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Advanced Smart Helmet

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Abstract: Owing to the lack of real-time monitoring and the resultant delay in detection, crutial industrial and road accidents cause major and serious injuries. To improve the safety of bike riders, and industrial workers this paper gives best solution that combines IoT, embedded machine learning and multimodal sensing. This system usesgas sensors for detection, heart rate and SpO_2 sensors for real health monitoring, IMU sensor for fall detection and GPS for real time location. Compared to cloud-based solutions , the proposed helmet anomaly detection capability on the hardware itself improves the reliability of the system and helps to reduce latency by utilizing TinyML-based edge intelligence. In an IoT –enabled environment this system increase accuracy, reaction time and safety of bike riders and industrial workers. With some technological developments, this paper proposes an AI-Supported Edge-Intelligent Smart Helmet that combines multimodal sensing, secure communication channels, TinyML edge intelligence and scalable IIoT infrastructure. The proposed system combines the functionalities of fall detection, physiological sensing, environmental harmful sensing and grolocation tracking into a single platform. The proposed system capitalizes on the advantages of running lightweight machine learning models on the devide to overcome communication latency, bandwidth and functionality even in conditions of poor network connectivity. Secure IoT communication channels facilitate efficient emergency notification systems, while cloud connectivity facilitates historical data analysis and system-wide optimization.

Keywords: Smart Helmet; IoT; Edge Computing; TinyML; Accident Detection; Health Monitoring; GPS Tracking; IIoT; Wearable Sensors.

I. INTRODUCTION

In day -to-day life industrial workplace accidents of workers, road traffic accidents are still serious international safety issues, resulting in high number of fatalities and injuries as well as economic costs. A vast number of victims have been reported to suffer from late emergency responses during accidents, the absence of real-time physiological monitoring, and the lack of intelligent warning systems. Traditional helmets are manufactured for passive head protection. This helmets lack active accident detection, health monitoring, automated emergency notification systems and environment awareness. The Internet of Things (IoT) technology has revolutionized the design of traditional safety devices and transformed them into smart IoT devices. Initial designs of smart helmets with the help of IoT technology were limited to accident detection and SMS notification services through internal sensors and GPS modules[1]-[3]. These designs proved the concept of combining microcontrollers and wireless communication for emergency notifications. Later designs included alcohol detection systems to prevent drunk driving and ensure rider compliance [6], [8], [12]. Other designs were centered on IoT-based rider safety systems that integrated crash detection with real-time location tracking[7], [10], [11].

With the advent of wearable sensing technology, there has been a focus on multimodal safety monitoring in recent studies. Analysed results shows that the combination of physiological, environmental, and motion sensors has successfully improved safty and health awareness[4].Industrial – oriented solutions such as smart helmet 5.0 have shown the combination of wearable sensors with edge analytics for Industrial Internet of Things(IIoT) applications[5].Impact and trauma detection through vibration and piezoelectric sensing techniques have also been investigated[9], leading to more accurate accident detection systems. Moreover, many of the existing smart helmet systems have been cloud-centric, leading to increased latency and network dependency problems during accident emergencies.Recent technological breakthroughs in edge computing and embedded artificial intelligence have made local data processing and intelligent decision-making possible. TinyML enables machine learning inference on low-power embedded systems[13], while secure edge analytics platforms improve wearable health monitoring systems[14].

Detailed learning approaches for sensor-based human activity recognition have shown higher accuracy in fall detection and anomaly recognition tasks [15]. Communication infrastructure is also a critical aspect of vast-scale implementation. Comparative study analysis of LPWAN technologies have shown the effectiveness of LoRa, NB-IoT, and other similar technologies for IoT-based safty systems[16]. The integration of 5G networks further enables ultra-reliable, low-latency communication for safety-critical applications [17].

The underlying architectures and technologies of IoT that enable scalable and interoperable deployments are comprehensively studied in [18], where the discussion on layered IoT architectures, communication protocols, middleware, and security solutions is explored in detail. These architectural solutions are based on device-layer sensing, network-layer connectivity and application-layer intelligence which form the backbone infrastructure of massive smart safety systems. In the context of safety-critical applications such as efficient data transfer mechanisms(MQTT/CoAP), communication protocols,smart helmets, and secure authentication mechanisms play a crucial role in ensuring seamless data transfer and system integrity.

