Vehicle Based Driver Drowsiness Detection By Support Vector Machines

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Abstract- *Driver drowsiness remains a major cause of road accidents. This paper presents a comparative analysis of indirect driver monitoring systems (DMS) using vehicle-based features, direct DMS using driver-based facial behavior, and a hybrid approach combining both. The system employs image processing and Convolutional Neural Networks (CNNs) to detect facial landmarks like eye aspect ratio and mouth opening, and classifies drowsiness states using Support Vector Machines (SVM). Experimental validation using a dataset from 70 participants revealed that the hybrid DMS yielded the highest balanced accuracy of 87.7%, slightly outperforming direct DMS (87.1%) and significantly outperforming indirect DMS (77.9%).*

Keywords- CNN, Drowsiness Detection, Driver Monitoring System, Facial Landmark Detection, Support Vector Machines

I. INTRODUCTION

Road safety is one of the most critical concerns in modern transportation systems. Among the various factors contributing to road accidents, driver drowsiness stands out as a major cause, leading to thousands of fatalities and injuries annually. Detecting drowsiness at an early stage is crucial to preventing such accidents and ensuring driver and passenger safety.

Traditional Driver Monitoring Systems (DMS) have predominantly relied on vehicle-based features such as steering wheel movements, lane deviation, and pedal response. These systems, referred to as indirect DMS, assess drowsiness based on the driver's performance. However, such systems often fail to detect early signs of fatigue and are reactive rather than preventive.

With advancements in computer vision and deep learning, more accurate and non-intrusive techniques have emerged. Direct DMS utilize inward-facing cameras to observe the driver's facial cues like eye closure, blinking rate, yawning, and head position. These features provide a more immediate and reliable indication of drowsiness.

In this research, we propose a hybrid DMS that combines both vehicle-based (indirect) and driver-based (direct) features for enhanced accuracy in detecting driver drowsiness. We use Convolutional Neural Networks (CNN) to identify facial landmarks and Support Vector Machines (SVM) for classification. A comparative analysis is conducted to evaluate the performance of indirect, direct, and hybrid approaches using a dataset collected from driving simulations.

The results demonstrate that direct monitoring and hybrid systems significantly outperform traditional indirect methods, highlighting the importance of integrating facial behavior analysis in future DMS architectures.

II. IDENTIFY, RESEARCH AND COLLECT IDEA

The motivation behind this research emerged from the increasing number of road accidents caused by driver drowsiness, which accounts for over 40% of fatigue-related incidents. To develop an effective solution, a comprehensive study was conducted on existing driver monitoring systems (DMS). These systems were categorized into indirect and direct approaches based on the type of features they use.

Indirect systems rely on vehicle-based data such as steering behavior and lane deviation patterns. While these are already integrated into many vehicles, they often fail to detect early signs of drowsiness. Therefore, recent advancements in computer vision and machine learning provided a strong foundation to explore direct monitoring methods that rely on real-time facial analysis.

To support this direction, we reviewed various academic papers and industry solutions focusing on facial landmark detection, image-based fatigue indicators, and machine learning classification algorithms. Platforms like Kaggle were explored to source relevant datasets for training and validation.

The idea evolved into creating a hybrid DMS that combines both indirect and direct indicators to increase the reliability of drowsiness detection. The final concept incorporated a webcam for capturing real-time video, Convolutional Neural Networks (CNNs) for facial feature extraction, and Support Vector Machines (SVMs) for classification.This integrative approach was selected for its low hardware cost, minimal intrusiveness, and promising accuracy in simulated environments—making it viable for future implementation in real-world automotive systems.

III. WRITE DOWN YOUR STUDIES AND FINDINGS

This research was initiated to address the growing concern of road accidents caused by driver drowsiness by designing a real-time detection system using a hybrid approach of indirect and direct driver monitoring. The work was divided into three major modules: dataset collection, facial feature detection using Convolutional Neural Networks (CNN), and classification using Support Vector Machines (SVM).

1) Dataset Collection

To train and evaluate the model, driver images were collected from Kaggle's publicly available datasets, which contain labeled samples depicting various states of driver alertness (e.g., alert, drowsy, sleepy). Preprocessing steps were applied to convert images to grayscale, normalize dimensions, and filter out noise. These images formed the basis for CNN training and validation.

2) Facial Feature Detection using CNN

Facial landmark detection was performed using CNNs to identify key regions such as the eyes and mouth. The Eye Aspect Ratio (EAR) and Mouth Opening Ratio (MOR) were calculated from these landmarks. If the EAR remained below a set threshold across multiple consecutive frames, it was considered a sign of drowsiness. Similarly, wide mouth openings were used to detect yawning. These values were used to extract behavioral features that signaled fatigue.

