

Leveraging Generative AI in Vehicles for Enhanced Driver Safety and Advanced Communication Systems

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Abstract

This paper proposes an integrated artificial intelligence-based driver assistance system for electric vehicles (EVs) that combines computer vision-based drowsiness detection with a generative artificial intelligence (GenAI)-driven conversational interaction framework to enhance driver safety and human-vehicle interaction. The primary objective of this work is to reduce fatigue-related driving risks while enabling natural, hands-free, and context-aware communication between the driver and the vehicle. The core idea is to tightly couple real-time driver state monitoring with intelligent conversational feedback, allowing safety alerts and voice interactions to adapt dynamically to the driver's condition. Driver drowsiness is detected using non-intrusive visual indicators, namely eye closure duration and blink rate, extracted from an in-vehicle camera. A drowsy state is identified when eye closure exceeds 10 s or when the blink rate exceeds 6 blinks within a 6 s interval. Upon detection, the system generates multi-modal alerts consisting of audio warnings and vibration feedback, while a GenAI-based natural language processing module provides real-time, hands-free voice interaction. Experimental evaluation was conducted on an ESP32-based embedded prototype across five predefined driving scenarios representing normal and fatigued conditions. The results show stable face and eye detection under normal driving and achieved 100% correct alert triggering in all drowsiness-related cases (3 out of 5 scenarios), with zero false positives observed during non-drowsy conditions (2 out of 5 scenarios). The system demonstrated consistent real-time response and reliable alert activation under fatigue conditions. The main contribution and novelty of this research lie in the real-time integration of generative AI-driven conversational intelligence with embedded computer vision-based drowsiness detection within a unified, resource-constrained platform, which is rarely addressed jointly in existing systems. Overall, the proposed framework provides a practical, scalable, and human-centered solution for intelligent driver assistance in semi-autonomous and future autonomous EV environments.

Keywords: Computer Vision, Generative AI, Natural Language Processing, ChatGPT, EV, Process Innovation

1. Introduction

The rapid advancement of Electric Vehicles (EVs) and semi-autonomous driving technologies has increased the demand for intelligent systems that can enhance both driver safety and human-vehicle interaction. Despite significant progress in vehicle automation, driver involvement remains critical, particularly in semi-autonomous driving scenarios where human alertness directly affects road safety. Driver fatigue and drowsiness continue to be among the leading causes of traffic accidents, highlighting the need for effective real-time driver monitoring and responsive assistance systems. At the same time, modern vehicles are expected to provide intuitive, hands-free interaction to reduce cognitive and physical distractions during driving.

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Generative Artificial Intelligence (GenAI) has emerged as a transformative technology capable of addressing these challenges by enabling advanced perception, reasoning, and natural language interaction within intelligent transportation systems. In connected and autonomous vehicles, GenAI supports real-time decision-making, adaptive vehicle control, and efficient data exchange among EVs, thereby improving automation and overall driving experience [1]. In particular, advancements in Natural Language Processing (NLP) have enabled conversational interfaces that allow drivers to interact with vehicles using natural voice commands, enhancing usability and reducing manual interaction [2]. Moreover, multilingual and context-aware language models further improve accessibility and interaction quality across diverse driving environments [3].

In addition to communication, GenAI has demonstrated strong potential in improving driver safety and situational awareness. AI-driven vehicle systems have been shown to support intelligent human–vehicle interaction and enhance responsiveness under dynamic driving conditions [4]. Advanced interaction frameworks further improve driver awareness during transitions between manual and automated driving modes [5]. Real-time conversational intelligence also enables vehicles to respond dynamically to driver queries and driving contexts, contributing to safer driving behavior [6].

Parallel to these developments, driver drowsiness detection has been extensively studied using computer vision–based approaches. Vision-based systems typically analyze facial features such as eye closure duration, blink rate, yawning frequency, and head posture to assess driver alertness [7], [8]. More advanced driver monitoring systems employ machine learning and neural network–based models to detect prolonged eye closure and fatigue patterns, enabling timely warning generation and accident prevention [9]. Real-time monitoring platforms and alert mechanisms have further demonstrated their effectiveness in reducing fatigue-related accident risks [10], [11].

Recent studies have explored the integration of generative AI with intelligent vehicle systems, highlighting its potential to enhance vehicle intelligence through human-in-the-loop decision-making and real-time data analysis [12], [13]. Improvements in NLP models have also led to more accurate, responsive, and context-aware voice command systems for in-vehicle applications [14]. Beyond safety and communication, GenAI contributes to sustainable transportation by supporting intelligent infrastructure, safer driving behavior, and efficient vehicle operation [15], [16], [17]. Furthermore, intelligent control strategies in EV power electronics, including advanced DC–DC converter designs, enhance energy efficiency, voltage regulation, and system reliability, supporting secure and sustainable vehicle operation [18], [19].

Despite these advancements, a significant research gap remains. Existing studies largely address conversational AI systems and driver monitoring mechanisms as separate components. Drowsiness detection systems often operate independently without integration into intelligent, context-aware interaction frameworks, while conversational AI systems primarily focus on infotainment and navigation without considering real-time driver physiological or behavioral states. This lack of integration limits the system’s ability to provide adaptive and personalized safety responses, particularly in EVs and semi-autonomous vehicles where continuous driver engagement is essential.