In addition to architectural scalability security and data privacy plays a very important role in wearable safety systems. Privacy-preserving distributed learning methods such as federated learning make it easier to train models on edge devices in a decentralized manner without the necessity for edge devices to send raw sensitive physiologicsl or behavioural data to remote cloud servers[19]. This method enhances user data privacy while still enabling collaborative model development among multiple deployed devices. These methods are especially important when monitoring personal health parameters wuch as activity levels, oxygen saturation (SpO_2), heart rate which requires absolute privacy

In addition, the wereable ecosystems that integrate cloud connectivity, edge analytics, and big data processing platforms demonstrate the scalability of intelligent protective clothing in the connected world[20]. The wearable ecosystems enable real-time health analysis, predictive risk analysis, and large-scale safety monitoring in industrial and smart city settings. The systems balance low-latency response and large-scale data insights by using cloud-assisted storage for historical analysis and edge computing for real-time analysis.

II. LITERATURE SURVEY

Rahman et al. [1] proposed an IoT-based smart helmet and accident identification system that consisted of accelerometers, GPS, and GSM modules. It continuously monitors the tilt and vibration of the helmet to detect any collision. Once it detects an accident, it automatically sends the GPS location to the emergency contact through GSM. The experimental results showed a significant reduction in emergency response time and proved that IoT-based solutions are reliable for real-time accident reporting.

Alim et al. [2] designed an IoT-based smart helmet integrated with cloud-based monitoring. The system consisted of multiple sensors that were used to detect rider motion and accident conditions, and all the data was transmitted to the remote server via an internet connection. This work demonstrated the role of cloud computing in large-scale monitoring of rider safety and post-accident analysis.

The well-known "Konnect" smart helmet system developed by Chandran et al. [3] is considered one of the pioneering works in smart helmet research. Their helmet integrated GPS, GSM, and IoT connectivity together for accident detection and notification to emergency responders. It also had a mechanism for helmet wear detection to ensure compliance. Most modern smart helmet architectures are rooted in this study.

These studies together establish the fact that integration of IoT significantly improves road safety systems by enabling automated accident detection, real-time location, and immediate emergency notification.Lee et al. [4] performed a comprehensive scoping review on smart helmets with multimodal sensing for safety and healthcare applications. As part of the study, they analyzed over 100 research articles related to wearable technologies in helmets. In such helmet mechanisms, accelerometers, gyroscopes, gas sensors, and physiological sensors were found to be in major usage by the research authors. The review has established that a multi-sensor approach improves reliability and reduces the possibility of false accident detection.

Campero-Jurado et al. [5] proposed the Smart Helmet 5.0 for industrial safety based on wearable sensors and analytics at the edge. The system provides real-time processing of the data locally before sending its results to a central server. This solution minimizes communication delay and power consumption. Even though the system is designed for industrial workers, the architecture and the techniques used for processing the data apply directly to road safety smart helmets.These review studies highlight the requirement of multimodal sensing and real-time processing to enhance the accuracy and efficiency of smart helmet systems. Tapadar and Ray [6] introduced a Bluetooth-integrated smart helmet with the functionality of detecting alcohol concentration using an MQ-3 sensor. The system did not allow the vehicle to be switched on when the percentage of alcohol in the rider's exhaled breath exceeded the threshold limit. Moreover, accident notifications were sent through Bluetooth and mobile applications. This research proved that sensor-enabled ignition interlock systems can be quite efficient in reducing drunk-driving behavior.

Vanaja [8] proposed a smart helmet based on drunk-and-drive detection and alerts for riders. A real-time alert mechanism is integrated with the alcohol sensor, showing high detection accuracy in the testing of the developed prototype. It was observed from the experiment that automatic alcohol detection could be of great potential in avoiding road accidents. Varshini et al. [12] integrated alcohol detection with accident reporting based on GPS using IoT technology.

Their system not only restricted vehicle ignition when intoxication was detected but also sent emergency notifications in the case of an accident. The alcohol sensing was reliable, and GSM-based communication was effectively implemented.These studies in summary show that alcohol detection using MQ-series gas sensors is a critical and effective feature of the modern smart helmet system.

