Middle East Journal of Pure and Applied Sciences (MEJPAS)
Online ISSN: 3062-343X
Volume 1, Issue 3, 2025, Page No: 7-13
https://mideastjournals.com/index.php/mejpas

Towards Safer Driving: A Review of Real-Time Drowsiness and Hypoglycemia Detection Using Embedded Machine Learning and IoT-Based Alerts

Aml Ahmed Kanbo [1], Ahmed Salem Daw Alarga [2*], Elhadi Elfitory Algarai [3]
[1] Computer Science Department, Libyan Academy of Postgraduate Studies, Al Khoms, Libya
[2] Electrical Engineering Department, Elmergib University, Khums, Libya
[3] Software Engineering Department, Elmergib University, Khums, Libya

نحو قيادة آمنة: مراجعة لاكتشاف النعاس ونقص السكر في الزمن الحقيقي باستخدام التعلم الآلي المضمن وتنبيهات إنترنت الأشياء

أمل أحمد كنمبو [1]، أحمد سالم الأرقع [2]، الهادي الفيتوري الجراي [3]
[1] قسم علوم الحاسوب، أكاديمية الدراسات العليا فرع الخمس، ليبيا
[2] قسم الهندسة الكهربائية، جامعة المرقب، الخمس، ليبيا
[3] قسم هندسة البرمجيات، جامعة المرقب، الخمس، ليبيا

*Corresponding author: ahmedar82.as@gmail.com

Received: April 22, 2025	Accepted: June 29, 2025	Published: July 16, 2025

Abstract:
Traffic accidents often result in both human casualties and economic losses worldwide. Among the major causes of these accidents are driver drowsiness and hypoglycemia. In recent years, artificial intelligence technologies have significantly advanced and been applied across many domains, including road safety, particularly in detecting abnormal driver states such as drowsiness or low blood sugar. Computer vision techniques based on cameras have been used to monitor facial features such as blink rate, yawning, and head movement. Additionally, physiological sensors have been integrated into these systems using various biosensors. IoT technologies have also been employed to send alerts for remote driver monitoring, enhancing system reliability. This study aims to provide a comprehensive review of the technologies used to detect drowsiness and hypoglycemia in drivers and to highlight the progress made in this area. The goal is to emphasize the importance of research toward developing integrated systems that can simultaneously detect both conditions. The study concludes that integrating computer vision, biosensors, and machine learning algorithms can significantly contribute to the development of high-accuracy systems that improve road safety.

Keywords: Machine Learning, Drowsiness and Hypoglycemia Detection System, Computer Vision, Biosensors.

الملخص
غالبًا ما تؤدي حوادث المرور الى خسائر بشرية وخسائر اقتصادية على مستوى العالم، ومن أهم الأسباب التي تؤدي إلى حوادث المرور هو حالات النعاس وهبوط سكر الدم للسائق. شهدت السنوات الأخيرة تطورا كبيرا في تقنيات الذكاء الاصطناعي، حيث دخلت في العديد من المجالات من بينها مجال السلامة المرورية، و تحديدا معرفة حالة السائق الطبيعية من الغير طبيعية (نعاس او هبوط سكر الدم)، وقد تم استخدام تقنيات الرؤية الحاسوبية المعتمدة على الكاميرا لمراقبة معالم الوجه مثل معدل رمش العين والتثاؤب وحركة الرأس، كما دخلت المستشعرات الفسيولوجية ف تصميم هذه الأنظمة بالاعتماد على مجموعة حساسات بالإضافة إلى استخدام تقنيات إنترنت الأشياء في ارسال تنبيهات لمراقبة حالة السائق عن بعد لزيادة موثوقية الأنظمة. تهدف هذه الدراسة إلى تقديم مراجعة شاملة حول التقنيات المستخدمة في الكشف عن نعاس او هبوط السكر لدى السائقين وما توصلت إليه الأبحاث في هذا المجال، وذلك من أجل تسليط الضوء على أهمية البحث في تطوير أنظمة متكاملة تجمع بين مؤشرات النعاس وهبوط السكر معا. وقد توصلت هذه الدراسة إلى أن التكامل بين الرؤية الحاسوبية والمستشعرات الحيوية وخوارزميات تعلم الألة من شأنه أن يساهم في تطوير أنظمة ذات دقة عالية تعمل على تحسين السلامة المرورية.

