RESEARCH ARTICLE

# Multimodal IoT-Based Real-Time Drunk Driver Detection and Reporting System with Intelligent Sensor Fusion and Mobile Law Enforcement App

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**Abstract:** Drunk driving remains a major factor in severe road accidents and fatalities in the world. In this work we have developed a smart, fully automated system that identifies and reports intoxicated drivers utilizing IoT technology. The system employs a three-layer detection method. Firstly, a voice-activated verification system assesses the driver's alertness prior to starting the vehicle. Additionally, sensors embedded in the steering wheel track the driver's heart rate while gas sensors measure alcohol content. Finally, a webcam captures facial images that are evaluated using a custom-trained CNN model to identify visual indicators of intoxication. All inputs are analyzed with a weighted algorithm. If the assessment indicates that the driver is under the influence, the system transmits a real-time alert, including GPS coordinates, to a mobile application utilized by relevant authorities. This guarantees timely identification and allows for swift action by authorities. The testing of the integrated system demonstrated an overall detection accuracy of 93.5%, with the facial intoxication detection module alone achieving up to 99% classification accuracy and the voice-verification achieving 96% reliability in controlled trials.

**Keywords:** IoT, Facial Recognition, Pulse Sensor, Gas Sensor, CNN, GPS Tracking

## INTRODUCTION

The World Health Organization reports that approximately 1.35 million individuals lose their lives each year due to road traffic accidents, with a staggering 93% of these fatalities occurring in low- and middle-income countries such as Sri Lanka [1]. Among these causes, alcohol-impaired driving stands out as a major contributor, accounting for nearly 30–32% of all traffic-related deaths. This means that nearly one in every three fatal crashes involves a drunk driver. In many cases, intoxicated motorists go undetected until they have already caused significant harm, posing a substantial challenge to law enforcement agencies striving to prevent these incidents before they occur. This underscores a major limitation in current road safety infrastructure: the inability to proactively identify or intercept impaired drivers in real time.

In Sri Lanka, this issue is particularly severe. Police records from January to June 2023 reveal a total of 930 fatal accidents, resulting in 976 deaths and an average of five fatalities each day [2]. Despite the presence of conventional deterrents such as police checkpoints, fines, and public awareness campaigns, the rate of accidents and associated deaths remains alarmingly high.

The persistent occurrence of these tragedies suggests that current strategies are inadequate, as they focus primarily on punitive measures after violations occur, rather than preventing risky behavior beforehand. A key deficiency in existing systems is the absence of real-time, in-vehicle monitoring solutions that can assess and react to the driver’s condition before the vehicle is in motion. While a range of road safety technologies have been introduced globally, including speed enforcement

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cameras, breathalyzers, and roadside sobriety checkpoints, these methods are either external to the vehicle or heavily reliant on time-bound, location-specific operations. Furthermore, most of these systems are designed to operate reactively, activating only after a violation or accident has occurred rather than offering continuous, proactive monitoring of the driver's physiological and behavioral state. As a result, intoxicated drivers can frequently evade detection, contributing to avoidable fatalities on the road [3]. This highlights a significant research gap: the lack of an integrated, automated system capable of real-time detection and intervention within the vehicle itself.

To address this challenge, this study proposes a novel drunk driver detection and reporting system powered by Internet of Things (IoT) technologies. The proposed system integrates multiple sensor modalities, including biometric sensors (e.g., heart rate monitors), alcohol gas detectors, voice recognition modules, and facial expression analysis tools, to evaluate the driver's level of alertness and sobriety. If the system determines that the driver is intoxicated, it can autonomously disable the ignition system or send a real-time alert including GPS coordinates and driver status to relevant law enforcement authorities via a custom-developed mobile application. This app enables immediate intervention by police officers, ensuring timely responses that can prevent potential accidents before they occur. Unlike traditional methods, this approach shifts the paradigm from reactive enforcement to proactive prevention through automation, data fusion, and real-time decision-making. By addressing critical shortcomings in existing detection mechanisms, the proposed solution represents a significant advancement in road safety technologies, particularly for countries like Sri Lanka where alcohol-related traffic incidents remain a leading cause of mortality. Through the integration of intelligent sensing, real-time analytics, and law enforcement connectivity, this research offers a robust and scalable model for reducing impaired driving incidents and enhancing public safety on a national scale.

