

Real-Time Drowsiness Detection System for Driver Safety Based on Computer Vision

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Received: 1/04/26, Revised: 9/5/26, Accepted: 11/5/26

Abstract

This study proposes a lightweight real-time driver drowsiness detection system based on traditional computer vision and machine learning techniques for resource-constrained environments. The proposed framework integrates Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) for face detection, followed by facial landmark analysis and Eye Aspect Ratio (EAR) computation using Euclidean distance to estimate eye closure and detect drowsiness. The system was evaluated using real-world driving video datasets collected from multiple drivers under practical driving conditions, including variations in illumination, head pose, and driver behavior. Experimental results demonstrate that the proposed method achieves an average accuracy of 82% with a low False Negative Rate (FNR) of 0.099 while maintaining low computational complexity. The proposed approach provides a practical balance between detection performance and hardware efficiency, making it suitable for real-time deployment on CPU-based and low-cost embedded systems.

Keywords: Driver Drowsiness Detection, Computer Vision, Facial Landmark, Real-Time System, Low-Cost Device

1. Introduction

Driver drowsiness is one of the major causes of road accidents worldwide, as it reduces driver alertness, reaction time, and decision-making ability. Therefore, the development of effective drowsiness detection systems has become an important research topic in intelligent transportation and road safety applications. Previous studies in Thailand reported that approximately 75% of commercial drivers experienced drowsiness while driving, and 28% experienced microsleep episodes related to traffic accidents. In addition, sleepiness-related conditions contributed to approximately 20.3% of reported road accident cases among public transportation drivers [1]. These findings highlight the importance of developing reliable driver drowsiness detection systems to improve road safety [2]. Existing approaches for drowsiness detection can be broadly categorized into physiological-based, vehicle-based, and vision-based methods. Among these, vision-based techniques have gained considerable attention due to their non-intrusive nature and ability to monitor driver behavior in real time. In recent years, deep learning-based approaches, such as Convolutional Neural Networks (CNNs), have demonstrated high accuracy in detecting drowsiness.

However, these methods typically require large-scale datasets, high computational resources, and powerful hardware, which limit their applicability in real-world scenarios, especially on low-cost or embedded devices. To address these limitations, this study proposes a lightweight driver drowsiness detection system based on traditional computer vision and machine learning techniques [3]. The proposed approach employs Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) for efficient face detection, followed by facial landmark analysis and Euclidean distance-based eye state estimation to determine drowsiness. This design significantly reduces computational complexity while maintaining reliable performance.

In addition, the dataset used in this study was collected from real-world driving environments, ensuring that the proposed system can handle practical conditions such as variations in lighting, head pose, and driver behavior. This enhances the robustness and applicability of the system in real-time scenarios.

The main contribution of this work is the development of a lightweight and efficient drowsiness detection system that does not rely on deep learning, making it suitable for deployment on resource-constrained devices while maintaining satisfactory detection performance in real-world conditions

2. Related Work

Driver drowsiness detection has been widely studied due to its importance in reducing road accidents [4]. Existing approaches can generally be categorized into three groups: physiological-based methods, vehicle-based methods, and vision-based methods [5].

Physiological-based approaches utilize signals such as electroencephalogram (EEG), electrooculogram (EOG), and heart rate to detect driver fatigue. These methods often provide high accuracy; however, they require specialized sensors attached to the driver, making them intrusive and less practical for real-world applications [6].

Vehicle-based approaches analyze driving patterns such as steering wheel movement, lane deviation, and acceleration behavior. Although these methods are non-intrusive, they are often affected by road conditions and driving styles, which may reduce their reliability in detecting early signs of drowsiness [7].

Vision-based approaches have gained significant attention due to their non-invasive nature and ability to directly monitor driver behavior. These methods typically

focus on facial features such as eye closure, blinking rate, and yawning. Traditional computer vision techniques, including Histogram of Oriented Gradients (HOG) and Haar-like features, continue to be used for feature extraction due to their efficiency [8]. When combined with machine learning classifiers such as Support Vector Machine (SVM), these approaches can achieve reliable performance with relatively low computational cost [9].

Facial landmark detection has become an essential component in many vision-based systems. It allows precise localization of facial key points, enabling accurate extraction of regions of interest such as the eyes and mouth. Recent studies have utilized facial landmarks to compute geometric features such as Eye Aspect Ratio (EAR), which remains an effective indicator of eye closure and drowsiness [10].

