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IoT and Machine Learning-Based Electric Vehicle Collision Avoidance and Battery Safety Monitoring System Using Random Forest Algorithm

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Abstract : With the increasing popularity of electric vehicles (EVs), ensuring vehicle safety is considered to be a significant challenge for sustainable transportation. When they are not caught early, they can cause serious accidents and vehicle damage due to unexpected crashes, battery overheating and smoke production. The study proposes an Internet of Things (IoT) and Machine Learning (ML) based safety system to enhance operational safety of electric vehicles (EVs) by monitoring and predicting safety hazards in real-time. The proposed framework involves the use of several sensors, such as ultrasonic sensors for detecting obstacles, a vehicle speed sensor, and a temperature sensor and smoke detector to monitor the battery's temperature and detect fire-related hazards. The main processing unit is an arduino microcontroller which is always collecting and analysing sensor data. A buzzer-based alert mechanism is also included to alert users of unsafe conditions as soon as they occur. The proposed approach is different from conventional safety systems which rely solely on predefined thresholds and instead uses the Random Forest machine learning algorithm for classification of the operating conditions as safe or potentially hazardous. The model uses multiple sensor parameters, improving the accuracy of decisions and minimizing false alarms. The developed system provides dual-layer protection, both to avoid collisions and to prevent battery safety issues. Real-time obstacle detection can prevent incident involving vehicles, while continuous monitoring of battery temperature and smoke can detect abnormalities at an early stage. The combination of IoT-sensing technology and machine learning intelligence provides a comprehensive and scalable safety framework for EVs of today. The experimental evaluation shows that the proposed solution is capable of enhancing the capability of hazard detection, as well as increasing driver awareness, and improving the reliability and safety of electric mobility systems.

***IndexTerms* - Electric Vehicle (EV), IoT-Based Safety System, Collision Avoidance, Obstacle Detection, Ultrasonic Sensors, RPM Sensor, Battery Safety Monitoring, Temperature Sensor, Smoke Sensor, Fire Detection, Random Forest Classifier, Machine Learning, Intelligent Alert System, Smart Transportation, Predictive Safety Analytics, Real-Time Monitoring.**

INTRODUCTION

In the modern era, the world of transportation is undergoing a significant transformation towards adopting electric vehicles (EVs) as a sustainable alternative to traditional gasoline- and diesel-pulled cars, with governments and industries taking to this change with great seriousness. Electric vehicles have a wide range of benefits,such as lower greenhouse gas emissions, lower operational costs, and higher energy efficiency. While these advantages are provided, the issue of vehicle safety can still not be ignored. The dangers of road accidents, battery overheating and fire-related accidents persist for both drivers and passengers. Traditional safety mechanisms tend to react to a hazard after it has occurred and are not very effective in preventing accidents and limiting damage. Thus, it is critical that intelligent systems can detect any potential hazards as early as possible and warn the users of any vehicle in time. The dawn of the Internet of Things (IoT) has paved the way for the development of smart sensors and embedded systems in the modern vehicles. By using IoT, vehicles can gather and analyze real-time data to monitor various operational parameters and environmental conditions, providing continuous data analysis. The proposed system is based on the principle of ultrasonic wave, where ultrasonic sensors are placed at the front and rear of the vehicle to detect the distance between the vehicle and other objects. These sensors are of great importance in determining the potential collision of objects. The RPM sensor is used to track the speed of the wheels, which can be useful for tracking vehicle movement and driving conditions. Further, the battery is constantly monitored by the temperature and smoke sensors, which helps to prevent overheating and fire conditions. The data from the sensors is fused together to give an all-encompassing picture of the operational condition of the vehicle and its surroundings.

