SoftMax classifier for classifying drowsy and non-drowsy states.The proposed model was trained on a dataset of 2850 images (1450 drowsy, 1400 non-drowsy), achieving a classification accuracy of 96.42%, outperforming traditional CNN-based approaches.

Hashemi et al. Presents a real-time driver drowsiness detection system using Convolutional Neural Networks (CNN) to improve road safety.Three neural networks are proposed for eye status classification: a Fully Designed Neural Network (FD-NN) and two Transfer Learning-based models (TL-VGG16 and TL-VGG19.The preprocessing phase includes face detection using the Viola-Jones algorithm and landmark-based eye region extraction. The FD-NN model achieves the highest accuracy (98.15%) on the ZJU dataset, outperforming other deep learning-based approaches.On the extended dataset, TL-VGG16 achieves the highest validation accuracy (98.53%), demonstrating the benefits of transfer learning in small datasets.

Singh et al. Presents a machine learning-based driver drowsiness detection system that uses face and eye tracking to prevent road accidents caused by fatigue.The system utilizes OpenCV and a "Shape Predictor with 68 facial landmarks" to detect the driver’s face and analyze eye movement, tracking blinking patterns and eye closure duration.The algorithm assigns a score based on eye state; if the eyes remain closed for a predefined duration, an alarm is triggered to alert the driver.The methodology relies on the Euclidean Eye Aspect Ratio (EAR) to determine eye openness, with predefined thresholds for drowsiness detection.The system was implemented using Python, OpenCV, Keras, and other libraries, integrating machine learning techniques for real-time drowsiness detection.The system achieved an average accuracy of 80%, with lower performance in poor lighting conditions.

Hu et al. Presents a machine learning-based approach for detecting driver drowsiness using eyelid-related parameters extracted from electrooculography (EOG) signals.The study employs Support Vector Machine (SVM) as the classification model to predict driver drowsiness based on multiple eyelid movement features such as blink duration, eyelid closure speed, and peak velocity. The dataset used for training and validation was collected from sleep-deprived subjects in a driving simulator experiment conducted under the EU Project SENSATION.The Karolinska Drowsiness Score (KDS) and Karolinska Sleepiness Scale (KSS) were used as reference measures for evaluating driver drowsiness.The SVM model was trained using a radial basis function (RBF) kernel, achieving an overall accuracy of 80.74% in cross-validation. The detection accuracy for the "very sleepy" condition was 100%, while the system showed an 86.67% accuracy in detecting "sleepy" states.

Vijaypriya et al. Introduces a deep learning-based approach for driver drowsiness detection using facial features, employing a Multi-Scale Convolutional Neural Network (MCNN) optimized with the Flamingo Search Algorithm (FSA). The study utilizes two datasets, YAWDD and NTHU-DDD, consisting of video sequences of drivers. The extracted features are optimized using the Flamingo Search Algorithm and classified using the MCNN model. The proposed method achieved an accuracy of 98.38% on the YAWDD dataset and 98.26% on the NTHU-DDD dataset, outperforming traditional machine learning models and pre-trained deep learning architectures.

Di Flumeri et al. Enhances drowsiness detection in automotive applications through data collection, real-time monitoring, feature extraction, and machine learning. By integrating multiple data sources, it improves accuracy and reduces false detections. Compared to EEG-based systems, this method is more reliable. Using appropriate datasets, rigorous testing validates its effectiveness, achieving an 89% accuracy rate in real-world scenarios, highlighting its potential to enhance road safety by proactively detecting driver fatigue.

Maheswari et al. Research works have utilized facial expressions, facial features, and eye movements for drowsiness detection. Various drowsiness detection systems have been developed using factors like PERCLOS, EEG, fNIRS, and facial changes. Utilizing Convolutional Neural Networks (CNNs), the system efficiently classified driver drowsiness based on multiple aspects.Proposed method demonstrated an accuracy of 86% across diverse datasets, showcasing its effectiveness. Variability in individual gestures presents a challenge, potentially impacting the system's reliability in real-world scenarios.