الكلمات المفتاحية: التعلم الالي، نظام كشف النعاس وهبوط السكر، الرؤية الحاسوبية، المستشعرات الحيوية.

Introduction

The introduction should be typed in Times New Roman with font size 10. Author can select Normal style setting from Styles of this template. The simplest way is to replace (copy-paste) the content with your own material.

According to the General Directorate of Traffic and Licensing in Libya, more than 3,000 fatalities were recorded in road accidents throughout the year 2024 [1]. Among all the possible causes, human factors are considered one of the main contributors to these incidents, particularly due to conditions such as drowsiness and hypoglycemia experienced by drivers. This highlights the urgent need to develop effective systems capable of promptly detecting drowsiness or hypoglycemic episodes in drivers, thereby reducing accident risks and enhancing road safety.

The development of intelligent systems for early detection of drowsiness and hypoglycemia is of great significance as it relies on several interdisciplinary scientific fields, most notably machine learning, embedded computing, computer vision, biosensing, and the Internet of Things (IoT). The integration of these disciplines ensures the provision of high-accuracy technological solutions capable of real-time patient monitoring.

This study aims to provide a comprehensive review of the current technologies used in detecting driver drowsiness and hypoglycemia. It highlights the main advantages and challenges faced by these systems, reviews the various technologies employed in their development, and analyzes previous studies that have addressed the design of such systems. The goal is to discuss their differences and provide a well-rounded knowledge base for researchers and developers working in this vital field.

Background

Machine learning technologies form the core of real-time intelligent detection systems, enabling the processing and analysis of vast amounts of behavioral and physiological data collected from drivers. By leveraging machine learning algorithms, the accuracy of traditional systems is significantly improved when deployed on embedded computing platforms such as Arduino, ESP32, or Raspberry Pi. These platforms offer good processing capabilities, low power consumption, lightweight, and portability — features that contribute to the development of optimal systems for detecting drowsiness or hypoglycemic episodes, making their integration into vehicles a practical approach to improving road safety [2].

Drowsiness detection systems can be categorized into three main types based on their operating mechanism: behavior-based systems, physiology-based systems, and vehicle-based systems [3].

a) Behavior-based systems focus on monitoring the driver's external behaviors that indicate drowsiness, such as prolonged eye closure, blink rate, head movement, and yawning. These systems typically use computer vision techniques to detect such signs using a camera. The captured data is then processed using the well-known OpenCV library, which is compatible with major operating systems like Windows, Linux, Android, iOS, and Mac, and supports common programming languages including C, C++, Python, and Java. OpenCV accelerates real-time image processing by utilizing the GPU, enabling the detection of facial features associated with drowsiness. Once these features are extracted, classification is performed using machine learning algorithms to determine whether the driver is drowsy or alert [3].

b) Physiology-based systems rely on biosensors to monitor physiological parameters indicative of drowsiness. These include devices for Electroencephalogram (EEG), Electrocardiogram (ECG), Electrooculogram (EOG), and Galvanic Skin Response (GSR). The signals collected by these sensors are processed and analyzed using machine learning algorithms to classify the driver's state [4].

Since both behavior-based and physiology-based systems are centered around the driver's condition, their design steps are generally similar. The following figure illustrates the workflow involved in designing driver detection systems based on behavioral and physiological approaches.

c) There are also other drowsiness detection systems that rely directly on vehicle behavior, such as lane deviation, sudden changes in speed—whether acceleration or deceleration—or irregular use of the vehicle's brakes. All of these indicators suggest that the driver may be in an abnormal state, which can be measured using intelligent sensing systems, including specialized sensors, cameras, or even by monitoring the duration of driving [3].

