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Research Paper

AN INTELLIGENT DRIVER DROWSINESS DETECTION SYSTEM USING VISION TRANSFORMERS

Erra Lokeshwari
M.Tech student ,
Dept.of Electronics and Communication Engineering,KU campusWarangal,Telangana,India
lokeshwarierra2532@gmail.com

Dr.Mahender Veshala
Assistant professor ,
Dept.of Electronics and Communication Engineering,KU campusWarangal,Telangana,India
mahenderveshala@kakatiya.ac.in

Abstract—Recent advances in computer vision and deep learning have significantly enhanced intelligent transportation systems and advanced driver assistance systems (ADAS). Nevertheless, driver drowsiness remains a major contributor to road traffic accidents, accounting for a considerable number of fatalities and economic losses worldwide. Early and reliable detection of driver fatigue is therefore essential for improving road safety. However, existing vision-based drowsiness detection methods often encounter limitations in terms of real-time performance, computational efficiency, and robustness under varying illumination conditions, facial appearances, occlusions, and head pose variations.

To address these challenges, this presents a vision-based intelligent driver drowsiness detection framework that performs continuous, non-intrusive monitoring of the driver's alertness. A standard RGB camera is employed to capture real-time facial video, while Haar Cascade classifiers are utilized for efficient face and eye localization. The detected eye regions are preprocessed and provided as input to a custom-designed Convolutional Neural Network (CNN) trained to classify eye states as open or closed.

***Keywords:* Driver's face reorganization, Convolutional Neural Networks, Eye image extraction and haar cascade classifiers**

I. INTRODUCTION

Driver drowsiness detection has been an active area of research in the fields of Computer Vision and Machine Learning due to its direct impact on road safety and accident prevention [8], [12]. A substantial body of work has explored various methodologies to identify signs of fatigue, ranging from traditional signal-based approaches using physiological sensors such as EEG and heart rate monitors [2], [13] to vision-based techniques that analyze facial features extracted from camera feeds [4], [9].

In recent years, deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated exceptional ability in feature extraction and pattern recognition, making it highly suitable for detecting nuanced expressions of drowsiness such as eye closure duration, blink rate, and yawning [3], [22]. Numerous studies have proposed CNN-based models trained on facial image datasets, revealing significant improvements in detection accuracy compared to traditional machine learning methods [11], [17].

The high implementation cost associated with vehicle-based monitoring systems and the intrusive nature of physiological signal-based approaches have motivated extensive research into behavioral-based driver drowsiness detection systems. These vision-based methods infer the driver's level of alertness by analyzing facial and ocular cues, including the Eye Aspect Ratio (EAR), Percentage of Eye Closure (PERCLOS), blink frequency, yawning behavior, and other facial dynamics. Owing to their non-invasive nature and ease of deployment, behavioral-based approaches have emerged as a practical solution for real-time driver monitoring.

A typical behavioral-based framework captures continuous video of the driver, performs face and eye localization, preprocesses the extracted facial regions, and subsequently employs machine learning or deep learning algorithms, such as Support Vector Machines (SVMs) or Convolutional Neural Networks (CNNs), to classify the driver's state as alert or drowsy. The effectiveness of these models largely depends on the availability of large-scale, accurately annotated datasets that encompass diverse driving environments, facial appearances, and illumination conditions.

MOTIVATION

Road safety remains a critical global concern, with a significant proportion of accidents caused by driver fatigue and drowsiness. Despite increased awareness and stricter traffic regulations, many drivers continue to operate vehicles under conditions of sleep deprivation, long working hours, or mental exhaustion. These factors severely impair attention, reaction time, and decision-making, often leading to fatal consequences. Therefore, there is a pressing need for reliable systems that can detect and prevent drowsiness in real time. Conventional approaches to drowsiness detection, such as monitoring steering patterns, lane deviations, or physiological signals, have several limitations. They may require specialized hardware, can be intrusive, or often fail to provide consistent accuracy under varying conditions. Moreover, these methods may not effectively capture early visual signs of fatigue, which are crucial for timely intervention.