To address this gap, this paper proposes a novel integrated driver assistance framework that combines real-time computer vision–based drowsiness detection with a generative AI–driven voice interaction system. The proposed approach enables simultaneous monitoring of driver alertness and intelligent conversational interaction, allowing safety alerts and voice-based responses to be dynamically adapted based on the driver’s real-time condition. The novelty of this work lies in the unified architecture that embeds generative AI–based NLP and vision-driven fatigue detection on an embedded platform, providing a human-centered, adaptive, and safety-oriented solution for electric vehicles.

2. Literature Review

The application of artificial intelligence in intelligent transportation systems has evolved significantly with the emergence of Generative Artificial Intelligence (GenAI), which enables advanced perception, reasoning, and interaction capabilities in connected and autonomous vehicles. Recent studies have shown that GenAI enhances the Internet of Vehicles by supporting intelligent data exchange, adaptive vehicle control, and real-time decision-making, particularly in electric vehicle (EV) environments where efficiency and safety are critical [20]. These capabilities provide a foundation for more intelligent and responsive human–vehicle interaction systems.

2.1. Generative AI and Conversational Systems in Vehicles

Conversational artificial intelligence has become an essential component of modern in-vehicle human–machine interfaces. Advances in Natural Language Processing (NLP) have enabled vehicles to support voice-based interaction that is more natural, intuitive, and context-aware than traditional command-based systems [21]. Generative language models further enhance these systems by enabling multi-turn dialogue management, contextual understanding, and adaptive response generation, which are essential for real-time vehicle interaction [22].

Several studies have demonstrated that conversational AI improves accessibility, reduces driver distraction, and enhances overall user experience in connected and autonomous vehicles [23]. Intelligent interaction frameworks have also been shown to support driver situational awareness, particularly during transitions between manual and automated driving modes [24]. Real-time conversational engines integrated into intelligent driving systems allow vehicles to dynamically respond to driver queries, navigation requests, and vehicle status checks, thereby contributing to safer and more efficient driving behavior [25]. However, most existing conversational AI implementations remain focused on infotainment and navigation services, with limited consideration of real-time driver state information.

2.2. Driver Monitoring and Drowsiness Detection Systems

Driver drowsiness detection has been widely investigated as a critical safety mechanism in intelligent vehicle systems. Vision-based approaches are among the most commonly adopted techniques due to their non-intrusive nature and ability to continuously monitor driver behavior. Existing methods typically analyze eye closure duration, blink frequency, yawning behavior, and head posture to assess driver alertness [7], [8]. These visual indicators have been validated as reliable measures of driver fatigue under various driving conditions.

More advanced driver monitoring systems incorporate machine learning and neural network–based models to improve detection accuracy and robustness [9]. Real-time monitoring frameworks deployed on embedded and mobile platforms have demonstrated the feasibility of continuous fatigue detection and timely alert generation [10]. In addition, deep learning–based approaches utilizing three-dimensional neural networks have shown improved performance by capturing temporal dependencies in driver behavior [11]. Despite their effectiveness, most drowsiness detection systems operate as standalone safety modules and lack integration with intelligent conversational or decision-support systems.

2.3. Integration of GenAI with Intelligent Vehicle Systems

Recent research has begun to explore the integration of generative AI models into intelligent vehicle architectures. Studies have shown that generative models can enhance vehicle intelligence by supporting human-in-the-loop decision-making and real-time data analysis [12], [13]. Improvements in NLP and generative modeling have also led to more accurate, responsive, and context-aware voice command systems for in-vehicle applications [14]. These findings indicate strong potential for GenAI to move beyond basic interaction tasks and contribute to adaptive safety and assistance functions within vehicles.

2.4. Sustainability and Intelligent Control in EV Systems

In addition to safety and interaction, artificial intelligence plays an important role in supporting sustainable transportation systems. Intelligent AI-driven vehicle technologies contribute to safer driving behavior, efficient infrastructure utilization, and reduced environmental impact [15]–[17]. In EV systems, intelligent control strategies in power electronics, such as advanced DC–DC converter designs, have been shown to improve energy efficiency, voltage regulation, and power-sharing capability, thereby enhancing overall system reliability and operational safety [18], [19]. These advancements highlight the importance of integrating AI-driven decision-making with intelligent control mechanisms to support secure and sustainable EV operation.

Although extensive research has been conducted on conversational AI and driver monitoring systems, existing studies largely address these components independently. Conversational AI systems are primarily designed for infotainment, navigation, and basic vehicle control, while driver drowsiness detection systems focus solely on fatigue monitoring without incorporating adaptive interaction mechanisms. The lack of integration between real-time driver state monitoring and generative AI–driven conversational intelligence limits the system’s ability to deliver personalized, context-aware, and adaptive safety responses. This research gap motivates the development of an integrated framework

that combines computer vision-based drowsiness detection with generative AI-driven voice interaction, particularly for EVs and semi-autonomous driving environments and enhance digital system [26].

3. Methodology

This section describes the proposed methodology for the integrated driver assistance system, including the system architecture, voice interaction framework, drowsiness detection mechanism, alert generation strategy, and hardware implementation. The proposed method is designed to simultaneously monitor driver alertness and enable intelligent voice-based interaction in real time.