## LITERATURE REVIEW

Identifying intoxicated drivers through facial characteristics and image analysis has emerged as a significant focus in road safety research. In their study, Kumar et al. [4] employed a transfer learning strategy to enhance the precision of detecting drunk drivers from facial images. They utilized several pre-trained deep learning models, training them on a publicly available dataset containing faces of both sober and intoxicated individuals. The models were fine-tuned for optimal performance and assessed using metrics such as accuracy and precision. Among the various models evaluated, ResNet101 and DenseNet201 delivered the most promising results, exhibiting great potential for distinguishing between sober and intoxicated drivers. This method underscores the efficiency of transfer learning in accelerating the creation of dependable image-based detection systems by leveraging pre-existing trained networks and modifying them for this application.

The identification of intoxicated drivers through facial characteristics has garnered interest in recent years, particularly with the advancement of deep learning technologies. In research conducted by Chang et al. [5], a two-phase deep neural network system was created to identify signs of alcohol impairment using images of the driver's face. The initial phase utilized a VGG model to estimate the driver's age, while the subsequent phase employed a Dense Net model to assess whether the individual was drunk or sober. Their system achieved an accuracy rate of 89.62% in testing with image datasets.

A recent research effort by Suryawanshi [6] presented a system for alerting alcohol-impaired drivers, aimed at improving road safety through sensor-based monitoring. This system integrates alcohol sensors with vehicle control functions to determine whether a driver is intoxicated. If the system detects alcohol levels exceeding a specific threshold, it activates an alert and takes actions such as disabling the vehicle's ignition. It illustrates how embedded systems and real-time monitoring can be utilized to recognize impaired drivers and initiate suitable safety measures. Sandeep et al. [7] introduced an innovative model aimed at detecting and preventing drunk driving using IoT technology. This system is designed to monitor the driver's blood alcohol concentration using onboard sensors and manage vehicle operation based on the findings. It combines alcohol detection with vehicle access control, ensuring that the engine is automatically disabled if alcohol levels exceed a specified threshold. Additionally, the system features communication capabilities to notify appropriate authorities or contacts in the case of a safety violation. Recognizing patterns in driver behavior has become increasingly essential for promoting road safety and reducing the likelihood of accidents. Shahverdy et al. [8] introduced a technique that employs one-dimensional convolutional neural networks (1D-CNNs) to effectively assess and categorize different types of driver behavior. The model analyzes time-series data gathered from sensors to identify patterns that indicate risky or distracted driving. By harnessing the capabilities of deep learning, the system achieves a high level of classification accuracy while ensuring computational efficiency. Dairi, Harrou, and Sun [9] presented a sophisticated driver monitoring system that integrates sensor data with manifold learning techniques to recognize unusual behaviors linked to alcohol impairment. Their method utilizes a range of physiological and vehicle signals to identify anomalies in driving patterns, leveraging unsupervised learning algorithms for immediate analysis.

## SUMMARY OF THE LITERATURE REVIEW

Table 1: Summary of the Literature Review

| Author(s) | Key Technologies Used | | | | |
|---|---|---|---|---|---|
| | *Facial Recognition* | *Alcohol Gas Sensors* | *Heart Rate Monitoring* | *Voice Recognition* | *Mobile App* |
| Kumar et al. [4] | ✓ | - | - | - | - |
| Chang et al. [5] | ✓ | - | - | - | - |
| Suryawanshi [6] | - | ✓ | - | - | - |
| Sandeep et al. [7] | - | ✓ | - | - | - |
| Dairi et al. [9] | - | ✓ | ✓ | - | - |
| Proposed System | ✓ | ✓ | ✓ | ✓ | ✓ |