In recent years, deep learning methods such as Convolutional Neural Networks (CNN) [11] and Recurrent Neural Networks (RNN) [12] have been applied to drowsiness detection tasks. These models can automatically learn complex features and temporal patterns, achieving high accuracy. However, they typically require large datasets, high computational resources, and powerful hardware, which may not be suitable for real-time or embedded applications [13].

Therefore, lightweight approaches based on traditional feature extraction and machine learning techniques remain highly relevant for driver drowsiness detection systems. In particular, the integration of HOG for feature extraction, SVM for classification, and facial landmark detection for region localization provides a good balance between detection accuracy and computational efficiency. As a result, such approaches are well suited for real-time driver monitoring applications, especially in resource-constrained environments.

In addition, this study emphasizes the evaluation of the proposed method using a real-world dataset collected under actual driving conditions. The dataset includes variations in illumination, head pose, and driver behavior, which more closely represent practical driving scenarios. Unlike many previous studies that rely on public datasets collected in controlled environments, the proposed approach is evaluated in unconstrained conditions to better assess its practical applicability and robustness in real-world situations.

3. Methodology

The proposed driver drowsiness detection system is developed as a real-time vision-based framework that integrates Histogram of Oriented Gradients (HOG), Support Vector Machine (SVM), and facial landmark analysis, as illustrated in Figure 1. The system begins by acquiring a video stream from a camera positioned in front of the driver. The video is then segmented into individual frames to enable detailed frame-by-frame analysis. Each frame is resized to a lower resolution to reduce computational complexity and improve processing speed. Subsequently, the images are converted from RGB to

grayscale to simplify the data while preserving essential structural information.

After preprocessing, the facial region is analyzed using the HOG feature extraction method, which captures gradient orientation and edge information to effectively represent facial structures. The extracted HOG features are then fed into an SVM classifier for face detection, enabling accurate localization of the face in each frame. Facial landmark detection is subsequently applied to identify key points on the face, particularly around the eyes. These landmarks are used to define regions of interest and support further analysis of the eye state.

The eye state is evaluated using Euclidean distance between selected landmark points, allowing the system to quantify eye opening and closure. Metrics such as the Eye Aspect Ratio (EAR) are derived from these geometric relationships to detect eye closure. A sustained decrease in these measurements over consecutive frames indicates a high likelihood of drowsiness.

Finally, the system determines the driver's condition based on predefined thresholds. When the detected indicators exceed these thresholds, the system classifies the driver as drowsy and triggers an alert for safety purposes.

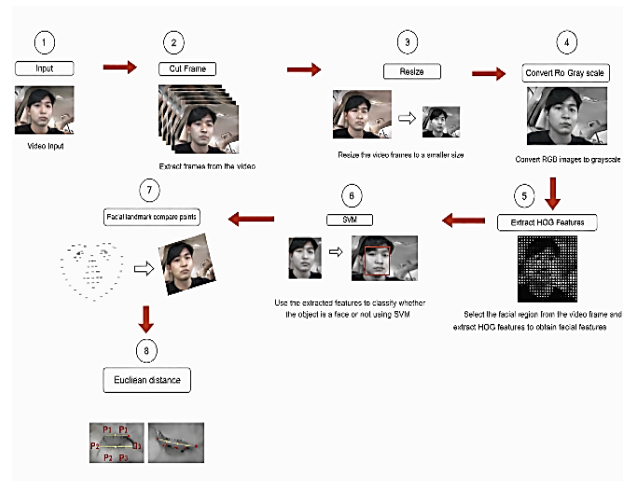


Fig. 1 Overview of the proposed driver drowsiness detection system



Fig. 2 Camera placement for driver drowsiness detection

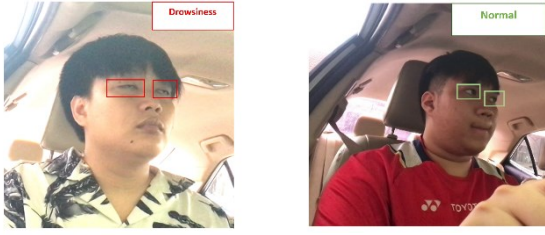


Fig. 3 Drowsiness detection result with an audio alert triggered when fatigue is detected.