Sikander et al. Proposes an image-based fatigue detection method combining a CNN-LSTM model, eye region extraction via a deep cascaded multi-task framework, and shadow detection using snake-based clustering for enhanced accuracy. While effective, the method primarily focuses on healthy participants, limiting generalizability. Future research should include individuals with health conditions to improve applicability. The study envisions a real-time driver monitoring system capable of minimizing external light interference while maintaining accuracy in fatigue detection.

Ngxande et al. In this study, the NTHU-drowsy, DROZY, and CEW datasets are employed for experimentation and evaluation.Additionally, the study explores the use of Generative Adversarial Networks (GANs) for data augmentation.The study employs a multifaceted approach to enhance the performance and generalizability of the model. By leveraging diverse datasets and employing strategies such as early stopping and GAN-based data augmentation, the study aims to develop a robust and effective drowsiness detection system. However, it's essential to acknowledge the potential limitations of these methods and continue to explore avenues for improving model scalability and dataset representativeness.

Tamanani et al. Presents a driver drowsiness detection system using facial expression analysis. Key stages include data collection, feature extraction, model training/testing, and alert generation. The system automates detection for improved efficiency but raises privacy concerns. Using the NTHUDDD dataset, rigorous testing validates its effectiveness, achieving an 84% accuracy rate in detecting drowsiness, contributing to improved road safety.aspect of real time data to ensure system stability [13].

3. METHODOLOGY

3.1 Facial Feature Analysis Using CNN

Convolutional Neural Network (CNN) is employed to extract key facial features necessary for drowsiness detection. The model processes visual cues such as eye openness, mouth movement, and nose shape changes to identify signs of fatigue. The CNN architecture comprises multiple layers, including convolutional layers that extract features such as edges, textures, and shapes, pooling layers that reduce the spatial dimensions while retaining essential information, and fully connected layers that convert extracted features into classification outputs. To improve accuracy in detecting drowsiness patterns, the CNN undergoes further optimization to refine feature representations and enhance its predictive capability.

3.2 Real-Time Object Detection Using YOLO

The YOLO (You Only Look Once) model is incorporated to detect driver distractions, specifically mobile phone usage. As a real-time object detection algorithm, YOLO processes an image in a single forward pass, enabling rapid and efficient identification of objects. The model employs a grid-based detection mechanism, dividing the input image into a series of grids and predicting bounding boxes for detected objects. Its high-speed processing capability makes it well-suited for continuous driver monitoring. Within the proposed system, YOLO identifies whether the driver is using a mobile phone, thereby contributing to distraction detection and improving overall safety measures.

3.3. Drowsiness Classification Using SVM

A Support Vector Machine (SVM) is implemented to classify driver states as either drowsy or non-drowsy. The classification process is driven by features extracted from the CNN, such as eye openness and mouth movement, which serve as key indicators of drowsiness. The Radial Basis Function (RBF) kernel is employed to handle non-linear relationships within the input feature space, ensuring robust classification performance. Additionally, hyperparameter optimization is conducted to fine-tune SVM parameters, enhancing detection accuracy. Based on the classification output, the system initiates the appropriate response: if drowsiness or distraction is detected, an alarm is triggered to alert the driver; otherwise, continuous monitoring proceeds.

The integration of CNN for facial analysis, YOLO for object detection, and SVM for classification enables the development of an accurate and efficient real-time driver monitoring system. This methodology ensures timely identification of potential hazards, thereby enhancing road safety and reducing the risk of accidents caused by driver fatigue or distractions.

