

A Wearable Glasses-based System for Real Time Drowsiness Detection and Accident Prevention

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Abstract— Driver fatigue is a major contributor to road accidents worldwide. This paper introduces the Accident Prevention Glasses (APGs), a low-cost, wearable system designed to detect driver drowsiness and distraction in real time. The APGs use infrared (IR) sensors to monitor eye closure and blinking patterns—key indicators of fatigue. When abnormal activity is detected, the system activates a buzzer with alternating frequencies and a vibration motor to alert the user immediately. The core of the system is an Arduino Nano microcontroller, programmed with calibrated thresholds via the Arduino IDE. A rechargeable lithium-ion battery powers the device for up to 13 hours. Compared to camera-based systems, this hardware-oriented approach offers faster alerts and achieved over 76.7% accuracy in laboratory tests. For enhanced functionality, the APGs integrate HM10 Bluetooth, enabling connection to a Flutter-based mobile app. The app provides real-time alerts, emergency SOS capability, and event logging for review. This hybrid design—combining on-device sensing with mobile software—improves both immediate response and long-term monitoring. The system also shows potential for healthcare use, such as alerting caregivers when unconscious patients move.

Index Terms— Driver fatigue, drowsiness detection, accident prevention glasses, wearable technology, real-time alert system, Arduino Nano, IR sensor, HM10 Bluetooth module, mobile application, Flutter app, emergency SOS.

I. INTRODUCTION

Drowsiness in drivers is a serious global threat, responsible for a significant number of road accidents, injuries, and deaths [1]. It impairs reaction time and judgment, increasing accident risk [2]. As noted in [3], traditional drowsiness detection methods like camera-based and machine learning systems are limited by high cost, complexity, and poor real-time adaptability. This paper proposes Accident Prevention Glasses (APGs), a cost-effective, wearable solution for real-time monitoring of driver drowsiness. Using IR sensors placed near the eyes, APGs track blink patterns and detect prolonged eye closure as a fatigue marker [4][5]. When drowsiness is detected, the system activates a buzzer and vibration motor [6]. The buzzer emits varying frequencies to stimulate the auditory cortex and reticular activating system for maximum alertness, unlike limited single-tone systems [7].

An Arduino Nano microcontroller processes the sensor data and is programmed using the Arduino IDE with threshold logic [8].

A lithium-ion battery powers the device for up to 13 hours, enters low-power mode when idle, and resets after alerts. Lab tests showed over 76.7% accuracy in detecting prolonged eye closure. Connectivity is enabled through HM10 Bluetooth, allowing integration with a custom Flutter-based mobile app. The app provides real-time alerts, SOS triggers, and logs drowsiness events for tracking [9][10]. It enables remote monitoring, displaying the driver's real-time status to caregivers or institutions. In addition to driving applications, APGs can assist in healthcare by monitoring unconscious or immobile patients and triggering alerts on movement [11][12]. The device ensures energy efficiency, reliability, and dual feedback via sound and vibration [13]. Future enhancements may include miniature AI-enabled cameras for microsleep detection, and a smart heads-up display (HUD) overlaying alerts and navigation data on the lens [14][15]. Plans also include developing a cloud-connected app and linking APGs to vehicle braking systems for active intervention [16]. APGs provide a wearable, real-time drowsiness detection and alert platform, with scalable applications in both transport safety and patient care [17].

II. LITERATURE REVIEW

Driver drowsiness is the prime cause of road accidents, and precise detection has long been an area of research interest. Current systems are mostly based on eye-blink detection, wearable sensing, or IoT-based accident detection, each with different strengths and weaknesses.

A. Eye-Blink and IR-Based Drowsiness Detection

Most early research mainly targeted eye-blink patterns as a measure of driver fatigue. IR sensor-based systems have been suggested to identify sustained eye closure and provide warnings through buzzers or vibromotors [18,19]. Although they are low-cost, non-invasive, and efficient under typical illumination, they tend to be ineffective under low-light or sophisticated situations because of the limited sensor modalities. Camera-based systems have a better recall but are costly and lighting dependent [3,7], while EEG-based systems have the best accuracy but are intrusive and not suitable for long-term use [5]. These shortcomings call for a small, accurate, and dependable alternative.