3.1. Overall System Architecture

The proposed system adopts a modular and layered architecture that integrates computer vision-based driver monitoring with a generative AI-driven conversational interface to enhance driver safety and interaction. As illustrated in figure 1, the system consists of two main processing pipelines that operate in parallel: (i) a voice interaction pipeline for conversational assistance and (ii) an image processing pipeline for real-time drowsiness detection. Both pipelines are coordinated by an embedded microcontroller unit, which acts as the central processing and control component.

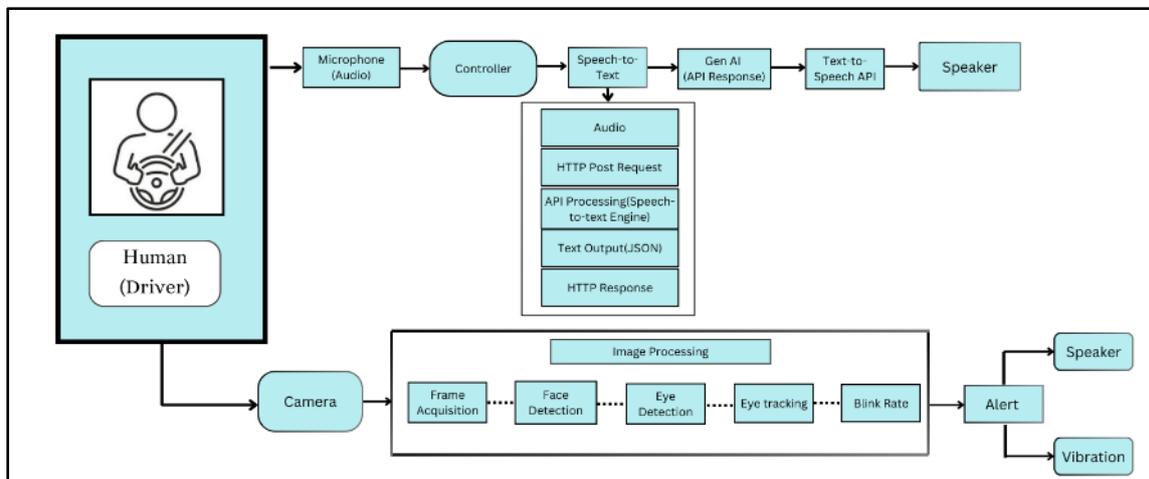


Figure 1. Overall System Architecture of the Proposed Driver Assistance System

In the voice interaction pipeline, audio input is captured through an in-vehicle microphone and forwarded to the embedded controller. The captured audio signal is transmitted as an HTTP request to a speech-to-text engine, where spoken commands are converted into textual form. The transcribed text is then processed by a generative AI module through an Application Programming Interface (API), enabling intent recognition and context-aware response generation. The AI-generated textual response is subsequently converted into audio using a text-to-speech module, and the resulting speech output is delivered to the driver through an onboard speaker. This pipeline enables natural, hands-free communication between the driver and the vehicle while minimizing manual interaction and cognitive distraction.

Simultaneously, the image processing pipeline continuously monitors driver alertness using an in-vehicle camera. Visual data captured by the camera are passed to the image processing module, where a sequence of operations is performed, including frame acquisition, face detection, eye detection, eye tracking, and blink rate analysis. These stages collectively extract visual features related to driver behavior and fatigue. Drowsiness is inferred based on predefined criteria derived from eye closure duration and abnormal blink patterns. When drowsiness is detected, the system generates a control signal that activates the alert module.

The alert module serves as the output interface of the system and delivers multi-modal warnings to regain driver attention. Audio alerts are issued through the speaker, while tactile feedback is provided via a vibration actuator. In addition, visual notifications may be displayed on an onboard screen to reinforce the warning message. By combining auditory, tactile, and visual feedback, the system ensures timely and effective driver notification under fatigue conditions.

Overall, the architecture depicted in [figure 1](#) highlights the seamless integration of sensing, processing, and actuation components within a unified framework. The parallel execution of conversational AI and computer vision-based monitoring enables the system to adapt its responses based on both driver commands and real-time driver state, forming a robust foundation for intelligent and safety-oriented driver assistance in electric and semi-autonomous vehicles.

3.2. Voice Interaction and NLP Module

The voice interaction and Natural Language Processing (NLP) module is designed to enable seamless, hands-free communication between the driver and the vehicle through a structured conversational AI pipeline. As illustrated in [figure 2](#), the interaction workflow follows a client-server architecture that supports robust, scalable, and context-aware voice-based communication.

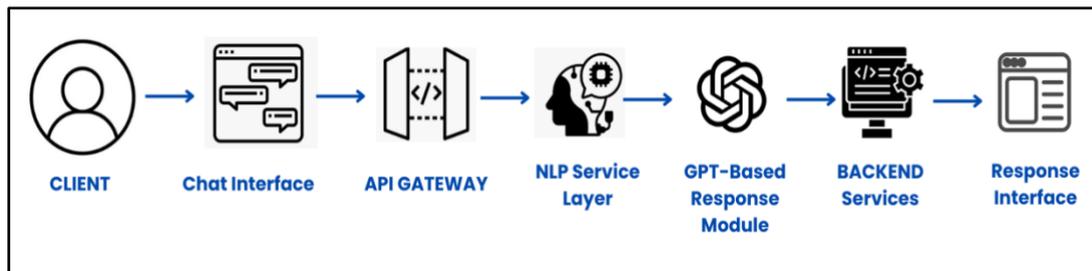


Figure 2. Voice Interaction and Conversational AI Workflow

The interaction begins at the client layer, where the driver issues a spoken command through the in-vehicle microphone. The captured audio signal is processed by the chat interface, which serves as the front-end interaction layer responsible for initiating communication with the backend system. The audio input is then transmitted through an API gateway, which manages request routing, authentication, and data transfer between system components.