Kumar [7] proposed an intelligent helmet system that used tilt, vibration and acceleration sensors to detect accident events. Once a serious impact was detected, alert messages containing the GPS location were sent via GSM to emergency contacts. The study showed that vibration-based detection is highly effective in identifying high-impact collisions. Different researchers [9], [10] used piezoelectric sensors and inertia-based motion sensors to detect impact force and jerk during the time of an accident. These systems depended on the pre-set threshold values for distinguishing between normal riding conditions and accidents. This study identified that accurate threshold calibration is crucial to avoid false triggers due to potholes, speed breakers, or rough roads.

In case of a crash, the helmet automatically sent accident information to emergency responders. Indeed, helmet compliance is the vital factor in reducing fatal head injuries. Several studies [10],[11] proposed

detection mechanisms for wearing helmets using pressure sensors and IR sensors, with switches embedded inside the helmet. These systems allow the vehicle to start only when the rider is wearing a helmet. This type of ignition interlock mechanism encourages strict adherence to helmet safety rules and reduces severe injury rates. The integration of helmet detection with alcohol sensing further strengthens safety enforcement and ensures that only sober and helmet-wearing riders can operate the vehicle [6],[12].

With the progress made in embedded artificial intelligence, the field of TinyML has gained popularity as a promising paradigm for the deployment of machine learning models on microcontrollers with limited resources. Lane et al. showed the feasibility of ultra-low-power machine learning inference on IoT edge devices, thereby reducing the dependency on the cloud and the latency involved [13]. This served as a foundation for real-time on-device anomaly detection in safety-critical systems. In the context of wearable health monitoring, Moosavi et al. [14] proposed the Secure and Efficient Edge Analytics (SEA) framework, which enables local analysis of physiological signals and ensures the secure transfer of data. The proposed framework aims to minimize bandwidth consumption and improve privacy, which are critical in wearable safety applications that monitor heart rate and oxygen saturation levels.

Wang et al. [15] offered a thorough survey on deep learning methods for human activity recognition using sensors. The authors' work demonstrated that convolutional and recurrent neural networks can greatly enhance fall detection and anomaly classification tasks over the traditional thresholding methods. Nevertheless, a number of these methods consume considerable computational power, making them unsuitable for direct implementation on embedded systems.

Communication infrastructure is another critical element of scalable IoT safety solutions. Mekki et al. [16] performed a comparative analysis of LPWAN solutions such as LoRa, NB-IoT, and Sigfox, based on their power consumption, latency, and range properties. The results of this study can be used as a guideline for choosing the appropriate communication solution for the large-scale implementation of smart helmet solutions. Li et al. [17] investigated the application of 5G in facilitating ultra-reliable low-latency communication for IoT. The significance of this study is that it explains how 5G can improve the response of safety-critical systems through the integration of edge computing with real-time data transfer.

From an architectural standpoint, Al-Fuqaha et al. [18] have given a thorough survey of the enabling technologies, protocols, and architectures for IoT. Their article describes the device layer, network layer, and application layer model, which constitutes the framework for a scalable smart safety system. Privacy protection for wearable technology has become a rising issue. McMahan et al. [19] proposed federated learning, a decentralized machine learning method that enables edge devices to jointly train models without exchanging raw data. This is especially useful for smart helmets that record sensitive physiological data. Smart wearable ecosystems that combine cloud computing, big data analysis, and IoT connectivity for sustainable health monitoring were discussed by Chen et al. [20]. The study demonstrated the advantages of edge computing and cloud analytics for balancing low latency and big data analysis.

III. DESIGN METHODOLOGY

The proposed smart helmet system is designed using a three-layer architecture consisting of the Sensing Layer, Edge Processing Layer, and Communication & Actuation Layer.

1) Sensing Layer: This layer includes the MQ-3 alcohol sensor, IR-based helmet detection sensor, and IR-based eye-blink sensor for drowsiness detection. These sensors continuously collect real-time physiological and behavioral data from the rider.
2) Edge Processing Layer: The Arduino Uno microcontroller performs local decision-making based on predefined safety thresholds. Sensor readings are processed in real time to classify the safety status as SAFE or UNSAFE.

3) Communication & Actuation Layer: The computed safety status is transmitted via a 433 MHz RF module to the bike unit. The receiver module controls the relay-based ignition system and activates alerts through an LCD display and buzzer.