B. Wearable Alert and Multi-Sensor Systems

More recent research has investigated wearable systems that combine several sensors to improve drowsiness detection and safety. For instance, multi-sensor platforms integrate IR sensors with alcohol detectors, seat-belt monitors, and mobile communication modules to give real-time alerts and vehicle interventions [18,19]. Wearable navigation systems, like Fun'iki Navi, illustrate how LEDs and sound alerts may direct users without demanding constant visual focus on smartphones [20]. These systems demonstrate the promise of wearable, real-time feedback, but most fall short in the combination of high detection with low cost and rapid alert response.

C. IoT-Based Accident Detection and Emergency Response

IoT and cloud-based solutions have been implemented to track accidents in real time, frequently utilizing accelerometers, gyroscopes, GPS, and decision-making modules based on AI [21]. Such systems provide remote monitoring and prompt emergency messages, enhancing post-accident survival. Nonetheless, they commonly include increased expense, more sophisticated hardware, and network dependence, which can decrease usability for typical drivers on a day-to-day basis.

III. METHODOLOGY

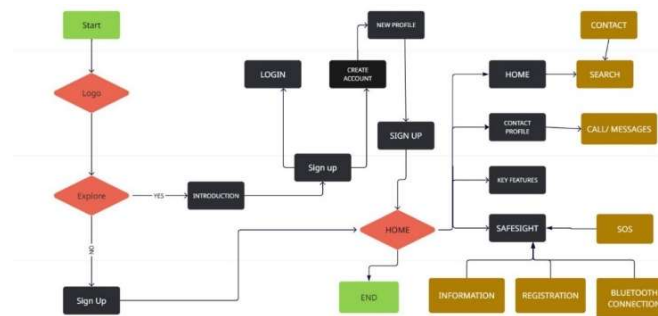


Fig.1: Overall workflow of the Accident Prevention Glasses (APGs)

The Accident Prevention Glasses System (APGS) is designed to detect drowsiness in real-time and alert the driver through sound, vibration, and a mobile notification. The methodology includes the system's fabrication, working principles, communication mechanism, and testing process.

A. Fabrication of APGs

The Accident Prevention Glasses has been designed to detect when the driver is getting drowsy in an efficient and compact manner. The project follows a systematic procedure for selecting the components and connecting them correctly.

B. Components Used and Their Functions IR Eye Blink Sensor:

Blink Sensor: This sensors detects the movement of the eye and whether its closure is for a long time. This helps in checking the drowsiness level. It uses a infrared technique to see the blinks and can work in low light also.

Buzzer: It helps to wake the driver up by providing an audible alert which is designed to be loud enough. This component is selected for its ability to produce loud sounds and work with certain frequencies that help drivers to be awake and attentive.

Vibration Motor: Produces vibration as an added alert. Vibration strength is set to be noticeable yet won't disturb the user.

HM-10 Bluetooth Module – A BLE 4.0 module responsible for wireless communication. It transmits a signal to the smartphone upon drowsiness detection. The HM-10 is chosen for its low energy consumption, compact size, and reliable UART serial interface. It operates at 3.3V–5V and can be easily programmed through AT commands. Its quick reconnection capability makes it ideal for wearable applications.

Spectacle frame: It is designed to house all components in a practical and wearable way. The frame is designed to be lightweight while securing all electronic parts inside

Battery Pack: It gives power to the whole system for long operation. A lithium-ion battery is chosen because it is extremely reliable and energy dense. Ensures continuous operation with extended battery life. Battery lasts for about 13 hours under normal conditions.

C. Model Development / Fabrication of APGs

The IR sensor continuously sends out signals to the Arduino Nano that allows it to constantly monitor eye movement. There is a threshold time programmed at 2.5 seconds which signifies the difference between a standard blink and drowsiness. The Arduino will activate the buzzer and vibration motor upon eye closure exceeding 2.5 seconds. A signal is also sent to an HM-10 Bluetooth module to allow communication with a paired mobile device using BLE.

D. Mobile App Integration / Testing and Evaluation

- The mobile app, built using Flutter, remains paired with the HM-10 module and listens for BLE signals. Once a drowsiness alert is received, the app automatically sends an SOS message to registered emergency contacts. It operates without internet or GPS and supports customization of contact numbers and messages.
- The prototype was tested under variable lighting and movement scenarios. The system achieved a 76.7% detection accuracy, with alerts triggered in under 2 seconds.