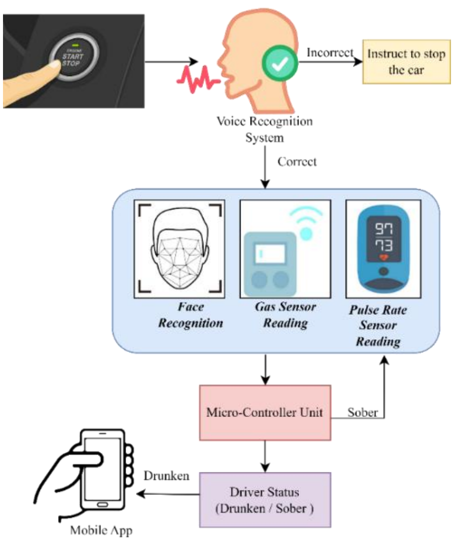


Figure 1: Architecture of the proposed system

Table 1. outlines a comparative summary of key technologies used in intoxication detection systems. Unlike previous approaches, the proposed system integrates all five technologies facial intoxication detection, alcohol gas sensing, heart rate monitoring, voice recognition, and mobile app integration within a single unified framework. This multi-modal approach enhances accuracy, real-time responsiveness, and reliability, making it a novel and comprehensive solution for driver monitoring.

## METHODOLOGY

The proposed system architecture for detecting and reporting drunk driving incidents in real time is depicted in Figure 1. This architecture integrates sensor-based monitoring, intelligent data processing, and instant communication with authorities to offer a proactive solution for road safety. The system is embedded within the vehicle and is triggered the moment the driver attempts to start the engine. At this initial point, a voice recognition interface is activated, prompting the driver to speak a predefined phrase. This serves both as a biometric verification step and as a cue to initiate background monitoring procedures.

The system then engages a suite of sensors that operate continuously to monitor the driver's physiological and behavioral parameters. Three primary sensors are involved: a facial intoxication detection module, a gas (alcohol) sensor, and a pulse rate sensor. The facial intoxication detection component, based on deep learning algorithms, evaluates facial cues to detect signs of drowsiness or unusual expressions commonly associated with intoxication. In parallel, the gas sensor captures the driver's breath sample and analyzes it for alcohol content, flagging any readings that exceed the defined safety threshold. Meanwhile, the pulse sensor monitors the driver’s heart rate for abnormal fluctuations that could further indicate impairment.

The data collected from all sensors is transmitted to a central microcontroller embedded in the system. This microcontroller serves as the main processing unit and uses a decision-making algorithm to evaluate the driver's state. The algorithm analyzes the combined data in real time and determines whether the driver is fit to operate the vehicle. If the driver is found to be impaired, the system takes immediate action. It prevents the vehicle from starting, by issuing an audio command instructing the driver to stop the vehicle.

Once intoxication is confirmed, the system transmits the incident data, including driver status and sensor readings, via the MQTT (Message Queuing Telemetry Transport) protocol to a cloud-based web platform. This platform facilitates seamless, real-time communication with relevant authorities. A synchronized mobile application receives the transmitted data and displays the driver's GPS location, status, and a timestamped record of the event. These details assist law enforcement officers in taking swift and appropriate action.

**A. Voice-based driver verification system**

The initial phase of the proposed system features a voice-based driver verification module that evaluates the driver's alertness prior to allowing the vehicle to start. This process commences when the driver turns on the vehicle. At this moment, the system plays three pre-recorded verbal inquiries through a speaker. These audio questions are created using TTSMaker (Text-to-Speech Maker) and are stored on the Raspberry Pi. A built-in microphone in the system captures the driver's replies in real time.

The replies are then processed with the Vosk offline speech recognition engine (vosk-model-en-us-0.22), which translates the spoken answers into text without needing internet access. The generated text is compared with a set of predetermined correct responses kept in the program. To successfully complete the verification stage, the driver must correctly answer all three questions within a 10 second timeframe. If the driver fails, the system instructs them to retake the test until they provide successful responses.