In contrast, hypoglycemia detection systems place greater emphasis on physiological indicators rather than visual cues captured by cameras, due to the higher accuracy of physiological measurements. These systems typically utilize a range of sensors, such as:

- Electrocardiogram (ECG) sensors
- Sweat sensors
- Continuous Glucose Monitoring (CGM) systems
- Electroencephalogram (EEG) electrodes

This is because increased heart rate and excessive sweating are among the most prominent symptoms of hypoglycemia [5].

Moreover, Internet of Things (IoT) technology has been integrated to streamline communication between the various components of these systems, including sensors, processing units, and alert mechanisms. Advanced communication protocols are employed to ensure secure and real-time data transmission, enabling the system to issue instant alerts to the driver—or even to emergency services or relevant authorities. This integration enhances the system's effectiveness in preventing accidents by allowing for early and proactive interventions [6].

Systematic Analysis of Previous Studies:

Numerous recent studies have explored a wide range of technologies and approaches for the early detection of driver drowsiness and hypoglycemia. Within this context, a non-invasive system was developed to detect episodes of hypoglycemia and hyperglycemia using wearable sensors based on electrocardiogram (ECG) and accelerometer data. This system aimed to provide a cost-effective alternative to traditional Continuous Glucose Monitoring (CGM) devices, which are typically expensive and complex. The system was tested on five healthy individuals over a two-week period, yielding accuracy results between 76–79%. However, it was noted that the system requires further development and improvement due to its small sample size and moderate accuracy [7].

Another study developed a drowsiness detection system based solely on facial expression analysis, utilizing the OpenCV library and Haar-cascade technique. While the results were promising, the system's performance could be significantly enhanced by integrating physiological data, which may increase its overall accuracy [8].

A third system was designed to detect both drowsiness and blood alcohol levels using Arduino, issuing alerts for either condition. This system incorporated an eyeblink sensor to monitor the driver's blink rate—identifying drowsiness when eye closure exceeded five seconds—and an MQ3 alcohol sensor to detect alcohol in the driver's breath. The system is notable for its low cost and reasonable accuracy due to its reliance on physiological indicators. However, its lack of artificial intelligence techniques categorizes it as a traditional system, which still requires significant development [9].

Additionally, another study [10] investigated a non-invasive method for glucose level monitoring based on machine learning techniques applied to cardiac signals and blood flow patterns. This represents an important step toward the development of non-invasive health monitoring devices, although the approach faces challenges in terms of data processing complexity and precise signal analysis.

Overall, these studies reflect a growing interest in combining wearable technologies, physiological monitoring, and AI-based analysis to enhance driver safety. However, limitations such as data accuracy, sample size, and system complexity remain key challenges to be addressed in future research.

An advanced driver drowsiness detection system was also developed, leveraging computer vision and machine learning techniques. The system operates through a webcam that continuously monitors the driver's facial expressions. Each video frame is analyzed using image processing techniques, focusing on three key facial landmarks: the eyes, mouth, and nose. The system accurately measures:

- Eye openness to determine the degree of eyelid closure,
- Mouth opening to detect yawning,
- Nose orientation to assess head tilt or position.

These measurements are compared against predefined reference values. If any of them exceed safe thresholds, the system triggers an immediate alert. The system demonstrated outstanding performance, achieving a sensitivity of 95.58% in detecting drowsiness. However, its heavy reliance on computer vision limits its effectiveness in low-light conditions or when the driver is wearing sunglasses or masks [11].

The Internet of Things (IoT) has also played a significant role in enhancing drowsiness and hypoglycemia detection systems. One study presented a drowsiness detection system that monitors heart rate using a Wemos D1 Pro ESP8266 microcontroller and a MAX30102 pulse sensor. The system was tested on 25 individuals during both drowsy and alert states. The results were displayed on a visual interface using the Blynk mobile application, and smartphone notifications were sent upon detecting drowsiness. The system achieved a detection accuracy of 98%. Nevertheless, it still requires further development due to the small sample size and the lack of AI algorithms, relying only on traditional heart rate thresholding [12].