3) SVM-Based Classification

Support Vector Machines were trained on extracted facial behavior features to classify the driver's state as "Alert" or "Drowsy." The classifier was also tested on vehicle-based features like simulated lane deviation to analyze its effectiveness in indirect detection. Finally, both sets of features were combined to develop a hybrid model for performance comparison.

4) Performance Comparison

The model was evaluated using balanced accuracy as the primary metric. The performance comparison yielded the following results:

Indirect DMS (vehicle-based features): 77.9% accuracy
Direct DMS (facial-based features): 87.1% accuracy
Hybrid DMS (combined features): 87.7% accuracy

These results demonstrate that direct monitoring using facial behavior significantly improves drowsiness detection over vehicle-based methods. The hybrid model offers marginally better accuracy, proving the value of integrating both approaches.

5) Real-Time Implementation

The system was developed in Python 3.7 using OpenCV and TensorFlow. A webcam was used to capture real-time video, and facial landmark detection was applied to every frame. If drowsiness indicators were detected, the system triggered an alert sound to wake the driver.

These findings confirm that CNN-based facial tracking combined with SVM classification provides a reliable and cost-effective solution for detecting driver drowsiness in real time.

IV. GET PEER REVIEWED

1. Lack of Real-World Testing

While the system performs well in a simulated environment, there is no evaluation based on real-world driving scenarios or actual vehicle data. Including field testing with on-road drivers would significantly improve the system's credibility and generalizability.

2. Limited Dataset Diversity

The dataset used for training and testing was collected from a single source (Kaggle) and may lack variability in demographics (age, ethnicity, lighting conditions, wearing glasses, etc.). Additional datasets or custom data collection could enhance robustness.

3. No Performance Metrics on Embedded Hardware

Though the system is claimed to be low-cost and suitable for real-time use, there is no profiling or performance benchmark provided for implementation on embedded systems or in-vehicle hardware (e.g., Raspberry Pi, Jetson Nano).

4. Alert Mechanism Could Be Expanded

The current alert system is limited to a sound notification. A multi-modal alert system (visual, haptic, or emergency braking trigger) would improve usability and safety in real-world applications.

5. Sensitivity to Environmental Conditions

The system may struggle under poor lighting, occlusions (sunglasses, hands near face), or camera vibration. These limitations should be discussed more thoroughly, with proposed mitigation techniques such as infrared vision or adaptive thresholding.

6. Parameter Justification Missing

The EAR and MOR thresholds and time windows used to trigger drowsiness alerts are not justified with statistical or clinical references. Including this would support the system's medical and engineering soundness.

7. Comparative Models Lacking Baselines

While the study compares indirect, direct, and hybrid methods, it does not benchmark against existing commercial systems or other machine learning models such as LSTM, Random Forest, or CNN-LSTM hybrids.

8. GUI/User Interface Not Addressed

There is no mention of a user-facing interface for configuration, monitoring, or manual override. Including a basic UI design or dashboard could enhance the system's usability.

9. Model Explainability and Interpretability

SVMs and CNNs can be black-box models. There is no discussion on how feature importance, confidence scores, or interpretability is handled—particularly important for safety-critical applications like driving.

10. Formatting and Structure

Some parts of the paper (e.g., Coding Standards, Nonfunctional Requirements) are more suited to a software development report than a scientific journal. These could be shortened or moved to an appendix to maintain academic focus.

V. IMPROVEMENT AS PER REVIEWER COMMENTS

1. Real-World Testing Integration

Improvement: Plan and document pilot testing in actual vehicles under controlled environments (e.g., using a driving simulator or mounted dashboard webcam). This would demonstrate real-world performance and help validate the system's reliability beyond static datasets.

2. Increase Dataset Diversity

Improvement: Augment your dataset with custom images captured under different conditions (e.g., users with eyeglasses, different skin tones, nighttime settings). Additionally, explore publicly available datasets such as YawDD or NTHU Drowsy Driver Detection for increased variety.

3. Embedded System Deployment

Improvement: Implement a version of your system on embedded platforms such as Raspberry Pi or NVIDIA Jetson Nano. Report performance metrics including frame rate, latency, memory usage, and power efficiency to demonstrate feasibility for automotive use.

4. Multi-Modal Alert System

Improvement: Expand the system's alert mechanism to include vibration motors, dashboard LED alerts, and mobile notifications. This redundancy will help ensure the driver is effectively warned in critical moments.