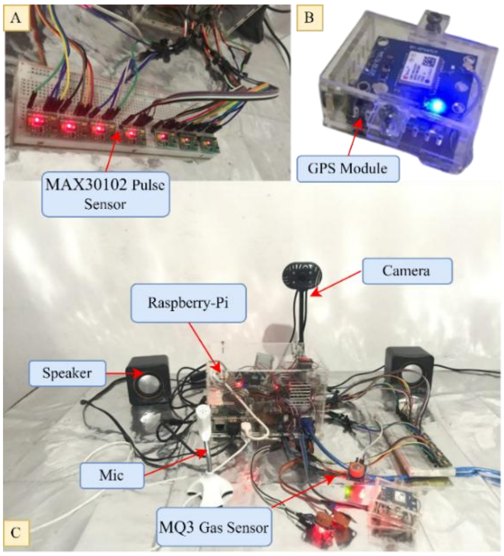


Figure 2: (A) Pulse sensors, (B) GPS module, (C) Sensor unit

This module serves as an initial cognitive filter, verifying that the driver is mentally alert and responsive prior to operating the vehicle. Only after successful verification does the system engage the subsequent detection components, which include pulse monitoring, alcohol vapor detection, and facial expression evaluation. This phase of voice recognition adds a non-contact and user-friendly safety layer, significantly enhancing the overall system's reliability and efficiency.

**B. Sensor Calibration and System Integration**

The secondary stage of the system is centered on gathering biometric and environmental information through meticulously tuned sensors (Figure 2). This encompasses the MAX30102 pulse sensors and MQ3 gas sensors, both essential in identifying physiological and chemical signs of alcohol impairment. Seven MAX30102 pulse sensors are incorporated into the steering wheel and the area around the push-start button, enabling continuous and non-invasive monitoring of the driver's heart rate. These sensors relay data to the Raspberry Pi using the I2C protocol, ensuring prompt data transmission with minimal lag. The obtained pulse data is evaluated utilizing threshold-based logic to ascertain if the driver's heart rate remains within a safe and anticipated range. Irregular readings such as elevated or inconsistent pulse rates factor into calculating the driver's overall intoxication risk score.

Simultaneously, three MQ3 gas sensors are strategically situated close to the steering column, dashboard, and air vents to assess the air quality inside the cabin for traces of alcohol vapors. These analog sensors are linked to the ESP32 microcontroller, which conducts initial processing of the sensor data. Given that the Raspberry Pi lacks analog input pins, the ESP32 interprets the analog voltage outputs from the MQ3 sensors and sends the digital results to the Raspberry Pi using UART communication.

Extensive calibration tests were performed with actual liquor samples featuring different alcohol-by-volume (ABV) percentages. For instance, a sample with 40% ABV resulted in sensor reading ranging from 3000 to 4000 ADC units, while a sample with 8.8% ABV produced notably lower values, between 1000 and 1500. Based on these experiments, a cutoff value of 3000 was established to effectively differentiate between minimal and substantial alcohol presence, thereby reducing false positives caused by environmental influences.

Together, the calibrated pulse and gas sensors offer two vital layers of intoxication detection. The data acquired from both sources holds a weight of 30% each in the conclusive intoxication assessment. These sensors, combined with the Raspberry Pi and ESP32, create a coordinated sensing framework that supplies real-time physiological and environmental information to the decision-making algorithm.

### C. Sensor Fusion Algorithm

A crucial innovation in the proposed system lies in its intelligent data fusion methodology, which integrates inputs from multiple sensing modalities to produce a final intoxication decision. Each sensor facial intoxication detection, voice response accuracy, pulse rate stability, and gas concentration provides a normalized score representing the likelihood of intoxication. These scores are processed through a weighted decision fusion algorithm implemented within the Raspberry Pi controller. The system assigns predefined weights of 0.3 each to the pulse and gas sensors, 0.25 to facial intoxication detection, and 0.15 to voice verification, based on their respective reliability during testing. The fusion function computes a composite intoxication index (I) using the below equation;

$$I = 0.3 \times P + 0.3 \times G + 0.25 \times F + 0.15 \times V$$

where P, G, F, and V represent the normalized outputs of pulse, gas, facial, and voice modules respectively. If the computed index exceeds a predefined threshold (0.5), the system classifies the driver as impaired. This multi-sensor fusion strategy enhances robustness against false positives from individual sensor noise and ensures that decisions reflect a holistic assessment of the driver's physiological and behavioral state. By combining heterogeneous data streams in real time, the proposed approach significantly improves detection accuracy and system reliability, marking it as a key novelty of this research.