In another study, a comprehensive IoT-based drowsiness detection system was developed using a combination of smart solutions. It utilized cameras for facial expression analysis and biometric sensors to monitor physiological indicators such as heart rate. The system processed data in real time and issued instant alerts upon detecting drowsiness. The detection accuracy reached 92% under varying driving conditions, confirming the system's effectiveness. However, the researchers identified several technical challenges, such as reduced system performance in low-light environments and the need to enhance the stability of device connectivity in IoT environments to prevent delays in data transmission [6].

Algorithms and Technologies Used

Driver drowsiness detection algorithms typically consist of multiple stages, utilizing a combination of computer vision, machine learning, and embedded systems. One widely adopted approach involves developing an automated fatigue detection system using Python programming and computer vision techniques. This system analyzes facial features such as drooping eyelids, head posture, and eye movement. It employs facial landmark detection algorithms like dlib and OpenCV, processes images by converting them into different color spaces (e.g., HSV, Grayscale), and applies filters to enhance accuracy.

Machine learning models are then used to classify fatigue levels. While the system demonstrated high prediction accuracy, it faced challenges related to lighting conditions and individual variations in facial expressions. These limitations highlight the need for further development to improve reliability in real-world applications such as truck driver monitoring or critical job roles [8].

Another system was implemented using Arduino to detect both drowsiness and alcohol consumption, relying solely on data from eyeblink and alcohol sensors, without incorporating machine learning techniques [9].

Image processing and embedded systems were also combined with Arduino boards, using advanced algorithms like YOLOv5 (You Only Look Once version 5). YOLOv5 offers high-speed and real-time detection capabilities, making it ideal for identifying drowsiness signs such as eye closure or head nodding quickly and accurately in mobile or vehicular environments [13].

In the domain of hypoglycemia detection, researchers have integrated physiological sensors with machine learning for non-invasive monitoring. For example, one study developed a system using HRV (Heart Rate Variability) and ECG data, applying the following algorithms:

- Linear Regression and Logistic Regression to model the relationship between HRV and glucose levels.
- Support Vector Machine (SVM) for classifying normal vs. abnormal states (hypo-/hyperglycemia).
- Random Forest to enhance prediction accuracy through multi-feature analysis of HRV and ECG data [10].

Another study employed a variety of machine learning algorithms—including Decision Trees, Logistic Regression, and more advanced methods like Random Forest and XGBoost—to improve classification accuracy. The model achieved up to 90% accuracy in detecting physical activity levels, illustrating the effectiveness of this approach in building intelligent, adaptive health monitoring systems [5].

Most of these systems perform data processing on embedded platforms, adopting edge computing techniques. This allows for real-time responsiveness, which is crucial in safety-critical applications. When necessary, the systems can also offload data to the cloud for deeper analysis, enabling a hybrid edge–cloud architecture that balances speed and analytical depth [2].

Sensors and Components Used

Embedded computing platforms such as the Raspberry Pi are considered core components in the design of most drowsiness and hypoglycemia detection systems. These platforms are widely favored due to their:

- Computational efficiency,
- Low cost,
- Ease of integration with AI technologies,
- And support for real-time processing of both physiological and visual data.

They can also connect seamlessly with cameras to capture images and video, which are used to detect eye states (open/closed) and facial expressions related to drowsiness. Furthermore, these platforms can interface with a wide range of physiological and environmental sensors, some of the key sensors used in these systems include [14]:

- Electroencephalogram (EEG): For brain activity monitoring

- Electrocardiogram (ECG): For heart signal tracking
- Electrooculogram (EOG): For eye movement detection
- Heart Rate Sensor (HRS): To measure pulse rate
- Galvanic Skin Response (GSR): For skin conductivity, often associated with stress or fatigue
- Sweat sensor: To detect perspiration levels
- Continuous Glucose Monitor (CGM): For non-invasive glucose monitoring
- Temperature sensors: For detecting abnormal changes in body temperature
- SpO_2 sensors: For measuring blood oxygen saturation non-invasively

These sensors are typically worn on the driver's body, providing continuous real-time monitoring of vital health indicators that are linked to hypoglycemia or drowsiness [10][4].