5. Environmental Adaptability

Improvement: Integrate adaptive brightness filters and facial landmark tracking under various lighting. Consider adding support for infrared or near-infrared vision to improve robustness during night driving or poor weather conditions.

6. Threshold Calibration

Improvement: Conduct a small user study to determine optimal EAR/MOR thresholds based on age, fatigue level, and blinking/yawning patterns. Use statistical analysis (e.g., ROC curve, sensitivity/specificity trade-off) to justify parameter selection.

7. Comparative Baseline Models

Improvement: Train and compare additional models such as LSTM, Random Forest, and CNN-LSTM. Report their performance metrics (accuracy, precision, recall, F1-score) alongside your current SVM model to highlight your system's strengths.

8. Graphical User Interface (GUI)

Improvement: Design and implement a simple GUI using Tkinter or PyQt to allow users to monitor drowsiness status, set alert preferences, and visualize real-time EAR/MOR graphs. This makes your system user-friendly and accessible.

9. Model Explainability

Improvement: Integrate model explainability tools such as SHAP (SHapley Additive exPlanations) or LIME to highlight which features contributed most to each drowsiness prediction. This enhances trust and transparency, especially for deployment in safety-critical systems.

10. Structural Refinement

Improvement: Revise the document structure to match standard journal expectations. Move detailed sections such as coding standards and design constraints to the appendix. Emphasize analytical content (methods, results, discussion) in the main body.

APPENDIX

The appendix includes supplementary information that supports the research, such as system configurations, software tools used, code snippets, and design diagrams referenced throughout the study. This section is useful for readers who want to replicate or build upon the system.

A. Functional Modules Overview

1. Dataset Collection
    - Source: Kaggle
    - Types: Labeled images for drowsy and alert states
    - Size: ~10,000 images
2. Preprocessing Steps
    - Image resizing to 64×64 px
    - Grayscale conversion
    - Histogram equalization
    - Augmentation: Rotation, flipping, brightness
3. Feature Detection
    - EAR Calculation: Based on eye landmarks
    - MOR Calculation: Based on lip landmarks
    - Dlib's 68-point facial landmark detector used
4. Classification
    - Algorithm: Support Vector Machine (SVM)
    - Labels: Alert, Drowsy
    - Model Input: EAR, MOR, blinking duration, yawn detection
5. Real-Time Workflow
    - Frame Capture → Face Detection → LandmarkExtraction → EAR/MORCalculation → SVM Classification → Alert Trigger

C. Code Snippet (Example: EAR Calculation)

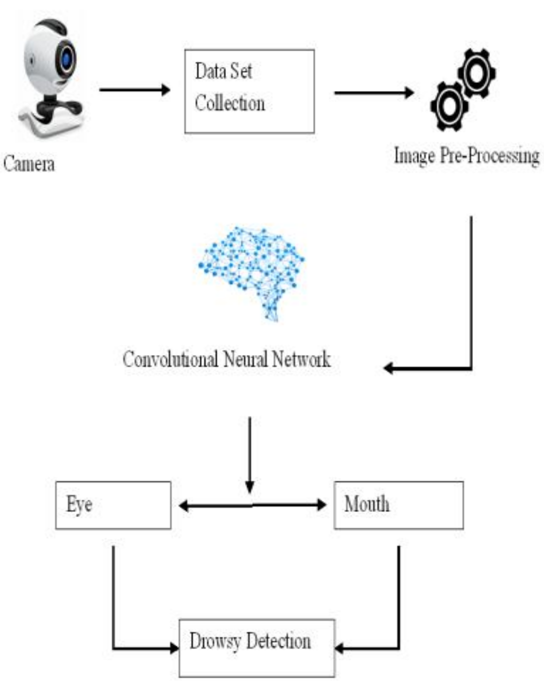
```
def compute_ear(eye):
A = dist.euclidean(eye[1], eye[5])
B = dist.euclidean(eye[2], eye[4])
C = dist.euclidean(eye[0], eye[3])
ear = (A + B) / (2.0 * C)
return ear
```