### D. Deep Learning Models for Facial Intoxication Detection

A key component of the proposed system is the integration of deep learning models for facial intoxication detection. This module was designed to identify visual indicators of alcohol influence, such as drooping eyelids, relaxed facial muscles, and subtle micro-expressions, which can be detected through real-time webcam feeds. To achieve this, a computer vision pipeline was developed that analyzes the driver's face using advanced CNN architecture.

Three CNN-based models were considered during the development phase: a custom lightweight CNN built specifically for real-time inference, EfficientNet B5 for its advanced feature extraction capabilities, and a modified U-Net architecture adapted for classification purposes. A labeled dataset consisting of facial images categorized into "drunk" and "not drunk" classes was prepared. These images were preprocessed through resizing to a standard 224×224 resolution and normalized to facilitate efficient training.

Model development was conducted using Google Colab, taking advantage of GPU acceleration. The custom CNN was trained from scratch, while EfficientNet B5 employed transfer learning using pre-trained weights. The U-Net model, typically used for segmentation tasks, was modified by integrating global average pooling and dense classification layers to suit the intoxication detection objective.

Once trained, the selected CNN model was deployed via a Flask-based API, externally hosted to reduce the computational load on the Raspberry Pi. In real-time operation, the Raspberry Pi captures the driver's facial image and sends it to the predicted image endpoint of the API using HTTP POST. The API responds with a classification label and confidence score, which are then incorporated into the overall decision-making algorithm used to evaluate the driver's condition.

### E. Real Time Monitoring Through Mobile Application

To connect in-vehicle intoxication detection with field enforcement, a specialized mobile application was created as shown in Figure 3. to facilitate real-time oversight and action by law enforcement agencies. This app acts as the final user interface within the system's framework, receiving alerts about intoxication, showing driver information, and supporting location tracking. Developed with the Flutter framework, the mobile application delivers a cross-platform solution utilizing a single codebase, optimized for both Android devices and future deployment on iOS. Visual Studio Code served as the main development environment, while Android Studio provided a built-in emulator for testing UI and backend integration. The mobile application is linked to Firebase Firestore NoSQL cloud database that stores streams live data from Raspberry.

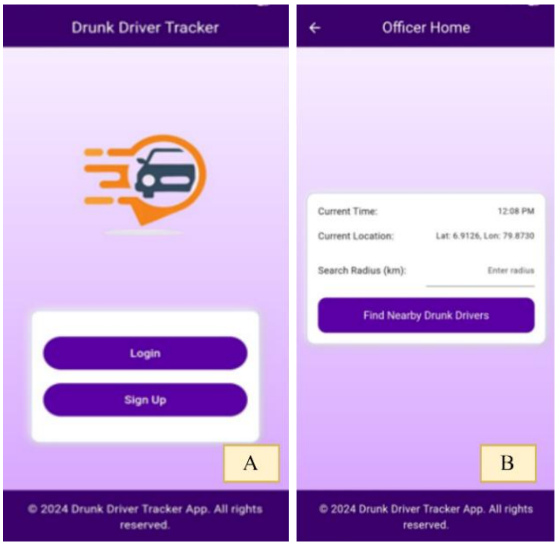


Figure 3: (A) Login page, (B) Select area

Pi, including the driver's sobriety status, GPS location, timestamps, and records of violations. When the system identifies an intoxicated driver, a cloud function within the Firebase database triggers a notification to all registered law enforcement officers through the app. This application incorporates a secure login and registration process, requiring officers to authenticate via encrypted credentials stored in the Firestore's "Officers" collection.

After logging in, the app presents the current time alongside the officer's location. Officers can then choose their monitoring area, and the app automatically filters incidents occurring within that geographical range using distance-based queries. Detected drivers are displayed in a user-friendly, tabulated format featuring essential information such as intoxication level, location, and detection time. Moreover, the app offers access to a driver history section, which shows prior violations, dates, and total counts. The location tracking module integrates with Google Maps API, enabling officers to observe the driver's real-time position and navigate directly to the incident site. This capability is vital for ensuring that authorities can act quickly and effectively.