A. Materials and Components

The components used in the project are as follows:

1) Arduino Uno: The system's primary controller is the Arduino Uno.One board is installed on the bike to regulate ignition based on the data it receives, while another is placed inside the helmet to gather and process sensor data. It controls wireless communication as well as all input/output functions.
2) Alcohol Sensor MQ-3: The MQ-3 sensor measures the amount of alcohol in the rider's breath. The system marks the situation as dangerous and stops the bike from starting if the alcohol content is higher than the specified limit.
3) Infrared Helmet Detection Sensor: The helmet's internal infrared proximity sensor determines whether it is worn correctly. To ensure rider safety, the ignition system is left off if the helmet is not detected
4) IR Sensor (Drowsiness Detection): To identify weariness or drowsiness, this sensor tracks the rider's eye-blinking pattern. A buzzer instantly notifies the rider if unusual blinking or prolonged eye closure is noticed.
5) RF Transmitter Module (433 MHz): The bike unit receives wireless safety status signals from the helmet that include alertness levels, alcohol detection, and helmet status.
6) RF Receiver Module (433 MHz): Based on safety circumstances, the bike's RF receiver receives transmitted data and determines whether to turn on or off the ignition.
7) I2C 16x2 LCD Display: The LCD shows system data in real time, including engine lock/unlock messages, alcohol detected alerts, and helmet wear status.
8) Module for Relays: The relay regulates the bike's ignition by acting as an electronic switch. Only when all safety requirements are met does it turn on; otherwise, it keeps the engine locked.
9) Battery / Power Supply: A rechargeable battery powers the helmet unit, while the bike side uses the vehicle’s internal power system to operate the control unit.

B. Algorithm

Step 1: Setting Up the System

Turn on the smart helmet system and set up the relay, buzzer, LCD display circuits, RF transmit/receive modules, IR helmet sensor, MQ-3 alcohol sensor, and eye-blink sensor.

Step 2: Acquisition of Sensor Data

Continue to gather real-time data from the helmet sensors to determine whether the helmet is worn correctly, measure the amount of alcohol in the rider's breath, and track the rider's level of alertness using eye-blink patterns.

Step 3: Assessment of Safety Conditions

Examine the sensor readings that were received and contrast them with safety thresholds that have been established. Check to see if each monitored condition—wearing a helmet, drinking alcohol, and being sleepy—satisfies the necessary safety requirements.Initialize components

Step 4: Decision on Safety Status

Create an overall safety status based on the evaluation:

- Label a situation as UNSAFE if it is unsafe (helmet not worn, excessive alcohol consumption, drowsiness detected, etc.).
- Classify the status as SAFE if every monitored parameter is normal.

Step 5: Data Transmission via Wireless

RF wireless communication is used to transmit the safety status from the Helmet Unit to the Bike Unit, guaranteeing safe and instantaneous data transfer between the two modules.

Step 6: Processing of Ignition Control

Obtain the safety status and choose ignition control at the Bike Unit:

A) Turn on the relay to turn on the car's ignition system and let the bike start if the status is SAFE.
B) Keep the relay deactivated if the status is UNSAFE to keep the engine locked and stop ignition.

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C. Communication Framework:
- The system uses a 433 MHz RF communication module for short-range data transmission between helmet and bike units. The transmitted data packet consists of a 1-byte safety status code (0 = UNSAFE, 1 = SAFE).
- The communication range was experimentally observed to be approximately 80–100 meters under open-field conditions. The average transmission delay was measured to be less than 100 ms, ensuring real-time response.

D. Flowchart

Fig. 1 illustrates the overall operational workflow of the proposed smart helmet system from sensor data acquisition to ignition control.

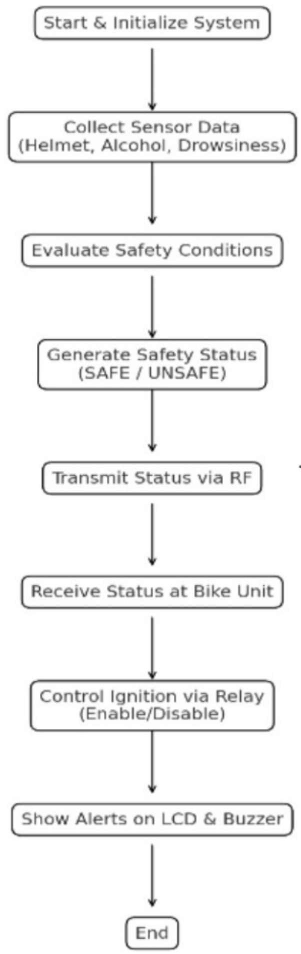


Fig. 1. Flowchart

E. Block Diagram

Fig. 2 presents the block diagram showing the interaction between sensing, processing, communication, and ignition control modules.