Within the backend, the audio data are first processed by the NLP service layer, where a speech-to-text engine converts the spoken input into textual form. This textual representation is analyzed to extract semantic meaning, user intent, and contextual information. The processed text is subsequently forwarded to the GPT-based response module, which employs a generative AI model to generate an appropriate and context-aware response. This response may include vehicle status information, safety-related messages, or confirmation of driver commands, depending on the interpreted intent.

Following response generation, the system interacts with backend services responsible for vehicle data retrieval, command execution, and system state management. These services ensure that the generated response is consistent with real-time vehicle conditions and safety constraints. The finalized response is then delivered to the response interface, where the text output is converted into speech using a text-to-speech engine and played back to the driver through the onboard speaker.

Overall, the workflow depicted in [figure 2](#) highlights a modular and extensible conversational AI architecture that decouples user interaction, language understanding, response generation, and vehicle service execution. This design allows the system to support real-time, context-aware voice interaction while maintaining scalability, reliability, and integration with other vehicle subsystems, thereby enhancing both driver convenience and safety.

3.3. Computer Vision-Based Drowsiness Detection

Driver drowsiness detection is implemented using a camera-based computer vision approach designed for real-time operation in an in-vehicle environment. As shown in [figure 3](#), the detection process begins with continuous video acquisition from an in-vehicle camera positioned to capture the driver's facial region. Each incoming video frame is preprocessed to improve robustness against illumination variations and noise, ensuring stable performance under changing lighting conditions.

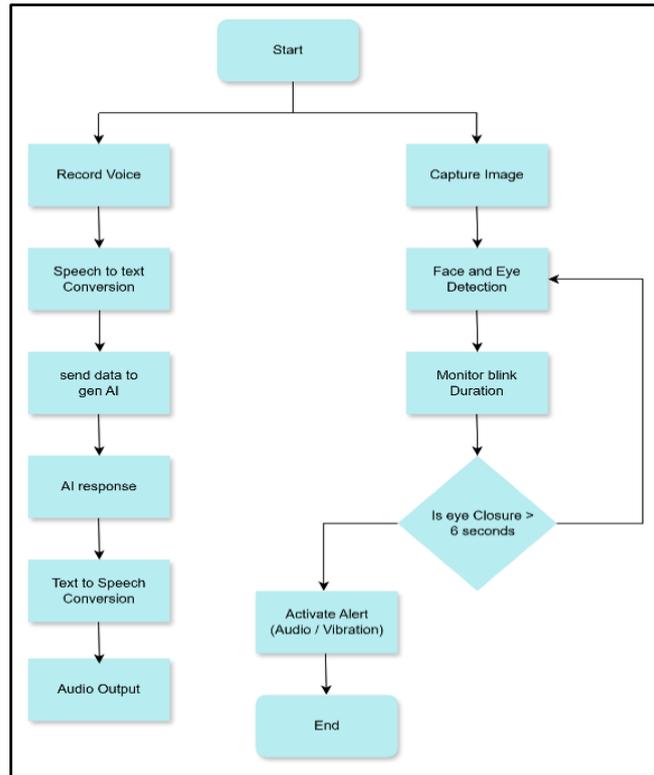


Figure 3. Flowchart of the Drowsiness Detection Process

Following preprocessing, face detection is applied to identify and localize the driver’s face within each frame. Once the facial region is detected, the system performs eye region extraction, focusing on the left and right eye areas for detailed analysis. These eye regions serve as the primary input for subsequent fatigue assessment. The system then monitors eye-related temporal features, including eye closure duration and blink behavior, across consecutive frames.

A Convolutional Neural Network (CNN)–based classifier is employed to determine the eye state in each frame, categorizing the eyes as either open or closed. The classifier operates on the extracted eye regions and provides frame-level eye state predictions. Based on these predictions, temporal metrics are computed to evaluate driver alertness. Eye Closure Duration (ECD) is calculated based on the number of consecutive frames in which the driver’s eyes are classified as closed. Mathematically, the eye closure duration is defined as:

$$ECD = N_c \times \Delta t \quad (1)$$

N_c represents the number of consecutive frames with closed eyes and Δt denotes the time interval per frame (in seconds).

A drowsiness condition based on eye closure duration is identified as:

$$D_{ECD} = \begin{cases} 1, & \text{if } ECD > T_{ec} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

T_{ec} is the predefined eye closure threshold, set to 10 seconds in this study.