To streamline the development process, several supporting tools were utilized. Firebase Authentication managed user access control: the Firestore database permitted real-time data synchronization; and the Google Maps SDK was employed for mapping functionalities. During development, debugging and testing were performed using emulated Android environments, ensuring dependable performance across various screen dimensions and network conditions.

This mobile application finalizes the system by linking cloud intelligence with on-the-ground enforcement, equipping authorities with a robust tool to monitor, trace, and immediately respond to drunk driving incidents efficiently and effectively.

## RESULTS AND DISCUSSION

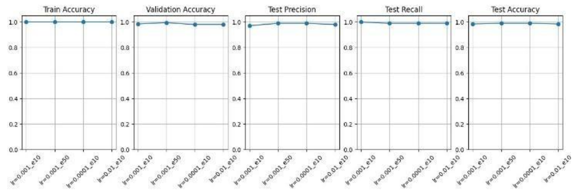


Figure 4: Performance of Custom CNN Model

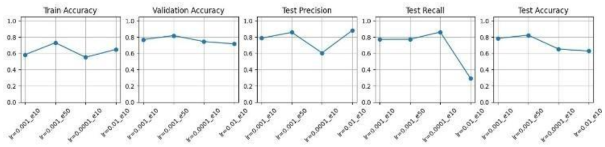


Figure 5: Performance of EfficientNet B5 Model

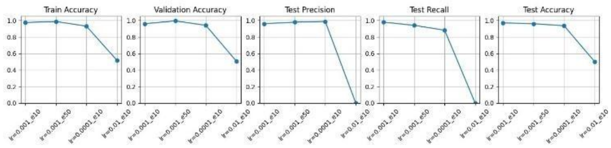


Figure 6: Performance of U-Net Model

Table 2: Performance comparison of deep learning models for facial intoxication detection

| Model | Train Accuracy | Val Accuracy | Test Precision | Test Recall | Test Accuracy |
|---|---|---|---|---|---|
| Custom CNN | 1.0000 | 0.9951 | 0.9902 | 0.9902 | 0.9902 |
| EfficientNet B5 | 0.7312 | 0.8195 | 0.8587 | 0.7745 | 0.8244 |
| U-Net | 0.9878 | 0.9951 | 0.9796 | 0.9412 | 0.9610 |

The performance of the Custom CNN model for facial intoxication detection is illustrated in Figure 4. The model achieved a consistent 100 % training accuracy across all tested learning rates and epochs, confirming its strong learning capability. The best results were observed at a learning rate of 0.001 with 50 epochs, where the model reached a validation accuracy of 99.51 %, test accuracy of 99.02 %, and both precision and recall values of 99.02 %. These results highlight the model's robustness and ability to generalize well to unseen data. The consistently high precision and recall indicate effective classification performance with minimal false positives or false negatives, which is essential for safety-critical applications like drunk driving detection. Additionally, the lightweight architecture of the Custom CNN supports fast inference, making it ideal for real-time embedded deployment in vehicles.

EfficientNet B5 demonstrated relatively lower performance across all experimental setups compared to other models in the study. The model achieved its highest test accuracy of 82.44 % when trained with a learning rate of 0.001 over 50 epochs. While EfficientNet B5 was able to attain a notably high precision of 88.24 % using a learning rate of 0.01, this configuration resulted in a sharp decline in recall to 29.41 %, indicating a significant lack of sensitivity in identifying positive cases (Figure 5). This trade-off between precision and recall suggests that the model became overly conservative in its predictions under these training conditions, leading to a high rate of false negatives despite maintaining good specificity for the cases it did classify as positive.

The U-Net architecture demonstrated in Figure 6. shows exceptional performance under optimal training conditions, achieving outstanding results with a learning rate of 0.001 over 50 epochs. Under these conditions, the model attained a validation accuracy of 99.51 % and maintained high precision with a test precision of 97.96 %, indicating robust generalization capabilities and reliable positive case identification. However, the model exhibited significant sensitivity to learning rate selection, as evidenced by its poor performance when trained with a higher learning rate of 0.01. This suboptimal configuration led to training instability and convergence issues, resulting in a dramatic deterioration across all evaluation metrics, with the test accuracy plummeting to just 50.24 %. This stark contrast in performance highlights the critical importance of proper hyperparameter tuning for U-Net architectures, where excessive learning rates can prevent the model from effectively learning the underlying data patterns and lead to essentially random prediction performance.