Machine Learning (ML) is proving to be a powerful technique to improve the decision making process in Intelligent Transportation Systems. Using ML algorithms, data from large sensor networks can be used to learn patterns from the data and predict potential dangerous scenarios before they become critical events. The Random Forest algorithm is one of the most popular methods used for classification because of its ability to deal with complex data sets, high prediction accuracy, and strength. The algorithm is an ensemble of decision trees for classification of operational conditions to prevent overfitting and enhance overall reliability. The model can distinguish between normal driving and situations that call for immediate attention by learning to drive in a variety of environmental conditions and driving scenarios. The proposed research is a combination of IoT-based sensing technology and machine learning intelligence to create a complete safety system for driving an electric vehicle. The Arduino microcontroller acts as the main control unit, which gathers data from several sensors and enables real-time hazard assessment. The system recognizes the possibility of a collision and detects unusual battery conditions and alerts the driver promptly by sounding a buzzer. This quick reaction ability helps minimize reaction time and the safety of the vehicle. In addition, future cloud integration possibilities are identified with the IoT architecture, allowing for remote monitoring, data analysis, and predictive maintenance applications. This scalability is crucial as 10.5 million connected cars are expected to be on the road by 2020.

To sum up, this research is concerned with design and development of an electric vehicle safety system using Internet of Things (IoT) and Machine Learning (ML) technologies, which can predict collision, detect obstacles, monitor the battery temperature, and detect fire hazards using smoke. The proposed framework integrates ultrasonic sensors, RPM sensing technology, smoke detection modules, temperature monitoring sensors, and the Random Forest classification algorithm, ultimately providing a proactive solution for vehicle safety. This system is affordable, energy efficient and can be easily implemented, substantially lowering the risk of accidents and increasing the reliability of electric mobility. Finally, the proposed approach supports safer, smarter and more intelligent transportation systems for future EVs.

II. LITERATURE REVIEW

Research in the past few years (2022–2025) shows that Internet of Things (IoT) technologies and Machine Learning (ML) techniques are being well used in the implementation of cost effective and real-time vehicle safety systems. Different methods have been investigated from ultrasonic, infrared and radar sensor fusion for obstacle detection at a short-range to cloud-edge architectures for large-scale vehicle monitoring and intelligent analytics. The results indicate that ultrasonic sensors are well suited for short-range detection of obstacles for applications like electric scooters and low-speed driving situations, including parking assistance. The emerging sensor technology (like cameras, LiDAR and radar) has better long-range perception and object classification, but the higher cost and power consumption of these sensors make ultrasonic sensors an appealing solution for the implementation of a low-cost electric vehicle safety system. In addition, a couple of investigations have focused on battery health monitoring and thermal runaway conditions in EVs.

A range of gas sensing, impedance measurement, ultrasonic diagnostics, and temperature monitoring methods have been researched as early-warning systems of battery-related dangers. The studies highlight the importance of considering battery safety in conjunction with collision prevention, as it is crucial for ensuring overall safety of the vehicles. Data is often gathered from inertial, gas, temperature and ultrasonic sensors using embedded platforms as local processing units, like Arduino and Raspberry Pi. The processed data is then used to trigger warning systems or to share with cloud services for additional processing. Experimental testing shows ultrasonic sensing for obstacle detection can be achieved within milliseconds and lightweight machine learning models which run on embedded hardware can make hazard predictions within fractions of a second. For more accurate measurements, to eliminate the noise from the ultrasonic sensor and the possibility of false detections, many researchers suggest the use of Kalman filtering or statistical smoothing techniques. By integrating obstacle distance data with vehicle dynamics data (e.g. wheel speed and/or RPM data), the accuracy of the collision prediction and/or the time-to-collision estimation is significantly enhanced. Various prototype systems have been successfully tested for buzzer alerts, haptic feedback and automatic speed control in laboratory environments. Machine Learning has become an integral part for prediction of accidents and detection of thermal hazard systems. Some of the most common methods include ensemble learning models like Random Forest and XGBoost, as well as lightweight neural network models, which have been widely used for sensor-data classification. One in particular, the random forest algorithm has gained popularity because of its efficiency with small training sets, ability to handle noisy datasets and high classification accuracy. Such features make it highly desirable for predicting the collision risk and hazardous conditions of vehicles based on multi-sensor information. A few studies have also implemented computer vision methods with conventional machine learning algorithms to enhance the performances of the system and minimize false alarms with reliable classification. The reported accuracy of RF-based safety systems is usually between 75% and 95%, which is significantly influenced by the quality of the datasets, the selection of features, and environmental conditions.