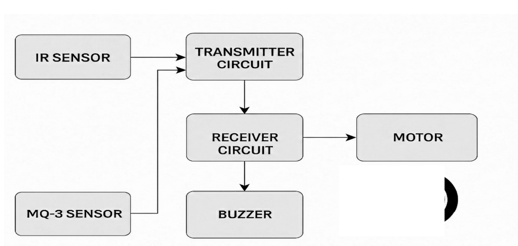


Fig. 2. Block Diagram

F. Circuit Diagram

Fig. 3 and 4 depicts the detailed circuit connections between the Arduino, sensors, RF modules, relay, buzzer, and display unit.

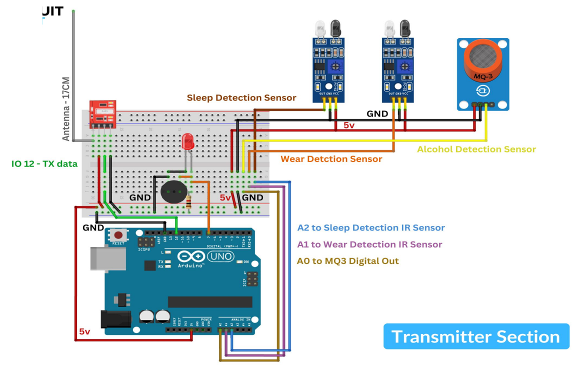


Fig. 3. Circuit Diagram
(Transmitter Section)

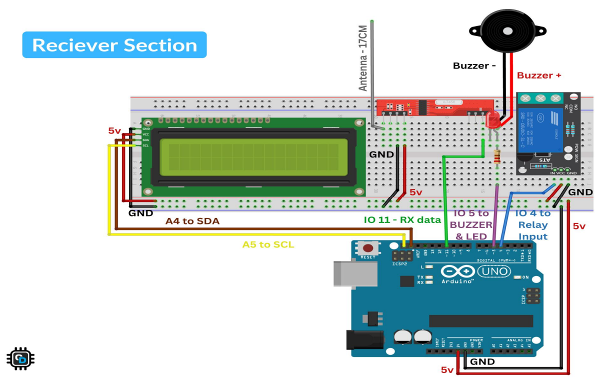


Fig. 4. Circuit Diagram
(Receiver Section)

G. Working Prototype

Fig. 4 shows the developed hardware prototype validating the practical implementation of the proposed system.