Figures 2 and 3 illustrate the camera installation and the detection results of the proposed system. As shown in Figure 2, the camera is mounted on the dashboard facing the driver to continuously capture facial images in real time. After the face region is detected, facial landmark points are extracted to locate key regions, particularly around the eyes. The system then analyzes the eye state by computing the Euclidean distance between selected landmark points. These geometric measurements are used to determine whether the eyes are open or closed. A consistent reduction in the distance over consecutive frames indicates eye closure, which is a key indicator of drowsiness.

As shown in Figure 3, the detection results are displayed on the driver's face with labels indicating the current state. When drowsiness is detected based on prolonged eye closure, an audio alert is triggered to warn the driver. This approach combines face detection and geometric analysis to provide an efficient and real-time drowsiness monitoring system.

4. Experiment and Results

4.1 Experimental Setup

The proposed system employs Histogram of Oriented Gradients (HOG) for facial feature extraction and a Support Vector Machine (SVM) classifier for face detection. The HOG descriptor was configured using a cell size of 8×8 pixels, a block size of 2×2 cells, and 9 orientation bins.

After face detection, facial landmark detection was applied to localize important facial regions, particularly around the eyes. The eye state was analyzed using the Eye Aspect Ratio (EAR), which was computed from Euclidean distances between selected eye landmark points. Drowsiness was detected when the EAR value remained below a predefined threshold over consecutive frames.

The performance of the proposed system was evaluated using Accuracy, Precision, Recall, F1-score, and False Negative Rate (FNR).

The proposed system was implemented using Python and OpenCV and evaluated on a laptop computer equipped with an Intel Core i5 processor and 8 GB RAM without GPU acceleration. All input images were resized to 224×224 pixels before processing to reduce computational complexity and improve real-time performance.

4.2 Experiment Result

In this study, drowsiness was detected when the Eye Aspect Ratio (EAR) value fell below 0.25 [14] for more than 15 consecutive frames, corresponding to approximately 0.5 seconds at 30 FPS. This criterion was adopted based on previous studies indicating that prolonged eye closure beyond normal blinking duration can be considered a sign of driver drowsiness [15].

Table 1. Performance evaluation of the proposed driver drowsiness detection system using six real-world test videos.

VDO	1	2	3	4	5	6	Avg.
TP	10	3	3	6	7	3	
FP	5	2	2	1	3	1	
TN	14	5	5	15	15	3	
FN	1	1	0	0	0	1	
FNR	0.091	0.250	0.000	0.000	0.000	0.250	0.099
P	0.667	0.600	0.600	0.857	0.700	0.750	0.696
R	0.909	0.750	1.000	1.000	1.000	0.750	0.902
F1-score	0.769	0.667	0.750	0.923	0.824	0.750	0.780
Acc.	0.80	0.73	0.80	0.96	0.88	0.75	0.82

Table 1 presents the performance of the proposed drowsiness detection system across six test videos in terms of True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN), False Negative Rate (FNR), Precision (P), Recall (R), F1-Score and Accuracy (Acc.). In this context, TP refers to correctly detected drowsy cases, TN represents correctly identified non-drowsy cases, FP indicates non-drowsy cases incorrectly classified as drowsy, and FN corresponds to drowsy cases that were not detected by the system.

The results show that the system achieves an average accuracy of 82% and an average FNR of 0.099, indicating that the system is capable of detecting drowsiness with a relatively low rate of missed detections. From the table, Videos 1 and 3 demonstrate stable performance with high TP and TN values, along with low FN, resulting in high accuracy and low FNR.

In contrast, Videos 2 and 6 exhibit higher FN values, leading to higher FNR (0.250), which indicates that some drowsiness cases were not detected. This may be due to challenging conditions such as variations in head pose, lighting, and partial occlusion.

Videos 4 and 5 show zero FN, meaning that all drowsy cases were successfully detected (TP), resulting in zero FNR. However, the presence of FP in these videos slightly reduces the overall accuracy, as some non-drowsy cases were incorrectly classified as drowsy.