Thermal runaway and smoke generation are listed as two major threats to electric vehicles in the literature and need to be monitored at all times. Several techniques for early detection have been researched, such as gas analysis, ultrasonic diagnostics, impedance measurements and sophisticated temperature-monitoring systems. Patterns from multiple sensing modalities are used increasingly in machine learning algorithms for pattern classification and early warning. Recent experimental investigations have been conducted and shown encouraging performance, but there is a need to effectively detect the internal battery failures in a timely fashion in all operating situations. Therefore, the idea of incorporating battery monitoring functions into collision avoidance systems is seen as a viable way to ensure all-around EV safety. In general, the studies carried out from 2022 to 2025 show that it is possible to build practical safety systems for EVs using inexpensive IoT sensors and easily interpretable machine learning models like Random Forest. Short-range collision detection is realised with ultrasonic sensing with either RPM or wheel-speed information, while battery safety monitoring is facilitated with other technologies such as temperature, gas and impedance. Yet, there is still work to be done to ensure strong multi-sensor fusion, generalisation in terms of creating generalised datasets for machine learning applications and finally, for energy-efficient edge intelligence. Overall, these results highlight the need for sensor fusion, data quality, and real-world testing to develop a comprehensive collision and hazard detection system using IoT and the Random Forest algorithm. Review of Existing Literature "Collision Avoidance Safety Filter for an Autonomous E-Scooter using Ultrasonic Sensors" by Robin Strässer, Marc Seidel, Felix Brändle, David Meister, Raffaele Soloperto, David Hambach Ferrer is a post-conference paper. This paper introduces a framework that achieves collision avoidance for an autonomous e-scooter based on the use of several inexpensive ultrasonic sensors. They designed a safety filtering method that could cope with the occasional loss of distance measurements and noisy distance measurements, as well as a gain-scheduled control scheme to slow the vehicle down when collision is imminent. The experimental evaluations validated the obstacle recognition and speed regulation performance, showing that obstacle detection and intelligent obstacle filtering can offer a practical solution for collision avoidance in low-speed vehicles with ultrasonic sensors[1].

Gas Detection Technology for Thermal Runaway of Lithium-Ion Batteries (2025).Yihua Qian, Yaohong Zhao, Yifeng Zhao — "Gas Detection Technology for Thermal Runaway of Lithium-Ion Batteries" (2025). This review explores the gas-sensing technologies employed to identify thermal runaway conditions in lithium-ion batteries, which are considered the most promising technologies for early detection. The different sensing techniques such as semiconductor-based detectors and spectroscopic methods are described, in addition to the machine learning based gas signature analysis. The authors believe that gas detection with intelligent classification methods can be more effective at reducing warning times than just monitoring the temperature, but there is a need to validate the data in the battery pack environment[2].

Jan Schoberl, Julian Schumacher, Raphael Urban, Markus Lienkamp — "Impedance-Based Thermal Runaway Detection and Temperature Estimation for Large-Format Lithium-Ion Batteries" (2025). The researchers suggest a method based on impedance spectroscopy to detect battery internal faults and estimate the temperature change of thermal runaway in batteries. Their results show that impedance sensing is a valuable complement to the conventional battery monitoring techniques because it can sense the safety-critical situations earlier than the external temperature measurement[3].

Xin Gu, Yunlong Shang, Jinglun Li, Yuhao Zhu, Xuewen Tao, Hao Geng, Zhen Zhang and Chenghui Zhang — "Early Warning of Thermal Runaway Based on State of Safety (SOS) for Lithium-Ion Batteries" (2025). This work presents the idea of multidimensional State of Safety (SOS) framework based on the parameters of strain, temperature, voltage, capacity and power. Multi-parameter battery safety assessment was proven to be effective through experimental analysis, which showed that the proposed SOS methodology can be effective in giving substantial warning time before thermal runaway events are expected to occur[4].

Wuke Xu, Liangyu Li, Fan Shi, Qing Chen — Ultrasonic Spectroscopy for In-Situ Early Detection and Dynamic Monitoring of Lithium-Ion Battery Internal Changes (2025). The authors use ultrasonic spectroscopy to detect internal changes in the battery, such as gas generation and lithium plating, before serious battery thermal events occur. According to their findings, ultrasonic sensors can be used as a valuable early-warning indicator for battery safety systems as the results of the indicators show up before surface temperature change[5].