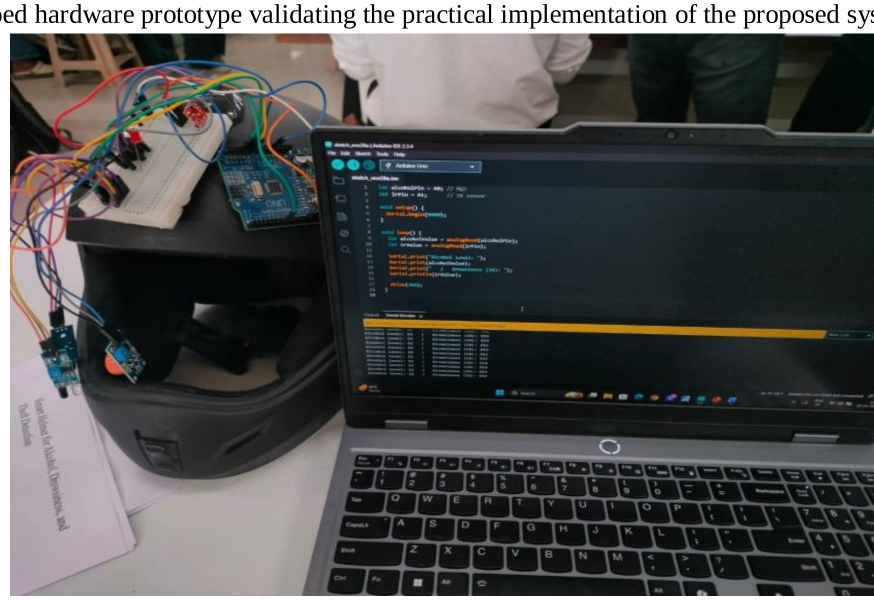


Fig. 5 Working Prototype

IV. RESULT AND DISCUSSION

A smart helmet prototype was designed to establish and test its functional reliability, operational stability and safety enforcement capability through controlled real time testing with a variety of practical scenarios such as helmet removal, simulated alcohol consumption and prolonged closed eyes to simulate drowsiness. The helmet detection system performed successfully in restricting the ability to start the ignition without the helmet being worn and allowed for the starting of the ignition only when the helmet was properly detected. The MQ-3 alcohol sensor had a consistent response when measuring alcohol levels above the calibrated limit and would stop the vehicle from starting if the alcohol level was above a safe threshold. Finally, the drowsiness detection unit generated alerts when the eye closure timing exceeded predefined limits.

The RF communications between the helmet unit and the bike unit were reliable in short-range distance throughout the trials conducted for this experiment. The ignition control system was also very responsive after receiving the safety status signal and was able to enforce the safety constraints in real-time. Some minor issues were observed with regards to the sensitivity calibration of the sensors and environmental noise, which may need to be optimized to allow for large-scale implementation. However, the prototype demonstrated stable operation during long-term testing and therefore proves the feasibility of the low-cost safety framework proposed.

Overall, the experimental evaluation validates that the proposed system effectively enforces predefined safety conditions prior to ignition and enhances rider safety through real-time monitoring and automated control mechanisms.

Table 1. Performance Evaluation of Individual Safety Modules

Module	Test Condition	Expected Output	Observed Output
Helmet Detection	Helmet Not Worn	Ignition OFF	Ignition OFF
Helmet Detection	Helmet Worn Properly	Ignition ON	Ignition ON
MQ3 Sensor	No Alchohol detected	Ignition ON	Ignition ON
MQ3 Sensor	Alchohol detected	Ignition OFF	Ignition OFF
Drowsiness Detection	Eyes Closed>3s	Buzzer Alert	Alert Activated
RF Communication	Safety Signal Transmission	Real Time Response	Stable Response

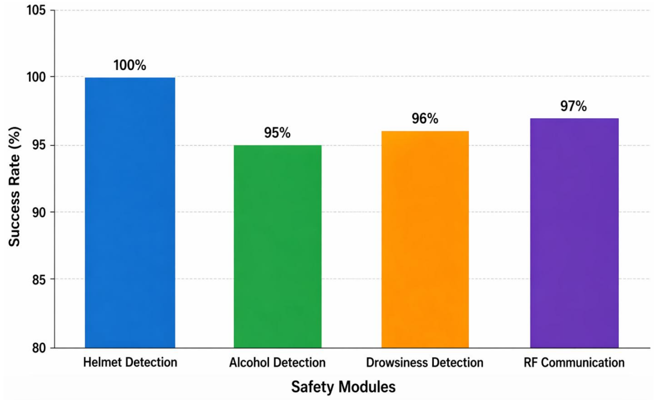
During testing, the ignition control accuracy from the helmets was determined to be ideal. The alchohol sensor was reliable; only significant variablility can be attributed to humidity and airflow (i.e., differences in environment). The drowsiness detection module was successful in detecting resets with very little latency from repeated blinking periods.

Table 2. Communication Performance Analysis

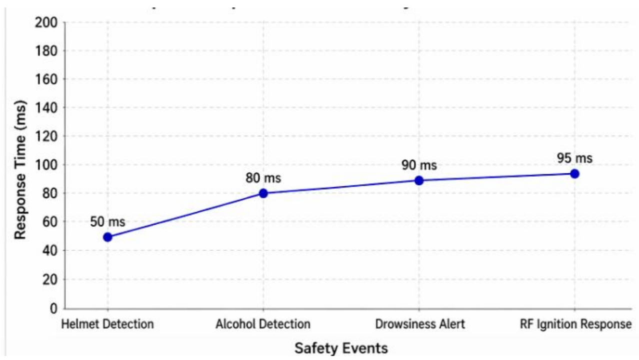
Parameter	Measured Value
Communication Frequency	433MHz
Effective Range	80 - 100 meters
Average Transmission Delay	< 100 ms
Packet Type	1-byte Safety Status
Communication Reliability	97%

The RF module's communications were stable over short distances in an open field during testing, yielding transmission delays of less than 100 msec (milliseconds); therefore it is suitable for safety systems requiring rapid ignition control.