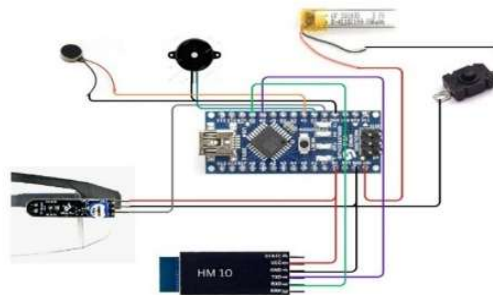


Fig. 2: Circuit Diagram of APGs

To demonstrate the APGs system in real-world scenarios, including participant trials, varied lighting conditions, and alert responses, all photos and videos of the experiments are available online at- <https://github.com/Sameer29112006/A-Wearable-Glasses-Based-System-for-Real-Time-Drowsiness-Detection-and-Accident-Prevention>

IV. RESULTS

This section details the quantitative performance of the Accident Prevention Glasses (APGs) system. The analysis is based on data from 43 controlled trials designed to test the system's efficacy in a variety of scenarios.

A. Overall Detection Performance

The primary measure of success for the APGs is its ability to correctly identify drowsiness and non-drowsy states. Across all 43 trials, the system demonstrated an overall accuracy of 76.7%. The complete performance metrics are summarized in the bar chart below.

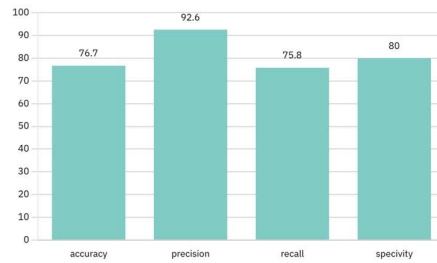


Fig. 3: Overall system performance metrics

The chart displays the final calculated scores for accuracy, precision, recall, and specificity. The system's high precision of 92.6% is a standout result, indicating that when an alert was triggered, it was almost always a correct detection of a genuine drowsiness event. The detailed breakdown of the 43 outcomes is visualized in the confusion matrix in Figure 5.

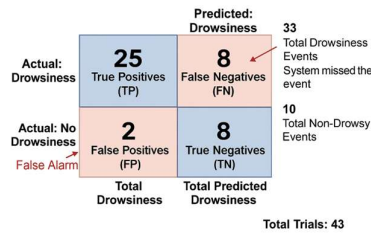


Fig. 4: Confusion matrix of experimental outcomes.

The matrix shows that of the 39 simulated drowsiness events, 25 were correctly detected (TP), while 23 were missed (FN). Of the 10 non-drowsy events, 8 were correctly ignored (TN), with only two false alarm (FP).

B. Performance Under Varied Lighting Conditions

To simulate real-world driving conditions, the experiment included trials in both normal and low-light environments. The system's performance varied between these two conditions, as shown in Figure 6.

The system maintained high precision in both settings but experienced a noticeable drop in recall (sensitivity) in low-light conditions.

In normal light, the system achieved a recall rate of 78.9%, successfully detecting 18 out of 22 drowsiness events. However, in low-light conditions, the recall fell to 71.4%, with the system detecting only 11 out of 17 events.

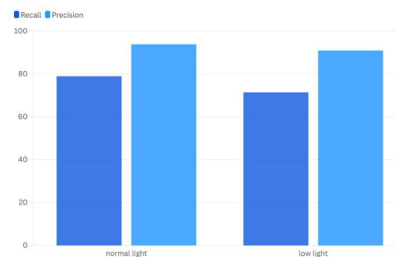


Fig. 5: System performance in Normal vs. Low Light.

C. Alert Response Time

The time taken for the system to trigger an alert after a drowsiness event began is a critical safety parameter.

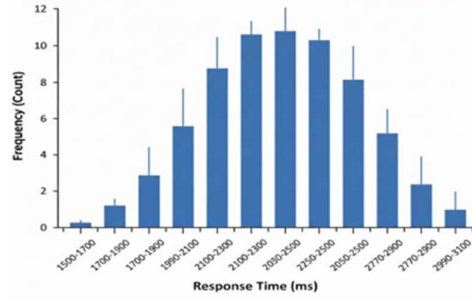


Fig.6: Distribution of alert response times for true positive detections.