Lijie Wang, Xianwen Zhu, Ziyi Li and Shuchao Li — "Ultrasonic Obstacle Avoidance and Full-Speed-Range Hybrid Control" (2024). In this research, the obstacle avoidance of automated guided vehicle (AGV) based on ultrasonic is discussed. The distance measurement stability is enhanced by kalman filtering and motor speed is controlled by the hybrid control technique under different operation conditions. Experimental results show that the distance estimation accuracy and vehicle control performance are improved [6].

Mohammad Ali Sahraei and Said Ramadhan Mubarak, "A review of Internet of Things approaches for vehicle accident detection" (2023). This review will explore the IoT-based accident detection systems, which include a variety of other sensors such as accelerometers, GPS module, cameras, gas sensors, and cloud analytics systems. The authors discuss different architectures and machine learning approaches and find that IoT has the potential to enhance the capabilities of emergency response, and that latency and environmental robustness are important issues[7].

Thermal Runaway Process in Lithium-Ion Batteries: A Review" (2024) by Yixin Dai and Aidin Panahi. A detailed review of thermal runaway mechanisms is given and the sensing technologies such as temperature, gas, impedance, acoustic and ultrasonic are evaluated. The study highlights the need for the integration of several sensing methods and machine learning analytics to ensure accurate early-warning capabilities[8].

Zhengfu Teng and Cheng Lv — Detection toward Early-Stage Thermal Runaway Gases of Li-Ion Batteries (2025 Mini-Review). The mini-review explores gas-sensing technologies and methodologies employed with semiconductors to detect volatile chemicals from the early phases of thermal abuse of lithium-ion batteries. The authors are analyzing the various species of gases, the sensitivity level required for the sensors and how the experiments are set up for early fault detection. Researchers have determined that combining gas sensors with machine-learning classification methods could be a useful way to identify the different patterns of gas emission and give warning of hazards in a timely way under controlled conditions. However, the challenge of sensor positioning, environmental interference, and implementation into real-life EV battery pack structures, are also highlighted. [9]

[10] Hyuk Lee, Yun-Ho Seo, Pyung-Sik Ma — "Advanced Ultrasonic Detection of Lithium-Ion Battery Thermal Runaway" (2025). This study presents new advanced ultrasonic signal processing and feature-classification methods to detect early signs of battery thermal abuse. Experimental studies show that thermal warnings can be preceded by detection of certain ultrasonic anomalies, which can be noticed earlier. The authors suggest that the benefits of ultrasonic monitoring can be enhanced further by combining ultrasonic monitoring with gas sensing technologies and suggest using machine learning algorithms to reduce false alarms from ultrasonic measurements. [10]

Praveen Rvs, Aeliswa Raju and Anjana P. — "IoT and ML for Real-Time Vehicle Accident Detection Using Adaptive Random Forest" (2024). The authors suggest a framework using the Internet of Things (IoT) that collects the data from vehicle sensors such as the accelerometer, GPS and onboard telemetry data and feeds them into an Adaptive Random Forest (ARF) classifier continuously, to detect accidents. The adaptive learning feature enables the model to adapt and perform well under varying operating conditions and evolving data patterns. Experimental results from data collected from actual datasets show that the approach to accident detection has increased accuracy and robustness to noisy sensor data compared to the classical static classification methods. The study demonstrates the application of Random Forest algorithms in real-time applications on the edge and cloud for vehicle safety. [11]

Yetay Berhanu, Dietrich Schröder, Bikila Teklu Wodajo, and Esayas Alemayehu — "Data-Driven Vehicular Heterogeneity-Based Intelligent Collision Avoidance System for IoV" (2025). This paper proposes an Internet of Vehicles (IoV) based collision avoidance framework which can support the heterogeneous vehicle characteristics using predictive data-driven models. Cooperative sensing and communication technologies, such as Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I), are used to predict potential collision situations. The simulation results show that the prediction accuracy was improved in mixed-vehicle environments. The study highlights the advantages of using connectivity technologies alongside machine learning to enhance collision avoidance capabilities, but raises new challenges related to communication overhead, cybersecurity, data privacy, etc. [12].