In addition, alert mechanisms can be integrated into these platforms to provide immediate warnings. This includes the use of [14]:

- Buzzers or speakers for audible alerts
- LCD displays for visual alerts or system feedback

Advantages and Challenges

Modern driver drowsiness detection systems—powered by cameras, sensors, and Internet of Things **(**IoT**)** technologies—offer advanced features that make them comprehensive solutions for enhancing road safety. These systems utilize cutting-edge computer vision techniques to accurately analyze facial features and eye **movements**, enabling the detection of key drowsiness indicators such as[15]:

- Prolonged eyelid closure**,**
- Frequent yawning**,**
- Head nodding or tilting**.**

They are designed for real-time responsiveness, issuing auditory, vibrational, or visual alerts as soon as risk conditions are detected. Moreover, integration with smart vehicle systems allows for automatic interventions, such as reducing vehicle speed in critical situations [15].

Other key advantages include [2]:

- Affordability and ease of installation, making them suitable even for older vehicles,
- Privacy compliance, as most systems rely on local data processing without sending sensitive information to cloud servers,
- Enhanced accuracy and comprehensiveness through hybrid systems that combine computer vision with biometric sensing, reducing the likelihood of false positives or detection errors.

Despite their many advantages, these systems still face several technical and practical challenges [15][4]:

- Environmental Limitations: Low-light conditions or direct sunlight can significantly impair the performance of computer vision components, reducing detection accuracy
- Individual Variability: Differences in facial features, skin tone, and expression patterns create additional challenges for achieving consistent accuracy across diverse user populations.
- Privacy and Security Concerns: The use of biometric data, whether processed locally or transmitted over networks, raises security and privacy risks, including the possibility of data breaches or unauthorized access
- Cost and Maintenance**:** Although these systems are becoming more affordable, initial development and deployment costs can still be high.
- Sensor calibration, maintenance, and ensuring long-term reliability present ongoing technical and financial burdens.

- Computational Demands**:** Real-time data processing requires significant computing resources. Low-cost embedded platforms may struggle to meet these demands, potentially limiting performance.
- Vehicle Compatibility**:** Systems may be less effective or harder to implement in older vehicles that lack the necessary infrastructure or power capabilities.
- User Acceptance and False Alarms**:** Frequent or incorrect alerts can lead to user annoyance, fatigue, or disengagement, reducing the system's overall effectiveness. This presents a behavioral and UX challenge that must be addressed during system design and evaluation.

Conclusions:

This study indicates that driver drowsiness and blood sugar level detection systems, which rely on artificial intelligence, edge computing, and the Internet of Things, represent promising solutions to enhance road safety. Despite technical challenges such as the impact of environmental conditions on camera accuracy and the difficulty of processing biometric data in real-time, models based on the integration of computer vision with physiological sensors and machine learning algorithms (such as YOLOv5 and Random Forest) have demonstrated encouraging performance, with accuracy in some systems reaching up to 95%.

The use of low-cost embedded platforms, such as Raspberry Pi and ESP32, is considered an important factor in making these solutions widely applicable, especially in resource-limited environments. However, there remains an urgent need to improve performance under challenging environmental conditions, such as low lighting or when the driver wears sunglasses, in addition to enhancing privacy and security levels when handling biometric data. It is also necessary to expand testing to include larger and more diverse human samples, along with developing mechanisms to simplify the integration of these systems into older vehicles that lack advanced technology.

In this context, integrating deep neural networks, such as LSTM, can enhance the systems' ability to analyze long time-series biological and behavioral signals, thereby increasing accuracy and responsiveness. Strengthening the communication infrastructure within the Internet of Things ecosystem will also help ensure safer and faster data transmission, supporting continuous analysis of driver performance.

Systems relying on physiological sensors, in particular, show a high degree of flexibility and adaptability to various environmental conditions, enabling accurate and stable monitoring throughout the day and under different lighting conditions. They also provide real-time monitoring and continuous analysis using advanced machine learning algorithms, with the ability to store and analyze data via cloud computing technologies, allowing ongoing development and improvement of system performance over time.