In addition to prolonged eye closure, blink behavior is analyzed to improve detection robustness. The blink rate (BR) is computed as:

$$BR = \frac{N_b}{T_w} \quad (3)$$

N_b is the number of detected eye blinks within an observation window T_w (in seconds). The driver is classified as drowsy based on blink behavior when:

$$D_{BR} = \begin{cases} 1, & \text{if } N_b > 6 \text{ within } T_w = 6 \text{ s} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

These thresholds are selected to balance detection sensitivity and false alarm reduction in real-time driving scenarios. The final drowsiness state is determined by combining both temporal indicators using a logical OR operation:

$$D = \begin{cases} 1, & (D_{ECD} = 1) \vee (D_{BR} = 1) \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

When a drowsy state is detected, the system immediately activates the alert mechanism, generating audio warnings and vibration feedback to regain driver attention. If no drowsiness condition is detected, the system continues monitoring without interruption, enabling continuous and non-intrusive driver supervision.

Representative visual results of the detection process are presented in [figure 4](#). Under normal driving conditions, the system correctly identifies open eyes and maintains a non-alert state, as indicated by bounding boxes around the detected face and eyes. In contrast, during drowsy conditions, the system accurately detects closed eyes across multiple frames, incrementing the frame count associated with eye closure. This temporal accumulation directly contributes to the drowsiness decision logic, demonstrating the effectiveness of the proposed approach in distinguishing alert and fatigued driver states.

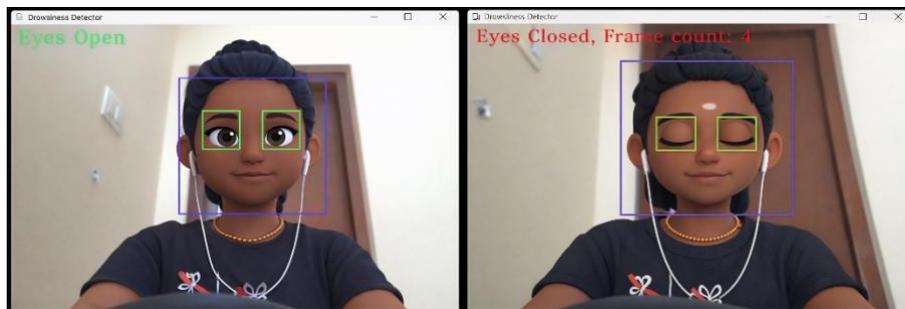


Figure 4. Face and Eye Detection Results under Normal and Drowsy Conditions

*Note: Due to privacy policy, all human images are replaced with special characters.

3.4. Alert Generation and Safety Response Mechanism

Upon detecting a drowsy driving condition, the system immediately activates a multi-modal alert mechanism designed to regain driver attention and mitigate potential safety risks. As described in the previous section, drowsiness is identified based on prolonged eye closure duration or abnormal blink patterns. Once a drowsy state is confirmed, the alert module is triggered with minimal processing latency to ensure timely intervention.

The alert mechanism employs multiple feedback modalities to maximize driver awareness. Audio alerts are delivered through the vehicle's speaker system to provide clear and immediate warnings. Simultaneously, vibration feedback is generated using a motor-based actuator to provide tactile stimulation, which is particularly effective in scenarios where auditory cues alone may be insufficient. In addition, visual notifications are displayed on an onboard LCD to present warning messages and system status information, reinforcing the alert through visual cues.

If the detected drowsiness condition persists over consecutive monitoring cycles, the system supports alert escalation, which may involve repeated warnings or intensified feedback to further prompt driver response. This layered alert strategy ensures adaptability to varying driver states and minimizes the likelihood of ignored warnings. The driver is expected to respond by regaining alertness, adjusting driving behavior, or taking a rest break when necessary.

Beyond fatigue-related alerts, the same response framework supports driver assistance functionalities through voice interaction. Voice commands are processed to provide real-time vehicle information, system notifications, and AI-generated guidance, thereby reducing manual interaction and cognitive load during driving. The relationship between detected driver states, system inputs, processing actions, generated outputs, and expected driver responses is summarized in [table 1](#).

Table 1. Mapping of Driver States, Alert Mechanisms, and System Responses

System Function	Input Source	Processing Action	Output Generated	Feedback Modality	Expected Driver Response
Drowsiness Detection	Camera (video feed)	Face and eye analysis, blink and closure detection	Drowsiness warning message	Audio, vibration, visual	Regain alertness or take a break
Alert Escalation	Prolonged drowsy state	Repeated or intensified alert triggering	Recurrent warning signals	Audio, vibration	Immediate corrective action
Driver Assistance	Voice commands (microphone)	Speech-to-text and intent recognition	Textual command interpretation	System-level processing	Follow system instructions
Information Display	Vehicle status and warnings	Data formatting and visualization	Speed, warning, and system status display	Visual (LCD)	Improved situational awareness
AI Response Delivery	AI-generated textual response	Text-to-speech conversion	Spoken system response	Audio (speaker)	Reduced distraction, informed driving

3.5. Hardware Implementation

The proposed driver assistance system is implemented on an embedded hardware platform designed to support real-time data acquisition, processing, and alert generation. The complete hardware prototype developed for system validation is illustrated in figure 5, which shows the physical layout, wiring, and interconnection of all major system components.