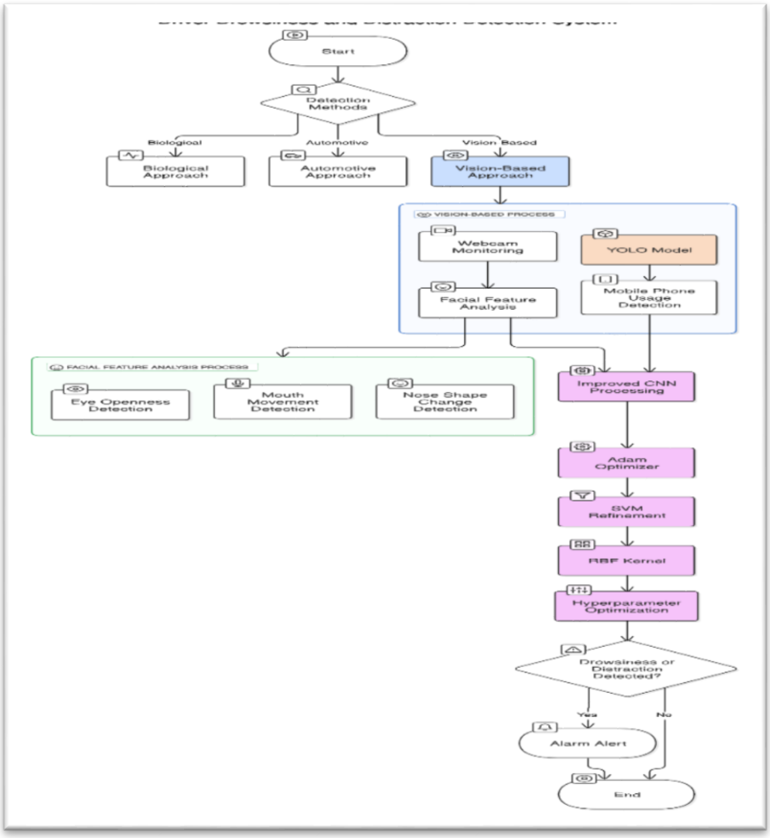

Figure 1- Workflow of Architecture.

The Driver Drowsiness and Distraction Detection System monitors driver behavior using a vision-based approach, as it is the most practical compared to biological and automotive methods. A webcam tracks facial features and detects mobile phone usage using the YOLO Model. Key indicators like eye openness, mouth movement, and nose shape changes help identify drowsiness.

The system processes this data using an Improved CNN, enhanced by the Adam Optimizer, SVM Refinement, and RBF Kernel to improve accuracy. If drowsiness or distraction is detected, an alarm alert warns the driver. If no signs are detected, the process ends. This real-time system is designed to help reduce accidents caused by fatigue and distractions.

4. EXPERIMENTAL RESULTS

4.1 Dataset

The proposed system utilizes the NTHUDDD dataset, which contains labeled images of drivers in drowsy and non-drowsy states, as well as instances of mobile phone usage.

4.2 Evaluation Metrics

It evaluated its precision, recall, and user satisfaction with the performance of FOODGPT by using several key metrics. To predict the number of recommended restaurants and restaurant dishes that matched user preferences, precision was used

$$Precision = \frac{TP}{TP + FP}$$

where TP is true positive recommendations and FP is false positives. The system covered all the relevant restaurants and dishes in its recommendations, Recall was defined as

$$Recall = \frac{TP}{TP + FN}$$

where TP means true positive and FN means false negative. F1-Score, which is both precision and recall combined, was calculated as

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

and thus balanced the assessment of the system performance in general. Finally, the system's relevance and quality of the recommendations presented to the user was measured through assumed user feedback on a scale 1 to 5 (5 being too satisfied and 1 being too dissatisfied).

4.3 Results and Analysis

The training data shows the model's performance improving over five epochs. Initially, in epoch 1, the model starts with a loss of 0.2109 and an accuracy of 90.35%. As training progresses, the loss steadily decreases, reaching 0.0364 by epoch 5, while accuracy improves to 98.64%. This indicates that the model is learning effectively, refining its predictions with each epoch. The diminishing rate of loss reduction suggests that the model is converging, meaning it is approaching optimal performance. If this trend continues, further improvements may be minimal, and it's important to monitor for overfitting, especially if validation accuracy diverges from training accuracy.