Graph 1. Fall Detection Model Performance



Graph 2. Response Time of Safty Event Detection



V. CONCLUSIONS

This project proposes an Arduino-based smart helmet system that effectively addresses the needs of two-wheeler riders to increase their safety. The system integrates helmet wear detection, alcohol sensing, accident detection, and real-time emergency alert transmission in compact form, thereby facilitating accident avoidance and rapid response in the case of an emergency. The experimental results assure the system's efficiency in preventing vehicle ignition under unsafe conditions and sending an alert message with the exact location in the case of an accident.

This proposed design is affordable, simple to implement, and suitable for real-world applications. Such a smart helmet system, when packaged with further improvement features, such as integration with a mobile app, cloud connectivity, and better power management, can be highly effective for large-scale implementations and can contribute considerably to road safety.

REFERENCES

[1] A. Ahsan, S. M. Ahsanuzzaman, I. Rahman, M. A. Rahman T. Ahmed, “IoT Based Smart Helmet and Accident Identification System,” in 2020 IEEE Region 10 Symposium (TENSYMP), Dhaka, Bangladesh, Jun. 2020.

[2] M. N. Dorabati, I. Hassoun, S. Ahmad, and M. E. Alim, , “Design & Implementation of IoT Based Smart Helmet for Road Accident Detection,” in 2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Nov. 2020.

[3] S. Chandrasekar, N. E. Elizabeth and S. Chandran, "Konnect: An Internet of Things (IoT) based smart helmet for accident detection and notification," in 2016 IEEE Annual India Conference (INDICON), Bangalore, India, Dec. 2016.

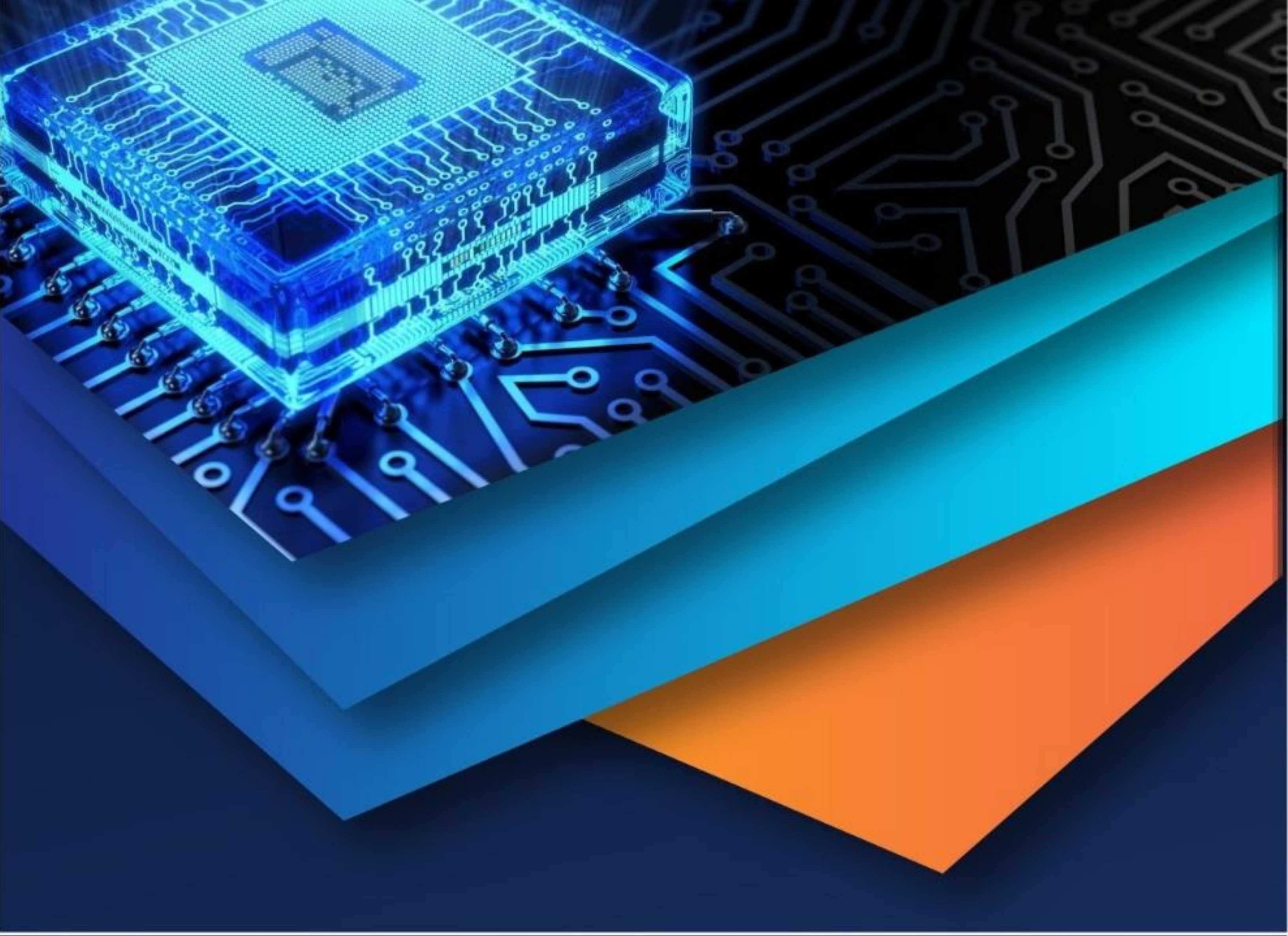
[4] A. A. Khan, T Chen, P. Lee, et al., “Trends in Smart Helmets With Multimodal Sensing for Health and Safety: Scoping Review,” JMIR mHealth and uHealth, vol. 10, no. 11, Nov. 2022.