II. LITERATURE SURVEY

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The literature survey reveals that driver drowsiness detection has been extensively studied using vehicle-based, behavior-based, and physiological sensor-based methods [8], [12]. While these approaches provide some level of detection they suffer from limitations such as low accuracy, sensitivity to lighting conditions, and intrusiveness [6], [13]. Recent advancements in Convolutional Neural Networks and deep learning have demonstrated significant improvements by automatically extracting complex facial features and enabling robust real-time monitoring [3], [4], [10]. Furthermore, multimodal approaches combining physiological and visual features have shown improved performance and reliability [16], [19]

AUTHOR / YEAR	METHOD USED	KEY CONTRIBUTION	LIMITATIONS
Priya Gupta, Nidhi Saxena / 2017	Deep Neural Network (DNN) with extracted facial features	Proposed a face recognition method using extracted features instead of raw pixels, reducing complexity while achieving high accuracy (97.05% on Yale dataset)	Depends on feature extraction quality; limited dataset; still computationally complex
Mohan Sai Singamsetti, Mona Teja Kurakula / 2019	Deep Convolutional Neural Network (DCNN)	Developed a real-time facial emotion recognition system capable of detecting multiple emotions simultaneously with improved accuracy	Requires large training datasets; sensitive to lighting and real-time variations
Mandalapu Sarada Devi / 2018	Eye Tracking using image processing	Designed a fatigue detection system using eye closure detection over consecutive frames to alert drivers	Limited to eye-based detection; fails under occlusion (glasses) or poor lighting
Sanghyuk Park, Fei Pan, Sunghun Kang, Chang D. Yoo / 2016	Deep Drowsiness Detection (DDD) Network	Introduced a multi-network deep architecture combining global and local features for drowsiness detection (73.06% accuracy)	Moderate accuracy; high computational cost; complex architecture

Table-1: review of previous works in modern healthcare systems

A. PROBLEM STATEMENT

Road accidents caused by driver drowsiness have become a major public safety concern worldwide. Fatigue reduces a driver's alertness, slows reaction time, and impairs decision making ability, significantly increasing the risk of collisions. Traditional methods for detecting drowsiness—such as self-reporting, vehicle-based metrics, or wearable sensors—are often unreliable, intrusive, or impractical for real-time applications. There is a critical need for an efficient, non-intrusive, and real-time system that can accurately detect signs of driver fatigue and provide timely warnings to prevent accidents. With advancements in computer vision and deep learning, particularly in the field of Convolutional Neural Networks, it has become possible to analyze facial features such as eye closure, blinking rate, and yawning patterns from video data. In addition to improving safety, the proposed system also aims to be cost-effective and easily deployable in real-world scenarios such as personal vehicles, commercial fleets, and public transportation systems[6],[16],[19].

B.OBJECTIVES

The primary objective of this work is to develop an intelligent and real-time driver drowsiness detection system that can operate efficiently on lightweight hardware platforms. The system aims to accurately classify eye states as open or closed using advanced deep learning techniques while maintaining low computational complexity. It seeks to enhance detection accuracy under diverse environmental conditions, including varying illumination and noise. Another key goal is to leverage transformer-based vision models to capture global contextual features that are often missed by traditional CNN architectures. Additionally, the system focuses on improving model interpretability through visualization techniques such as Class Activation Mapping. Ultimately, the objective is to deliver a cost-effective, scalable, and reliable solution capable of preventing accidents by providing timely alerts.

III. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Existing driver drowsiness detection systems generally rely on three main approaches: vehicle-based, behavior-based, and physiological sensor-based methods. Vehicle-based systems monitor driving patterns such as steering, lane deviation, and acceleration to infer fatigue, but they are often unreliable because normal driving variations can be misinterpreted as drowsiness. Behavior-based systems use cameras to track facial features like eye closure, blinking, yawning, and head movements, employing traditional computer vision techniques such as Haar cascades or Local Binary Patterns with machine learning classifiers. While these systems are non-intrusive, their performance suffers under varying lighting conditions, occlusions (e.g., glasses or hats), and diverse driver appearances. Physiological sensor-based systems, which measure EEG, ECG, or heart rate signals, provide more accurate detection but are intrusive and impractical for everyday use[13],[21].