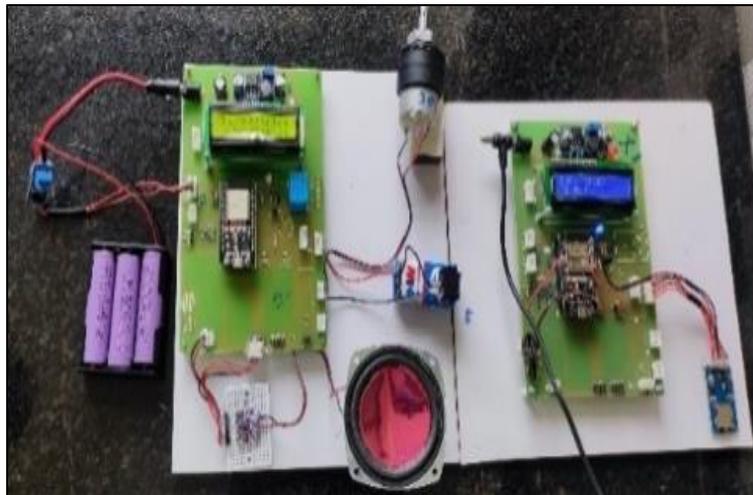


Figure 5. Hardware Prototype of the Proposed System

At the core of the hardware implementation is an ESP32 development board, which functions as the central processing unit responsible for coordinating sensor data acquisition, executing control logic, managing communication with external modules, and synchronizing the computer vision and voice interaction subsystems. An in-vehicle camera module is integrated to continuously capture the driver’s facial images for real-time drowsiness detection. For voice-based interaction, an INMP441 digital microphone module is used to acquire high-quality audio signals for speech-to-text processing.

System outputs are delivered through multiple feedback interfaces. A speaker module, driven by a MAX98357 audio amplifier, provides clear audio alerts and AI-generated voice responses. Visual system status information and warning messages are displayed on a 16×2 LCD module, enabling the driver to monitor system operation at a glance. To support tactile feedback, a low-speed DC gear motor is employed as a vibration actuator and is controlled through a relay module, allowing the system to generate vibration-based alerts when a drowsy state is detected.

The entire system is powered by a rechargeable lithium-ion battery pack, ensuring portable and stable operation. Voltage regulation and monitoring mechanisms are implemented to maintain reliable performance and protect hardware components during extended use. A detailed summary of the hardware components, including their specifications and functional roles within the system, is provided in [table 2](#), while the physical realization of the prototype is shown in [figure 5](#).

Table 2. Hardware Components and Specifications

Input	Face detection	Eye detection	Drowsiness detection	Eye status	Action triggered	comments
Initial state	Detected (Stable outline)	Not Detected (Blurred/occluded)	Not Applicable	Not Measured	No action	Face is detected but eyes are not clearly visible (due to occlusion or blur).
Normal Condition	Detected (Proper alignment)	Detected (Sharp focus)	Not Detected	Eyes Open	No action	Both the face and eyes are properly detected, and the eyes are in a normal state (open)
Drowsiness Condition	Detected (Proper alignment)	Detected (Sharp focus)	Detected (Long closure time)	Eyes Closed (Prolonged)	Trigger alert (sound/alarm)	Drowsiness detected based on prolonged eye closure beyond a threshold time (e.g., 6 seconds).

4. Results and Discussion

This section presents the experimental results obtained from the proposed integrated driver assistance system and discusses its performance in terms of drowsiness detection accuracy, alert responsiveness, and system reliability. The evaluation focuses on validating the effectiveness of the computer vision-based drowsiness detection module and the real-time responsiveness of the generative AI-driven interaction framework.

4.1. Experimental Setup and Evaluation Criteria

The experimental evaluation was conducted using the developed embedded hardware prototype under controlled driving conditions to assess the effectiveness and reliability of the proposed driver assistance system. The experimental setup, illustrated in [Figure 6](#), was implemented inside a passenger vehicle to closely replicate real-world driving scenarios while maintaining controlled testing parameters.



Figure 6. Experimental Setup for System Evaluation

*Note: Due to privacy policy, all human images are replaced with special characters.

As shown in [figure 6](#), the in-vehicle camera was mounted near the rear-view mirror and oriented toward the driver's face to ensure continuous monitoring of facial features and eye movements. This placement enabled reliable face and

eye detection while minimizing occlusion during normal driving posture. The ESP32-based processing unit, along with the associated electronic modules, was positioned within the vehicle cabin to facilitate real-time data processing and signal routing. Audio alerts were delivered through onboard speakers, while a vibration motor actuator provided tactile feedback. A 16×2 LCD display was used to present system status messages and alert notifications, and the entire system was powered by a portable battery power supply.

The system was evaluated across five predefined test cases representing different driver states, including an initial state, normal alert driving conditions, and varying levels of drowsiness. These test cases were designed to validate system behavior under both non-fatigue and fatigue scenarios. The evaluation criteria focused on face detection reliability, eye detection accuracy, drowsiness detection correctness, and alert triggering performance.

Drowsiness was classified based on temporal eye-related indicators, consistent with the proposed detection method. Specifically, a drowsy state was identified when either (i) the driver’s eye closure duration exceeded 10 seconds, or (ii) the blink frequency exceeded six blinks within a six-second interval. The system response was considered correct when alerts were triggered exclusively under drowsy conditions and remained inactive during normal alert driving.

Overall, the experimental setup depicted in Figure 6 ensured realistic system deployment while enabling controlled evaluation of detection accuracy, response latency, and alert reliability, thereby providing a robust basis for performance analysis.

4.2. Drowsiness Detection Performance

The performance of the proposed drowsiness detection module was evaluated by examining its ability to accurately identify different driver alertness states under the predefined test scenarios. The evaluation focused on the reliability of face detection, the consistency of eye detection, and the correctness of drowsiness classification based on temporal eye-related features.