References

[1] Libya Review, "Libya Records Over 3,000 Traffic Fatalities in 2024", Traffic Fatalities 3 March 2025.[online], avalible: https://libyareview.com/53583/libya-records-over-3000-traffic-fatalities-in-2024, (Accessed: 04:30PM, 15/03/2025).

[2] J. S. Bajaj, N. Kumar, R. K. Kaushal, H. L. Gururaj, F. Flammini, and R. Natarajan, "System and method for driver drowsiness detection using behavioral and sensor-based physiological measures," Sensors, vol. 23, no. 3, p. 1292, Jan. 2023.

[3] V. Saini and R. Saini, "Driver drowsiness detection system and techniques: a review," International Journal of Computer Science and Information Technologies, vol. 5, no. 3, pp. 4245–4249, 2014.

[4] Q. Abbas and A. Alsheddy, "Driver fatigue detection systems using multi-sensors, smartphone, and cloud-based computing platforms: A comparative analysis," Sensors, vol. 21, no. 1, p. 56, 2021.

[5] L. Dénes-Fazakas, M. Siket, L. Szilágyi, L. Kovács, and G. Eigner, "Detection of physical activity using machine learning methods based on continuous blood glucose monitoring and heart rate signals," Sensors, vol. 22, no. 21, p. 8568, 2022.

[6] S. Chaikhamwang, T. Darasawang, R. Sukjaimuk, T. Yuyen, and A. Chaikaew, "The driver drowsiness detection and alert system using internet of things (IoT) technology," International Journal of IoT and Data Science (IJIDS), vol. 3, no. 1, pp. 1-15, Jan.-Jun. 2025, doi: 10.34218/IJIDS_03_01_001.

[7] D. Dave et al., "Detection of hypoglycemia and hyperglycemia using noninvasive wearable sensors: electrocardiograms and accelerometry," J. Diabetes Sci. Technol., vol. 18, no. 2, pp. 351-362, 2024.

[8] A.Balasundaram, S.Ashokkumar, D.Kothandaraman, et al., "Computer vision based fatigue detection using facial parameters". In IOP conference series: materials science and engineering (Vol. 981, No. 2, p. 022005). IOP Publishing, December. 2020.

[9] J. Archana, A. K, J. Jayalakshmi, et al., "Driver drowsiness and alcohol detection system using Arduino," London Journal of Research in Computer Science and Technology, vol. 23, no. 3, 2023.

[10] M. Gusev et al., "Noninvasive glucose measurement using machine learning and neural network methods and correlation with heart rate variability," J. Sensors, vol. 2020, Art. no. 9628281, 2020.

[11] R. Chinthalachervu et al., "Driver drowsiness detection and monitoring system using machine learning," in Journal of Physics: Conference Series, vol. 2325, no. 1, p. 012057, Aug. 2022.

[12] Y. Yunidar, M. Melinda, K. Khairani, M. Irhamsyah, and N. Basir, "IoT-based heart signal processing system for driver drowsiness detection," Green Intelligent Systems and Applications, vol. 3, no. 2, pp. 98-110, 2023.

[13] S. S. Balwante, R. Kolhe, N. K. Pingale, and D. S. Chandel, "Drowsiness detection system: Integrating YOLOv5 object detection with Arduino hardware for real-time monitoring," International Journal of Innovative Research in Computer Science & Technology, vol. 12, no. 2, pp. 59-66, 2024.

[14] Y. Albadawi, A. AlRedhaei, and M. Takruri, "Real-time machine learning-based driver drowsiness detection using visual features," J. Imaging, vol. 9, no. 5, p. 91, 2023.

[15] T. S. Delwar, M. Singh, S. Mukhopadhyay, A. Kumar, D. Parashar, Y. Lee, and J. Y. Ryu, "AI-and deep learning-powered driver drowsiness detection method using facial analysis," Applied Sciences, vol. 15, no. 3, p. 1102, 2025.