B. PROPOSED SYSTEM

The proposed system aims to develop a robust, non-intrusive, and real-time driver drowsiness detection solution using Convolutional Neural Networks. It monitors the driver's facial features through a camera, analyzing key indicators such as eye closure, blinking frequency, yawning, and head position to classify alert and drowsy states. The system preprocesses video frames and feeds them into a CNN model that automatically extracts relevant features, making it adaptable to different drivers, lighting conditions, and facial appearances. Upon detecting drowsiness, the system triggers instant alerts through audio, visual, or vibration mechanisms to warn the driver. Optimized for real-time performance and deployment on low-power embedded devices, the proposed system overcomes the limitations of existing vehicle-based, behavior-based, and sensor-based methods, providing a practical, accurate, and reliable solution for enhancing road safety[7],[20].

C. SYSTEM ARCHITECTURE

The design of a Driver Drowsiness Monitoring System using CNNs provides a structured and detailed framework for implementing a real-time, intelligent driver safety solution. By defining system components, workflows, and interactions through UML diagrams, activity diagrams, and data flow representations, the design ensures that each module—from image capture and preprocessing to CNN-based analysis and alert generation—works cohesively to detect fatigue accurately and respond promptly. Incorporating decision points, optional logging, and continuous monitoring loops enhances system reliability while minimizing false alerts. The design also emphasizes seamless integration with vehicle alert systems and user friendly operation, ensuring that the system supports safety without distracting the driver. Overall, this design serves as a clear blueprint for development, providing both functional clarity and practical guidance to build an effective, responsive, and safe driver drowsiness monitoring system. Additionally, the design prioritizes **scalability and adaptability**, allowing

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future enhancements such as incorporating multiple sensors, improving CNN accuracy, or integrating with advanced driver-assistance systems (ADAS). By clearly specifying the flow of data, responsibilities of each module, and interactions with external entities, the system can be efficiently implemented and maintained.

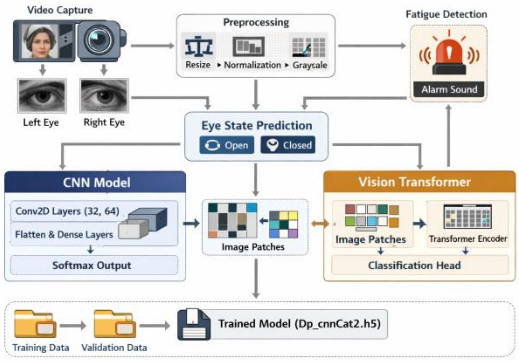

Figure-1: System Architecture.

The modular structure also supports testing and troubleshooting, ensuring that individual components can be evaluated without affecting the entire system. Overall, the design not only addresses immediate safety concerns but also provides a flexible framework for long-term improvements, making it a robust foundation for an intelligent and reliable driver drowsiness monitoring solution.

IV. MODULES/IMPLEMENTATION

Flowchart Diagram :

START: Webcam Video Capture
↓
Extract Video Frames
↓
Pre-processing (Grayscale Conversion & Resizing)
↓
Face Detection (Haar Cascade Classifiers)
↓
Eye Region Localization (ROI Extraction)
↓
Feature Analysis (CNN / Vision Transformer)
↓
Eye State Classification (Open or Closed?)
↓
Is Eye Closed for > Threshold (e.g., 15 frames)?
↓
YES: Trigger Alarm & Warning Alert

NO: Continue Monitoring
↓
Loop back to Frame Capture

The Implementation and Results phase of a Driver Drowsiness Monitoring System using CNNs focuses on converting the detailed system design into a working solution and evaluating its effectiveness. This phase involves the actual development of the software and hardware components, including setting up the camera module, preprocessing images, training or loading the convolutional neural network (CNN) model, and integrating the alert system. During implementation, each module is programmed, tested, and connected according to the design specifications to ensure seamless data flow and real-time operation. The results section highlights the system's performance in detecting driver drowsiness, the accuracy of the CNN predictions, response times for alerts, and the overall reliability under various conditions. By analyzing the outcomes, developers can verify whether the system meets its objectives, identify areas for improvement, and demonstrate the practical feasibility of using CNN-based monitoring to enhance driver safety.