Experimental results indicate that face detection was successfully achieved in all test cases where the driver’s face was unobstructed, demonstrating stable localization performance under real-time operating conditions. Eye detection accuracy remained high when the driver’s face was properly aligned with the camera and lighting conditions were adequate, enabling reliable extraction of eye regions for subsequent analysis. In scenarios where eye features were not clearly visible, the system appropriately refrained from performing fatigue assessment, preventing erroneous classification.

The proposed system achieved correct drowsiness detection in all scenarios where predefined fatigue conditions were met. Alerts were triggered in 100% of the test cases involving prolonged eye closure or excessive blink frequency, while no false alerts were observed during normal alert driving conditions. This behavior confirms the effectiveness of the selected thresholds and the robustness of the detection logic in distinguishing between alert and drowsy driver states.

A detailed summary of the detection performance across all test cases is presented in table 3. Cases 1 and 2 correspond to non-drowsy conditions, where no alert was generated, whereas Cases 3 to 5 represent drowsiness scenarios detected through eye closure duration, blink rate, or a combination of both, resulting in correct alert activation.

Table 3. Performance Analysis of Face Detection, Eye Detection, and Drowsiness Detection

Test Cases	Eyes Detected	Eye Closure(>10s)	Blink Rate(>6 counts in 6s)	Result
Case 1	No	No	No	No result
Case 2	Yes	No	No	No result
Case 3	Yes	Yes	No	Voice alert
Case 4	Yes	No	Yes	Voice alert
Case 5	Yes	Yes	Yes	Voice alert

Representative results of face and eye detection under both alert and drowsy conditions are illustrated in figure 7. The figure shows bounding boxes around the detected face and eye regions, along with system-generated labels indicating

eye state. Under normal conditions, the system correctly identifies open eyes and maintains a non-alert state. In contrast, during drowsy conditions, prolonged eye closure is accurately detected across consecutive frames, leading to timely alert generation. These visual results further validate the effectiveness of the proposed computer vision–based drowsiness detection approach.

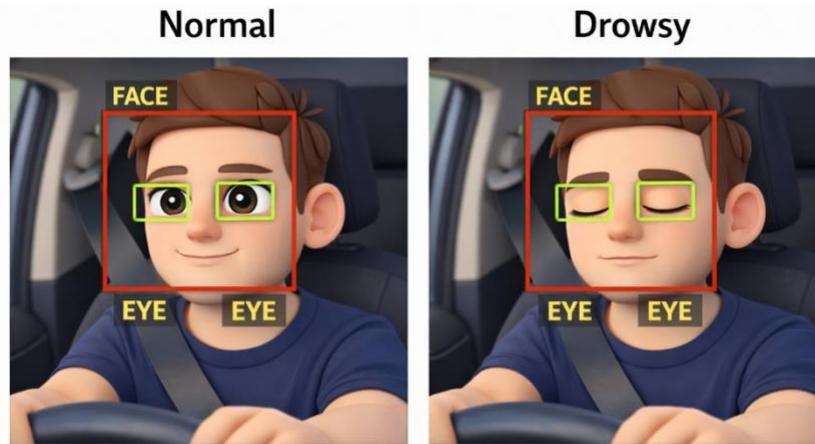


Figure 7. Face and Eye Detection Results under Normal and Drowsy Conditions

*note: Due to privacy policy, all human images are replaced with special characters.

4.3. System Testing and Alert Response Analysis

To further evaluate the reliability and robustness of the proposed system, a series of functional system-level tests were conducted to analyze alert triggering behavior under different driver conditions. Unlike the detection-focused evaluation presented in the previous subsection, this analysis emphasizes the correctness and responsiveness of the alert mechanism once drowsiness indicators are identified.

Five predefined test cases were executed based on the availability of eye detection, eye closure duration, and blink rate characteristics. These test cases were designed to validate whether the system correctly activates alerts only under fatigue-related conditions and remains inactive during normal driving states. The system behavior was assessed in terms of drowsiness classification accuracy and alert triggering consistency.

As summarized in table 4, the system demonstrated reliable alert generation performance. In non-drowsy conditions (Cases 1 and 2), where fatigue indicators were absent, no alerts were triggered, confirming the absence of false positives. In contrast, in all drowsiness-related scenarios (Cases 3 to 5), alerts were successfully activated when either prolonged eye closure, excessive blink rate, or a combination of both was detected. This resulted in 100% correct alert triggering for all predefined fatigue conditions.

Table 4. System Testing Results for Drowsiness Detection and Alert Generation

Test Case	Eyes Detected	Eye Closure > 10 s	Blink Rate > 6 in 6 s	Drowsiness Detected	Voice Alert Triggered
Case 1	No	No	No	No	No
Case 2	Yes	No	No	No	No
Case 3	Yes	Yes	No	Yes	Yes
Case 4	Yes	No	Yes	Yes	Yes
Case 5	Yes	Yes	Yes	Yes	Yes

The temporal analysis of alert activation indicates that the system responds immediately once predefined drowsiness thresholds are exceeded. This low-latency response ensures timely driver notification, which is critical for mitigating fatigue-related driving risks. The consistent alignment between drowsiness detection outcomes and alert generation confirms the effectiveness of the integrated detection–response framework and highlights its suitability for real-time driver assistance applications.