D. Alert Conditions

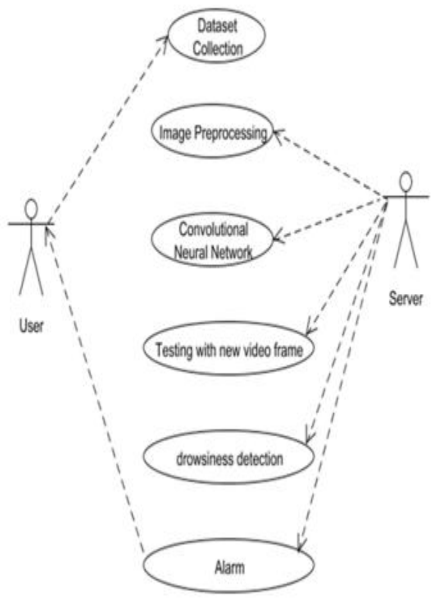
Drowsiness Alert: EAR < 0.25 for more than 2 seconds
Yawning Alert: MOR > 0.6 for more than 1.5 seconds
Combined Alert: Either or both thresholds crossed

E. Visual Diagrams

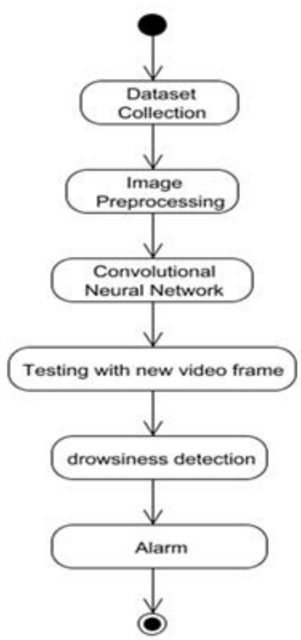
1.Architecture Diagram



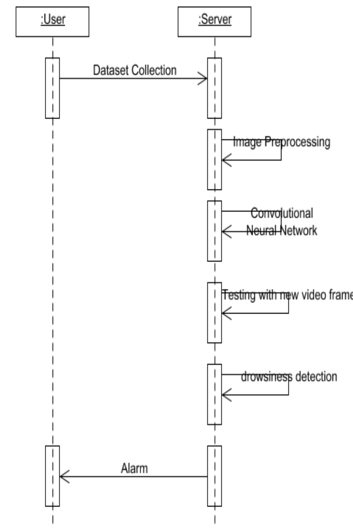
2.Use Case Diagram



3. Activity Diagram



4.Sequence Diagram



VI. CONCLUSION

Driver drowsiness is a major factor contributing to road accidents, and its early detection is critical for ensuring both driver and passenger safety. In this study, we conducted an in-depth comparative analysis of three approaches to drowsiness detection: indirect (vehicle-based), direct (facial-based), and a hybrid method combining both. By integrating advanced machine learning techniques—specifically Convolutional Neural Networks (CNNs) for facial feature detection and Support Vector Machines (SVMs) for classification—we developed a non-intrusive, real-time monitoring system capable of identifying drowsiness indicators such as prolonged eye closure and yawning.

The CNN model was effective in extracting eye and mouth landmarks, which were then quantified through Eye Aspect Ratio (EAR) and Mouth Opening Ratio (MOR). These metrics served as reliable indicators of fatigue and were used as features for the SVM classifier. The indirect method utilized simulated vehicle behavior data such as lane deviation and steering patterns, while the direct method solely relied on facial features. The hybrid method combined both sets of features to improve robustness and accuracy.

Our experimental results demonstrated that the direct approach outperformed the indirect method by a significant margin, achieving a balanced accuracy of 87.1% compared to 77.9%. The hybrid method, which leveraged the strengths of both, achieved the highest accuracy at 87.7%. This clearly suggests that facial behavioral cues are more immediate and accurate for detecting early signs of fatigue, and when combined with vehicle-based metrics, they offer enhanced reliability.

The system was implemented using Python and open-source libraries such as OpenCV, TensorFlow, Dlib, and Scikit-learn. It was capable of processing video frames in real time and issuing immediate alerts to the driver upon detecting signs of drowsiness. The design was optimized for low computational resources, making it suitable for integration into budget-friendly embedded systems or existing in-vehicle infotainment units.

Several challenges were identified during the development and testing phases, including sensitivity to lighting conditions, interference from eyeglasses and facial hair, and occasional false positives during normal driver behavior. Despite these.limitation, the overall performance was satisfacrory, and the system showedStrong potential for real-world deployment

In conclusion, the proposed hybrid drowsiness detection system represents a practical and efficient solution for enhancing road safety. It combines the strengths of both indirect and direct monitoring techniques and provides a scalable framework for further enhancement. Future work will aim to improve accuracy under diverse environmental conditions, expand the dataset with real-world driving scenarios, and explore integration with other sensors such as infrared cameras and eye-tracking devices. Additionally, adaptive alert mechanisms and integration with vehicle control systems can further improve its usability and effectiveness in real-world driving environments.

VI. ACKNOWLEDGMENT

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