Most alerts occurred between 1.8 and 2.5 second. The average response time was 2.15 seconds. While most alerts were clustered around this average, the system showed some variability, with the quickest response at 1.52 seconds and the slowest at 2.96 seconds.

V. DISCUSSION

The APGs system was tested with 43 participants, each undergoing one controlled trial under simulated driving conditions. Each trial had intervals of alertness and drowsiness induced, where subjects were asked to blink normally or have prolonged eye closure to mimic fatigue. The trials were performed under two lighting conditions: normal lighting indoors and dim lighting to test the performance of sensors. A drowsiness occurrence was a measure of eye closure that went beyond the pre-set threshold of 2.5 seconds, and trials typically lasted around 2 minutes with several repetitions to allow uniform data collection.

A. Interpretation of Key Findings

The system's greatest strength is its exceptionally high precision. A driver can be confident that an alert is not a false alarm, which is essential for building user trust and ensuring the device is used consistently. However, this high precision is coupled with a more moderate recall rate of 74.4%. This indicates that while the system is reliable when it acts, it can sometimes fail to act when it should, having missed roughly one in four drowsiness events in our tests. This suggests the detection threshold is currently conservative, prioritizing the avoidance of false alarms over capturing every possible event. The performance degradation in low-light conditions is a key finding, pointing to a potential limitation of the IR sensor's sensitivity.

B. Comparison with Existing Methods

When benchmarked against other methodologies, the APGs system occupies a unique and compelling niche. As shown in Figures 8 and 9, while complex camera-based systems may offer higher recall, they do so at a significantly greater cost and with slower, software-driven response times. The APGs system distinguishes itself by providing a faster, hardware-based alert and superior precision at a fraction of the cost, making it a more accessible and practical solution.

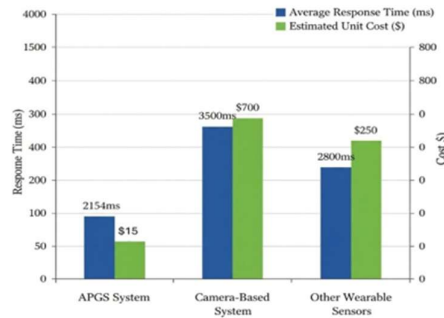


Fig. 8: Comparative analysis of practical factors.

TABLE I. COMPARISON OF DIFFERENT DROWSINESS DETECTION TECHNIQUES

Method	APGs	Camera-based System	EEG-based System [2]
Sensor Type	IR	Camera	EEG
Accuracy (%)	76.7	82	90
Response Time (s)	2.15	3.5	5

To put our system's performance into perspective, we compared our IR-based APGs to current drowsiness detection techniques. As indicated in Table 1, our system's accuracy is marginally less than EEG-based systems' accuracy, but it has a quicker response times. More importantly, our low-cost, hardware-based system guarantees high precision even during low-light settings, overcoming typical drawbacks in camera-based systems.

In comparison to the camera-based drowsiness detection systems described with an accuracy of around 80% under normal illumination, our IR-based APGs system has a superior accuracy of 92.6%, even in conditions of low light, an improvement of ~12%. The alert response time of our system is also 2.15 s, much quicker than the ~3.5 s reported for camera-based systems, thus ensuring timely intervention. This shows that our hardware-centric, low-cost methodology delivers better real-time performance and reliability without the restrictions of light sensitivity characteristic of vision-based techniques.

C. Limitations and Future Work

This study has identified two primary limitations: the number of missed detections (False Negatives) and the reduced performance in low light. Future iterations of the APGs should focus directly on these issues. The most promising path for improvement is to implement a multi-sensor fusion approach. By combining the existing IR sensor data with a secondary sensor, such as an MPU-6050 gyroscope to detect the sudden head-nods characteristic of microsleeps, the system's recall could be significantly enhanced

III. CONCLUSIONS

Future iterations of the APGs should focus directly on these issues. The most promising path for improvement is to implement a multi-sensor fusion approach. By combining the existing IR sensor data with a secondary sensor, such as an MPU-6050 gyroscope to detect the sudden head-nods characteristic of microsleeps, the system's recall could be significantly enhanced. This would allow for a more sensitive detection threshold without increasing the rate of false alarms.