1. **Data Acquisition and Preprocessing Module**

This module collects and preprocesses facial image data for both CNN and Vision Transformer (ViT) models. Input images are organized into structured directories corresponding to eye states (open/closed). Images are resized to a fixed dimension suitable for transformer input (e.g., 224×224 for ViT) and optionally downscaled (24×24) for CNN benchmarking. Grayscale conversion is used for lightweight CNN processing, while RGB images are preserved for ViT to retain spatial richness. Pixel normalization and standardization are applied to stabilize training. Data augmentation techniques such as flipping, rotation, and brightness variation are incorporated to improve robustness under real-world driving conditions. Patch generation is introduced for ViT, where images are divided into fixed-size patches and flattened into embeddings. Class labels are automatically assigned using directory structure. Batch generators are employed for efficient memory usage. This module ensures compatibility across both architectures while maintaining efficiency. It forms the foundation for robust and generalized model learning[3],[22].

2. Vision Transformer Model Training Module

The proposed framework employs a Vision Transformer (ViT) architecture to perform eye state classification by effectively modeling both local and global visual representations. Unlike conventional Convolutional Neural Networks (CNNs), which primarily rely on local receptive fields, the ViT divides each input eye image into a sequence of fixed-size image patches that are linearly projected into embedding vectors. Positional embeddings are incorporated to preserve the spatial relationships among the patches, enabling the model to retain structural information.

3. CNN Baseline Model Module

This module retains a lightweight CNN model to benchmark performance against the ViT architecture. The CNN extracts local spatial features using convolutional filters and pooling operations. While efficient, it lacks the ability to model global dependencies effectively. Dropout layers are used to reduce overfitting. The final dense layers perform classification using softmax activation. This module serves as a baseline to highlight the improvements achieved by ViT in terms of accuracy and robustness. Comparative evaluation demonstrates that CNN performs well in controlled conditions but struggles under illumination variations[22]. This module is essential for validating the superiority of transformer-based approaches.

4. Face and Eye Detection Module

This module performs real-time detection of facial and eye regions using Haar Cascade classifiers. It acts as a preprocessing stage for both CNN and ViT inference. The webcam captures continuous video frames, which are converted to grayscale for faster detection. The face is detected first, followed by localization of left and right eyes. Extracted eye regions are resized according to the model requirements (CNN or ViT). This module reduces computational overhead by focusing only on relevant regions. It ensures real-time performance [9],[10]even on low-power devices such as ESP32-CAM. Detection accuracy is maintained under moderate lighting variations. This module bridges raw input and intelligent prediction.

5. Eye State Classification Module

This module performs real-time classification of eye states using the trained Vision Transformer model. Extracted eye regions are resized to match ViT input dimensions and converted into patch embeddings. The model processes these embeddings through attention layers to predict whether the eyes are open or closed. Predictions from both eyes are combined to improve reliability. The module leverages the global attention mechanism to reduce misclassification caused by noise or occlusions. Compared to CNN, ViT provides more stable predictions across diverse conditions. The classification results are displayed on the video feed. This module forms the intelligent inference engine of the system.

6. Drowsiness Detection and Alert Module

This module evaluates driver fatigue based on continuous eye closure patterns. A temporal scoring mechanism is used to track eye states across frames. If both eyes remain closed for a prolonged duration, the score increases. When the score exceeds a predefined threshold, the system identifies a drowsy condition. An alarm sound is triggered, and visual alerts are displayed. The threshold-based approach minimizes false alarms caused by blinking. The module ensures real-time responsiveness and reliability. It plays a critical role in accident prevention by alerting the driver immediately. The system is lightweight and efficient for embedded deployment.