[5] A. B. Cid, F. Sanchez, and F. Sánchez, “Smart Helmet 5.0 for Industrial Internet of Things Using Wearable Sensors and Edge Analytics,” Sensors (Basel), vol. 20, no. 21, 2020, Art. no. 6241, doi: 10.3390/s20216241.

[6] S. Tapadar and S. Ray, “Accident and alcohol detection in Bluetooth-enabled smart helmet,” International/technical article (designs combining MQ-3 alcohol sensor + crash detection and BLE).

[7] M. K. Kumar, “Smart Helmet based Accident Detection and Notification,” E3S Web of Conferences, 2023.

[8] T. Vanaja, "Smart Helmet for Drunk & Drive Detection and Alert System," in E3S Web of Conferences, 2023.
[9] “Smart Helmet Using Internet of Things” — conference/ project article (piezo/piezoelectric or vibration sensing for trauma detection; ResearchGate preprints and project PDFs).
[10] M. A. Impana et al., “IoT-enabled smart helmet solution for riders,” Conference paper, 2019.
[11] A. Dwivedi et al., “Smart Helmet Based on IOTs,” AIP Conference Proceedings / related compendium, 2022.
[12] Varshini P. A., “Smart Helmet for Accident Detection and Alert Using IoT, GPS, and Alcohol Sensing,” IJSRED/ Zenodo (open DOI), 2025, doi:10.5281/zenodo.16750580.
[13] E. Georgiev, P Warden, and N. D. Lane, “TinyML: Enabling Ultra-Low-Power Machine Learning in IoT Devices,” Computer, vol. 52, no. 5, pp. 30–38, May 2019.
[14] S. Virtanen, A. M. Rahmani, T. N. Gia, E. Nigussie, S. R. Moosavi, H. Tenhunen, and J. Isoaho, “SEA: A Secure and Efficient Edge Analytics Framework for WearableHealthMonitoring,”IEEEAccess,vol.7,pp.1909
[15] S. Hao, X Peng, J. Wang, Y. Chen, and L. Hu, “Deep Learning for Sensor-Based Activity Recognition: A Survey,” Pattern Recognition Letters, vol. 119, pp. 3–11, Mar. 2019.
[16] F. Chaxel, E. Bajic, K. Mekki and F. Meyer, “A Comparative Study of LPWAN Technologies for Large-Scale IoT Deployment,” ICT Express, vol. 5, no. 1, pp. 1–7, Mar. 2019.
[17] S. Li, L. D. Xu, and S. Zhao,“5G Internet of Things: A Survey,” Journal of Industrial Information Integration, vol. 10, pp. 1–9, Jun. 2018.
[18] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of Things: Survey on Enabling Technologies, Protocols, and Applications,” IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2347–2376, Fourthquarter 2015.
[19] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-Efficient Learning of Deep Networks from Decentralized Data,” in Proc. 20th Int. Conf. Artificial Intelligence and Statistics (AISTATS), Fort Lauderdale, FL, USA, Apr. 2017.



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