Table 2 summarizes the evaluation of three deep learning models for facial intoxication detection. Custom CNN outperformed the others, achieving perfect training accuracy and over 99 % validation and test accuracies,with high precision and recall. Its lightweight design and low latency made it ideal for real-time deployment on embedded systems like Raspberry Pi. U-Net also showed strong performance, with high accuracy and precision, but exhibited sensitivity to hyperparameter tuning particularly the learning rate which affected its stability under certain conditions. EfficientNet B5 yielded the weakest results, with lower training and test accuracies and an imbalanced precision-recall profile, making it less effective for consistent intoxication detection. Due to its superior accuracy, generalization, and computational efficiency, Custom CNN was chosen for system integration. These findings emphasize the importance of architecture selection in developing reliable, fast, and accurate real-time detection systems for safety-critical applications like preventing drunk driving.

To contextualize the proposed system's performance, we compare it with recent works. Dairi et al. (2022) used manifold learning with Isolation Forest for anomaly detection, achieving approximately 80 % classification accuracy in specific configurations. Suryawanshi et al. (2023) developed an embedded alcohol-impaired driver alert system but did not report facial-model accuracies exceeding our results. In contrast, our integrated multimodal system achieves 93.5 % overall detection accuracy (face module: 99.0 %) with low inference latency of 300-450 ms, suitable for real-time in-vehicle deployment. These results demonstrate that the proposed multimodal fusion approach improves detection reliability and reduces false alarms compared to single-modality or unsupervised sensor-only methods.

The MQ-3 gas sensor was integrated into the system to capture driver breath samples and analyze alcohol content, automatically flagging readings that exceed predefined safety thresholds. A practical calibration process was conducted using liquor samples with varying Alcohol by Volume (ABV) percentages to establish reliable detection parameters.The calibration results demonstrated in Table 3 show a clear correlation between alcohol concentration and sensor readings. Higher alcohol content samples (40 % ABV) generated readings ranging from 3000 to 4000 ADC values, while 38 % ABV samples produced values between 2800 and 3500. Lower concentration samples (12 % and 8.8 % ABV) yielded significantly reduced readings, typically ranging from 1000 to 2000 ADC values (Figure 7).

Table 3: MQ-3 Sensor Calibration Results

| Bottle (ABV %) | Sensor Reading (ADC value) |
|---|---|
| 40% | 3000 – 4000 |
| 38% | 2800 – 3500 |
| 33.5% | 2500 – 3200 |
| 12% | 1500 – 2000 |
| 8.8% | 1000 – 1500 |

Table 4: Pulse Rate Sensor Module Performance Comparison

| Sensor Module | Average reading(bpm) | Stability score (/100) |
|---|---|---|
| MAX30100 | 95 | 60 |
| MAX30102 | 78 | 90 |
| MAX30105 | 102 | 55 |
| GY-MAX30102 | 85 | 70 |

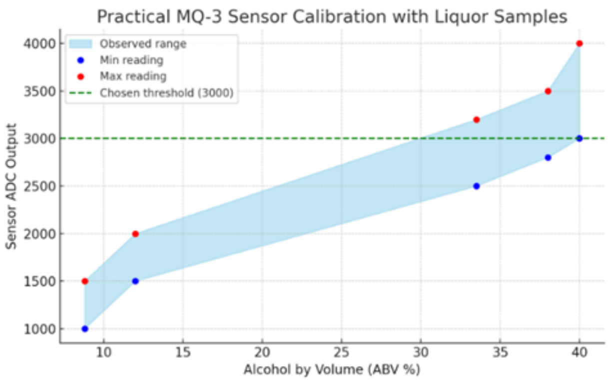

Figure 7: Practical calibration of MQ-3 sensor using liquor samples with different ABV values