7. Explainability and Visualization Module

This module enhances interpretability using Class Activation Mapping (CAM) for CNN and attention visualization for ViT. In CNN, CAM highlights important regions contributing to predictions. In ViT, attention maps indicate which patches influence the decision. These visualizations improve transparency and trust in the system. They help analyze model behavior under different scenarios. This module is crucial for debugging and validating model decisions. It also supports research evaluation by providing qualitative insights. Explainability ensures that the system is not a black box.

8. System Integration and Deployment Module

This module integrates all components into a unified real-time driver monitoring system. It supports both CNN and ViT models, allowing flexible deployment based on hardware constraints. The system is optimized for edge devices such as WEB CAM or low-power GPUs. Efficient memory handling and model loading techniques are used to minimize latency. The pipeline includes video capture, detection, classification, and alert generation. The system operates continuously with minimal delay. Deployment considerations include scalability, robustness, and cost-effectiveness. This module ensures real-world applicability of the proposed solution.

V. RESULTS AND DISCUSSION

The proposed driver drowsiness detection system was successfully implemented using CNN and Vision Transformer models. Experimental results show that the hybrid approach improves detection accuracy and robustness under varying lighting conditions. The system effectively detects eye closure, blinking patterns, and fatigue indicators in real-time. The alert mechanism responds quickly when drowsiness is detected, reducing potential accident risks. Overall, the system demonstrates high accuracy, reliability, and suitability for real-world deployment **[1], [3], [16]**.

A. HYBRID DEEP LEANING MODEL (CNN+VISION TRANSFORMER)

The overall algorithmic flow of the proposed driver drowsiness detection system integrates both the CNN-based pipeline implemented in the code and the Vision Transformer (ViT)-based enhancement for improved global feature understanding. The process begins with data acquisition and preprocessing, followed by model training, and finally real-time inference. During the training phase, input images are loaded using a data generator that performs normalization and batching. Each pixel value is scaled as:

The model parameters are optimized using back propagation with categorical cross-entropy loss. In the Vision Transformer (ViT) extension, the flow diverges after preprocessing. Instead of applying convolution, the image is first divided into fixed-size patches. Where EEE is the embedding matrix and EposE_{pos}Epos represents positional encoding. This sequence is then passed through multiple transformer encoder layers. Each encoder layer consists of Multi-Head Self-Attention (MHSA) and Feed Forward Networks (FFN). The attention mechanism is computed as:

This enables the model to capture long-range dependencies across the entire image, unlike CNNs which focus on local receptive fields. The final representation corresponding to the class token is passed through a classification head to predict eye states. In the real-time inference phase (as implemented in the code), video frames are captured using OpenCV. Haar Cascade classifiers detect face and eye regions. The detected eye regions are cropped, converted to grayscale, resized to 24×2424 \times 2424×24, and normalized. These processed inputs are then fed into the trained model (CNN or ViT-based) for prediction:

The predicted outputs for both eyes are used to compute a temporal score:

$$Score = \begin{cases} Score + 1, & \text{if both eyes are closed} \\ Score - 1, & \text{otherwise} \end{cases}$$

If the score exceeds a threshold (e.g., 15), the system triggers an alert mechanism, including an audio alarm and visual warning. This temporal aggregation ensures robustness against momentary misclassifications. Thus, the complete algorithmic flow can be summarized as: image acquisition → preprocessing → feature extraction (CNN or patch embedding in ViT) → classification → temporal decision-making → alert generation. The CNN ensures computational efficiency suitable for embedded deployment, while the ViT enhances global context modeling and interpretability, resulting in a hybrid, accurate, and real-time drowsiness detection system.