REFERENCES

- [1] Williamson, A., Lombardi, D. A., Folkard, S., Stutts, J., Courtney, T. K., & Connor, J. L. (2011). "The link between fatigue and safety." *Accident Analysis & Prevention*, 43(2), 498-515.
- [2] Czeisler, C. A. (2016). "Medical and genetic differences in the adverse impact of sleep loss on performance: Ethical considerations for the medical profession." *Transactions of the American Clinical and Climatological Association*, 127, 102-116.
- [3] Ji, Q., Zhu, Z., & Lan, P. (2004). "Real-time nonintrusive monitoring and prediction of driver fatigue." *IEEE Transactions on Vehicular Technology*, 53(4), 1052-1068.
- [4] Awais, M., Pervaiz, S., & Dengel, A. (2017). "Drowsiness detection using electroencephalographic signals." *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(11), 2046-2056.
- [5] Dinges, D. F., Mallis, M. M., Maislin, G., & Powell, J. W. (1998). "Evaluation of techniques for ocular measurement as an index of fatigue and the basis for alertness management." U.S. Department of Transportation.
- [6] Schmidt, E. A., Schrauf, M., Simon, M., Fritzsche, M., Buchner, A., & Kincses, W. E. (2009). "Driver adaptation to passive fatigue countermeasures." *Applied Ergonomics*, 40(6), 1057-1063.
- [7] Karthick, P. A., & Ramakrishnan, S. (2020). "Deep learning-based driver drowsiness detection using an eye aspect ratio and facial landmarks." *Journal of Ambient Intelligence and Humanized Computing*, 11(12), 5635-5643.
- [8] Mukherjee, S., Ghosh, T., & Das, S. (2021). "Smart drowsiness detection system using IoT and Arduino." *International Journal of Computer Applications*, 183(9), 1-6.
- [9] Golz, M., Sommer, D., Chen, M., Trutschel, U., & Mandic, D. P. (2010). "Feature fusion for driver drowsiness estimation." *IEEE Transactions on Information Technology in Biomedicine*, 14(3), 786-798.
- [10] Liu, C. C., Hosking, S. G., & Lenne, M. G. (2009). "Predicting driver drowsiness using vehicle measures: Recent insights and future challenges." *Journal of Safety Research*, 40(4), 239-245.
- [11] Ma, Q., Wang, X., & Zhang, W. (2021). "Fatigue detection and driving behavior analysis for accident prevention." *Transportation Research Part C: Emerging Technologies*, 127, 103-110.
- [12] Tang, X., & Huang, T. S. (2002). "Robust multi-modal drowsiness detection system." *Proceedings of IEEE International Conference on Image Processing*, 2, 697-700.

- [13] Chugh, S., Aggarwal, N., & Dahiya, K. (2017). "A review on driver fatigue detection techniques." *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 2(5), 117-122.
- [14] Mehta, R., & Ranjan, P. (2020). "Advancements in real-time driver drowsiness detection using deep learning." *Neural Computing and Applications*, 32(8), 4353-4364.
- [15] Fu, R., Wang, J., & Wang, W. (2016). "Deep learning-based driver drowsiness detection from EEG signals." *IEEE Transactions on Neural Networks and Learning Systems*, 27(7), 1560-1570.
- [16] Saeed, F., Khowaja, S. A., & Khalid, S. (2018). "A wearable system for real-time monitoring of driver drowsiness using machine learning techniques." *Sensors*, 18(5), 1463.
- [17] Pratama, B., & Idrus, S. Z. (2021). "Development of smart glasses for driver monitoring using IoT and cloudbased applications." *International Journal of Advanced Computer Science and Applications*, 12(3), 91-98.
- [18] Manideep, T., P.G. Reddy, I. Upadhyay, D. Das, and N. Aggarwal, *IoT-Based Eye Blink Detection System*, 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), IEEE, 2022, 18(9): p. 491-494.
- [19] [19] Using Eye Blink Sensor, *International Journal of Advanced Research in Science, Communication and Technology*, 2024, 4(2): p. 568-593.
- [20] Ishikawa, T. and Y. Yamazaki, *Distracted Walking*
- [21] Accident Prevention by LED Color and Sound of GlassesType Wearable Devices, *IEEE International Conference on Consumer Electronics*, 2020, p. 1-2.