4.4. Discussion

The experimental results confirm that the proposed system effectively integrates computer vision-based drowsiness detection with a generative AI-driven interaction framework to enhance driver safety and situational awareness. Vision-based fatigue indicators such as eye closure duration, blink rate, and prolonged eye closure have been widely validated as reliable measures of driver drowsiness in prior studies [7], [8], [9]. The results presented in Sections 4.2 and 4.3 demonstrate high detection reliability and consistent alert triggering behavior, with no false positives observed during normal driving conditions, which aligns with findings reported in real-time drowsiness monitoring systems [10], [11]. This indicates that the selected fatigue indicators and threshold values achieve a balanced trade-off between detection sensitivity and system robustness.

Compared to conventional drowsiness detection systems that typically operate as isolated safety modules, the proposed approach provides enhanced adaptability through the tight coupling of driver state monitoring and intelligent conversational interaction. Prior research has shown that integrating driver monitoring with intelligent human-vehicle interaction frameworks improves system responsiveness and driver engagement [4], [25]. By incorporating generative AI-driven conversational interfaces, the system is able not only to detect fatigue-related conditions but also to communicate warnings and guidance through natural voice-based interaction, which has been shown to reduce manual interaction and cognitive workload during driving [2], [22]. This capability is particularly relevant in semi-autonomous and electric vehicle contexts, where sustained driver awareness remains critical [1], [12].

The incorporation of multi-modal alert mechanisms further strengthens system effectiveness. Previous studies have demonstrated that combining auditory, visual, and tactile feedback significantly improves driver response time and reduces the likelihood of ignored warnings compared to single-modal alert systems [6], [23]. The system-level testing results indicate that this layered alert strategy contributes to timely driver notification and reinforces corrective action when fatigue indicators persist, consistent with findings from intelligent driver alert and monitoring platforms [10], [11].

Despite its demonstrated effectiveness, the current implementation has several limitations. As with most vision-based driver monitoring systems, detection performance may be affected by challenging lighting conditions, partial facial occlusions, or atypical driver postures [8], [9]. Additionally, the experimental evaluation was conducted using a limited number of controlled test scenarios, which may not fully capture the diversity of real-world driving environments. Similar limitations have been reported in prior studies, highlighting the need for extended field validation and large-scale datasets [11], [15].

Future research directions include the incorporation of adaptive thresholding techniques to account for inter-driver variability, which has been shown to improve detection accuracy and personalization in fatigue monitoring systems [9], [17]. The integration of additional physiological or behavioral signals, as well as the enhancement of robustness under adverse environmental conditions, also represents a promising direction for further development [15], [18]. Overall, the discussion of results confirms that the proposed integrated framework represents a practical and scalable solution for real-time driver monitoring and intelligent interaction, contributing to safer and more responsive driver assistance systems in electric vehicles [12], [20].

5. Conclusion

This paper presented an integrated AI-powered driver assistance system designed to enhance driver safety and human-vehicle interaction in electric vehicles. The proposed framework combines computer vision-based drowsiness detection with a generative AI-driven conversational interface, enabling simultaneous monitoring of driver alertness and intelligent voice-based interaction in real time. By analyzing eye closure duration and blink frequency through an in-vehicle camera, the system effectively identifies fatigue-related driving conditions and triggers timely multi-modal alerts, including audio warnings and vibration feedback, to mitigate accident risks.

Experimental results demonstrated that the proposed system reliably detected drowsiness under predefined fatigue conditions, achieving correct alert generation in all tested drowsiness scenarios while avoiding false alarms during normal driving conditions. The integration of a conversational AI module further enhanced system usability by enabling context-aware, hands-free interaction, thereby reducing cognitive distraction and improving driver

engagement. The unified architecture distinguishes this work from existing approaches that typically address driver monitoring and conversational intelligence as separate components.

The findings confirm that embedding generative AI-based natural language processing with vision-driven driver monitoring on an embedded platform provides a practical and effective solution for semi-autonomous and future autonomous electric vehicle applications. Despite its promising performance, the current system is limited by its dependence on visual cues and controlled testing conditions. Future work will focus on expanding real-world evaluations, incorporating additional physiological indicators, improving robustness under diverse lighting environments, and exploring adaptive learning mechanisms to further enhance detection accuracy and system reliability.

Overall, the proposed approach contributes to the development of intelligent, human-centered driver assistance systems that improve road safety, interaction efficiency, and driving comfort, supporting the ongoing evolution of smart and sustainable electric vehicles.

6. Declarations

6.1. Author Contributions

Conceptualization: V.K.P., S.A.G.T., M.B., S.N.K., G.D., B.K., K.T., L.P.S., and N.K.S.; Methodology: V.K.P. and S.A.G.T.; Software: M.B. and S.N.K.; Validation: V.K.P., G.D., and B.K.; Formal Analysis: K.T., L.P.S., and N.K.S.; Investigation: V.K.P., S.A.G.T., and M.B.; Resources: G.D. and B.K.; Data Curation: S.N.K., L.P.S., and N.K.S.; Writing Original Draft Preparation: V.K.P., S.A.G.T., and M.B.; Writing Review and Editing: V.K.P., G.D., K.T., and L.P.S.; Visualization: S.N.K. and B.K.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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