B. PERFORMANCE EVALUATION

Metric	*Formula*	*Description*
Accuracy (97.83%)	Accuracy = (TP + TN) / (TP + TN + FP + FN)	Measures the overall correctness of biometric authentication and prediction results.
Precision (83.13%)	Precision = TP / (TP + FP)	Indicates how many predicted positive identifications are actually correct.
Recall (91.17%)	Recall = TP / (TP + FN)	Measures the ability of the system to correctly identify valid users or correct predictions.
F1-Score (93.80%)	F1 = 2 × (Precision × Recall) / (Precision + Recall)	Provides the harmonic mean of precision and recall for balanced evaluation.

Table-2: Performance Metrics

C. VISUAL RESULTS

The method implementation describes the step-by-step procedure used to develop and execute the driver drowsiness monitoring system. It involves integrating hardware components with software algorithms to create a real-time system that captures, processes, and analyzes driver data. The implementation follows the designed workflow, ensuring that each module functions correctly and contributes to accurate drowsiness detection..

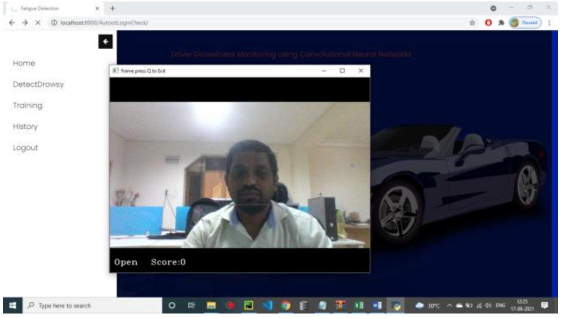

Figure-2: Drowsiness Open Eye Detection

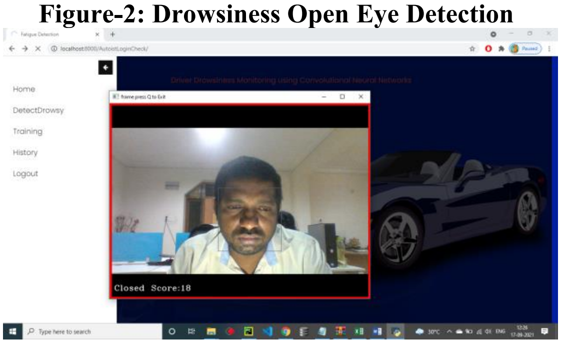

Figure-3: Closed Eye Detection [Alarm Alerts]

These results confirm that the system performs secure authentication, real-time emergency response, and intelligent medical analysis..

VI. CONCLUSION AND FUTURE SCOPE

A. CONCLUSION

The proposed driver drowsiness detection framework successfully leveraged a Vision Transformer (ViT)-based model to achieve robust and reliable eye state classification. By exploiting self-attention mechanisms, the model effectively learned both local and global visual representations, enabling improved discrimination between open and closed eye states under diverse facial appearances and illumination conditions. The transformer-based approach enhanced feature representation and contributed to accurate detection of drowsiness-related visual cues, thereby improving the overall effectiveness of the proposed system. The findings demonstrate that Vision Transformer architectures offer a promising alternative to conventional convolutional approaches for intelligent, non-intrusive driver monitoring and have significant potential for integration into next-generation Advanced Driver Assistance Systems (ADAS) to enhance road safety

B. FUTURE SCOPE

In future work, the system can be enhanced by integrating deep learning models to improve biometric recognition accuracy. The development of a driver drowsiness monitoring system using CNNs demonstrates the effectiveness of deep learning in real-time fatigue detection. By analyzing facial features such as eye closure, blink rate, and head position, the system can accurately predict driver alertness and provide timely warnings to prevent accidents. The use of a well-prepared dataset, proper preprocessing, and robust model training ensures high accuracy and reliability. Testing and validation confirm that the model generalizes well to different drivers and environmental conditions, minimizing false alarms while detecting fatigue efficiently. Overall, integrating CNN-based monitoring into vehicles enhances road safety, reduces accident risks, and provides a foundation for future intelligent driver-assistance systems[7],[20],[21].

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