Overall, the proposed system demonstrates reliable performance across different scenarios, with strong capability in detecting drowsiness (high TP) and maintaining low missed detections (low FN). However, variations in FP and FN across videos indicate that environmental conditions can influence system performance, highlighting the need for further improvements to enhance robustness in real-world applications. In addition, the system achieved an average Precision of 0.696, indicating moderate accuracy in positive drowsiness predictions, while the average Recall

of 0.902 demonstrates a strong ability to detect actual drowsiness events. The average F1-score of 0.780 further confirms a balanced performance between Precision and Recall, reflecting the effectiveness of the proposed approach in real-time driver drowsiness detection.

5. Discussion

The experimental results demonstrate that the proposed HOG + SVM + EAR framework can effectively detect driver drowsiness under real-world driving conditions while maintaining low computational complexity. The system was evaluated using real-world driving videos containing variations in lighting conditions, head poses, and driver behaviors. The proposed method achieved satisfactory detection performance with a low False Negative Rate (FNR) of 0.099, indicating its capability to reduce missed drowsiness detections, which is an important factor in real-time driver monitoring applications.

Traditional computer vision techniques based on HOG, SVM, and EAR remain attractive for lightweight real-time systems due to their lower computational requirements and efficient CPU-based processing capability. Previous studies, such as Yusri et al. (2021), demonstrated that the HOG + SVM + EAR framework outperformed the traditional Haar Cascade approach and provided robust frontal face detection performance in real-time scenarios. These findings support the effectiveness of traditional machine learning approaches for practical driver monitoring applications.

Although deep learning-based approaches, including MCNN + LSTM and CNN-LSTM, generally achieve higher detection accuracy, these methods typically require GPU acceleration, large-scale datasets, and significantly higher computational resources. Such requirements may limit their deployment on low-cost embedded platforms or commonly available hardware systems, including Raspberry Pi devices and standard CPU-based computers. In contrast, the proposed framework can operate without dedicated GPU hardware, making it more suitable for lightweight and cost-effective real-time deployment.

Table 2 compares the proposed method with several existing driver drowsiness detection approaches. The comparison shows that deep learning-based methods generally provide higher accuracy, whereas traditional methods offer lower hardware requirements and reduced computational complexity. Despite achieving lower accuracy than some deep learning models, the proposed method provides a practical trade-off between detection performance and computational efficiency for real-world applications.

Nevertheless, several limitations remain in the current study. The evaluation dataset consisted of only six real-world videos, which may not fully represent all driving conditions and driver variations. In addition, the system performance under nighttime or low-light conditions was not extensively evaluated. Future work will focus on expanding the dataset using public

benchmarks such as NTHU-DDD, YawDD, and DROZY, improving robustness under challenging environmental conditions, and integrating temporal modeling techniques to enhance detection consistency and overall performance.

Table 2. Comparison of Driver Drowsiness Detection Methods, Performance, and Hardware Requirements.

Ref.	Method	Dataset	Acc./ Performance	Hardware Requirement
Lyu et al. (2018) [16]	MCNN + LSTM	NTHU-DDD	90.05%	GPU
Yusri et al. (2021) [17]	HOG+ SVM+ EAR	Private Dataset	Outperformed Haar Cascade; robust for frontal face detection	CPU
Bakheet et al. (2021) [8]	Improved HOG + Naïve Bayes	NTHU-DDD	85.62%	CPU
Gomaa et al. (2022) [18]	CNN-LSTM	NTHU-DDD	97.31%	GPU
Cao et al. (2025) [19]	Multimodal Deep Neural Networks	DROZY	High robustness reported	GPU
Proposed Method	HOG + SVM + EAR	Real-world Videos	82.00%	CPU

6. Conclusion

This study presents a lightweight driver drowsiness detection system using HOG and SVM combined with facial landmark analysis and Euclidean distance for eye state estimation, enabling real-time operation with low computational complexity. The experimental results show an average accuracy of 82% and a False Negative Rate (FNR) of 0.099, indicating effective detection performance. The dataset was collected by the authors under real-world driving conditions, ensuring practical applicability of the system. The proposed method offers advantages in efficiency and low resource consumption, making it suitable for application development on resource-constrained devices. However, the current system may fail to detect drowsiness when the driver's eyes are not visible, particularly during downward head movements or head tilting conditions. Therefore, future work should incorporate additional behavioral features, such as head movement and head pose analysis, to improve robustness and detection reliability in real-world scenario.

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