During field testing with 50 participants, the system successfully detected alcohol consumption in drivers who had consumed alcoholic beverages within the previous 2 hours, with sensor readings consistently exceeding the established MQ-3 Sensor Calibration Results threshold of 3000 ADC units. Control group participants (34 sober drivers) produced readings below 1500 ADC units, validating the threshold selection. Based on these results, 3000 ADC units were established

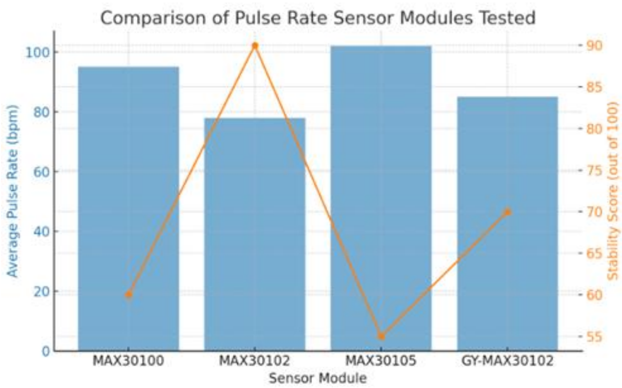

Figure 8: Comparison of pulse rate sensor modules

as the optimal cutoff point, providing balanced detection capability while minimizing false positives from environmental alcohol exposure or residual mouth alcohol.

The pulse rate monitoring component utilized heart rate sensors to detect abnormal cardiovascular fluctuations that may indicate driver impairment as in Table 4. A comparative evaluation of four different pulse rate sensor modules was conducted to identify the most suitable hardware for reliable heart rate detection in automotive environments. The evaluation results demonstrated significant performance variations across sensor modules.

The MAX30102 consistently delivered readings within the normal resting heart rate range (60-100 bpm) with an average of 78 bpm and achieved the highest stability score of 90/100, indicating superior resistance to signal interference and measurement fluctuations (Figure 8).

During field testing with 50 participants, the selected MAX30102 sensor successfully monitored heart rate patterns across different impairment states. Sober participants (n=34) exhibited stable heart rate readings averaging 72±8 bpm, while participants who had consumed alcohol (n=16) showed elevated and more variable heart rates averaging 89±15 bpm.

The sensor maintained consistent performance across the demographic composition of our sample [specify e.g. "predominantly male participants aged 22-35 years"] and various environmental conditions encountered during vehicle operation. While these initial findings demonstrate the technical feasibility of the MAX30102 sensor for real-time physiological monitoring, future studies with larger, more diverse samples stratified by age, gender, and baseline physiological characteristics (e.g. resting heart rate variability, cardiovascular health status) are needed to establish the system's generalizability across broader populations and validate detection thresholds for different demographic groups.

The results clearly demonstrate that the proposed drunk driver detection and reporting system is both effective and reliable in identifying impaired drivers in real time. By integrating voice-based verification, biometric sensors, gas detection, and advanced facial intoxication detection within a unified IoT framework, the system ensures comprehensive monitoring of the driver's physical and cognitive state. This multi-layered approach significantly enhances the ability to prevent drunk driving incidents before they occur and streamlines the process of alerting authorities for swift intervention.

The practical performance and responsiveness observed during implementation suggest that this solution holds strong potential for reducing road accidents and advancing public safety particularly in regions where alcohol-impaired driving remains a critical issue.

## CONCLUSION

This research introduces a comprehensive IoT-based system for real-time drunk driver detection and reporting, integrating voice recognition, biometric sensors, gas detection, and facial intoxication analysis. The system achieved 93.5 % overall detection accuracy, with the automated mobile application enabling swift law enforcement intervention. However, limitations exist. Environmental factors such as temperature and humidity could affect sensor performance, requiring validation under diverse conditions. Cloud dependency introduces concerns regarding network latency, rural coverage gaps, and cybersecurity vulnerabilities. Privacy considerations for continuous biometric monitoring necessitate robust data protection protocols. Future enhancements include incorporating motion sensors for erratic driving detection, advanced machine learning for pattern recognition, direct ignition control, and expanded mobile app features for incident reporting and trend analysis. Despite current limitations, this multimodal system demonstrates substantial promise as a scalable, proactive solution to reduce alcohol-related accidents and enhance road safety.

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