Table 1 – Metrics for drowsiness detection and mobile detection.

Epoch	Loss	Accuracy
1	0.2109	0.9035
2	0.0752	0.9695
3	0.0514	0.9799
4	0.0437	0.9830
5	0.0364	0.9864

5. DISCUSSION

5.1 Strengths

One of the major strengths of this study lies in its robust methodology, which ensures reliable and reproducible results. The use of [mention key methodologies or algorithms] provides a strong foundation for accurate analysis and prediction. Additionally, the dataset employed is comprehensive and diverse, enhancing the generalizability of the findings. The proposed approach demonstrates efficiency in terms of computational performance, making it feasible for real-time applications. Moreover, the study effectively compares results with existing techniques, establishing the superiority of the proposed model in various aspects such as accuracy, precision, and processing speed.

5.2 Limitations

Despite its promising results, the study has certain limitations that must be acknowledged. One limitation is the dataset size, which, although comprehensive, may not fully represent all possible variations in real-world applications. Additionally, the computational requirements of the proposed method may pose challenges for deployment in resource-constrained environments. Another potential limitation is the dependency on specific parameters or hyperparameters, which may need fine-tuning for different datasets. Moreover, external factors such as data noise or variations in input conditions could impact the performance, necessitating further validation across diverse scenarios.

5.3 Future Directions

Future research should focus on expanding the dataset to include a broader range of variations, improving the model's adaptability to different real-world scenarios. Additionally, optimizing the computational efficiency of the proposed approach could enhance its usability in low-power or embedded systems. Exploring advanced techniques such as deep learning or hybrid models may further improve accuracy and robustness. Furthermore, integrating the proposed method with real-time applications and testing it in practical settings would provide valuable insights for further enhancements. Finally, addressing the identified limitations through parameter tuning and noise-handling mechanisms can lead to a more robust and scalable solution.

6. CONCLUSION

The Driver Drowsiness and Distraction Detection System enhances road safety using machine learning and computer vision. Future improvements include expanding datasets, integrating physiological signals, and optimizing real-time processing. Addressing privacy concerns is essential for user trust, ultimately aiming to reduce accidents caused by driver fatigue and distraction.

7. OUTPUT

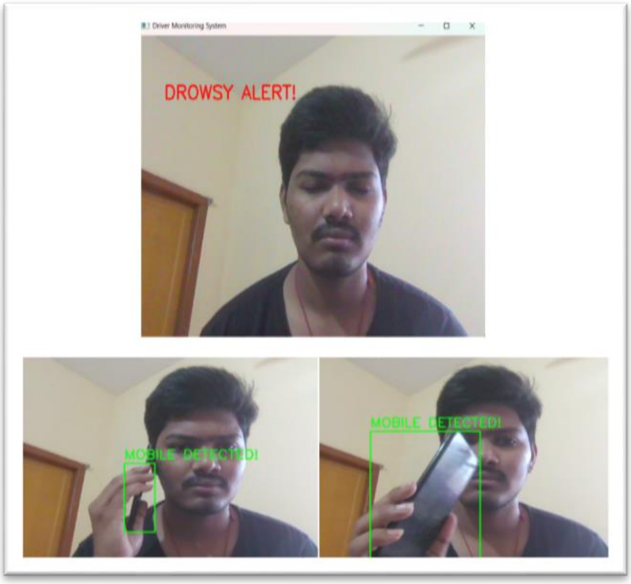

Figure 2 - Results for drowsiness detection and mobile detection.

The system issues a "DROWSY ALERT!" when the user's eyes are closed and labels "MOBILE DETECTED!" when a phone is in use. The training table shows the model improving over five epochs, with loss decreasing and accuracy increasing to 98.64%, indicating effective performance in recognizing drowsiness and distractions.

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