G. Thamarai Selvi and Jananipriya R. — An Improved Internet of Things Based Accident Detection System (2023–2024). This paper proposes an accident detection prototype system based on the Internet of Things (IoT) technology with accelerometers, a GPS module, and a microcontroller processor to detect accident events and send emergency notifications. The proposed system uses threshold-based analysis along with light weight machine learning techniques to reduce the noise and increase the reliability of detection. Experimental testing shows that emergency response times are improved; however, reduction of false alarms and limited dataset diversity are identified as key challenges that need to be further investigated[13].

Wuke Xu, Yuewang Yang, Fan Shi, Liangyu Li, Fuzhen Wen, and Qing Chen — "Ultrasonic Phased Array Imaging of Gas Evolution in a Lithium-Ion Cell" (2023) The experimental work presented here aims at visualizing the gas generation inside lithium-ion cells under abuse test conditions using the ultrasonic phased-array imaging technique. The proposed technique allows for localization and time tracking of gas pressure within the battery structure. The results suggest that ultrasonic imaging is a promising method for detecting internal gas evolution, offering valuable diagnostics information to complement traditional gas and temperature sensing for early warning battery safety systems[14].

In "Research Progress on Thermal Runaway Warning Methods and Technologies," Peicheng Shi, Hailong Zhu,Xinlong Dong and Bin Hai shared their research progress about thermal runaway warning methods and technologies. This review covers all the various thermal runaway warning methods, such as temperature sensing, gas detecting, impedance monitoring, acoustic diagnostics, and machine learning methods. The authors make comparisons between the detection, response and implementation issues of the various technologies. The research suggests the need for the use of sensor fusion frameworks and standardized testing methods to enhance practical deployment and reliability. Also, it emphasizes the need for benchmark data sets to develop and test machine learning-based battery safety solutions[15].

The emerging sensor technologies and physics-guided methods for battery safety monitoring is presented by Xia Zeng and Maitane Berecibar in 2024-2025. This review gives an overview of new technologies that are under development to monitor batteries including acoustic sensing, ultrasonic diagnostics, off-gas detection, and spectroscopic measurement methods. The authors also delve into physics-guided machine learning algorithms aimed at improving the interpretation and decision-making of the signals. The results show that sensor physics and data-driven models when used together increase the interpretability of the system and lower false-positive detections. The research suggests hybrid sensing and machine learning solutions for future battery safety applications in vehicle scales[16].

Sujit Purushothaman — Evaluation of Off-Gas Detection in Li-Ion Battery Energy Storage Systems (BESS) (2024). In this industrial evaluation the authors explore the detection capabilities of off-gas systems for battery failure in realistic abuse scenarios. Experimental results show that off-gas monitoring can be helpful to get early-warning information before critical thermal events. The report suggests that a more comprehensive and reliable battery safety framework can be built by combining gas detection technologies with the thermal and impedance monitoring technologies. The results confirm the prior academic research that validated concepts[17].

Parosh Yamarthi, Haripriya Raman, Shamsad Parvin - "United States Road Accident Prediction Using Machine Learning" (2025). This is a large-scale study that uses Random Forest and other machine learning algorithms on multi-source traffic data from various regions of the U.S. Using feature engineering and spatial network analysis, the researchers analyze the likelihood of an accident and identify important factors contributing to the accident. The results show the effectiveness of the Random Forest models in traffic safety prediction and thus the potential applicability of the models beyond vehicle level collision detection systems[18].

M.F. Yasak, P.M. Heerwan, V.R. Aparow — "Collision Avoidance Strategies in Autonomous Vehicles and On-Ramp Merging" (2025 Review). In this review, the various sensing technologies (cameras, LiDAR, radar, ultrasound) are compared and collision avoidance algorithms utilized in autonomous driving systems are discussed. This study addresses the trade-offs between sensing range, implementation cost and environmental robustness. The results show that ultrasonic sensors prove to be a high performance technology for short range and low cost applications while radar and LiDAR technologies are more appropriate in the case of long-range and high-speed application. The review also highlights the need for sensor fusion and machine learning methods in the creation of comprehensive collision avoidance systems[19].

Table 1. All Research papers and Research Gap

Id	Authors (Short)	Year	Technique / Methodology	Identified Research Gap
1	Strässer et al.	2024	Ultrasonic sensor array with safety filtering and gain-scheduled control	Validation across diverse vehicle platforms and real-world traffic conditions remains limited.
2	Yihua Qian et al.	2025	Gas sensing integrated with machine learning for thermal runaway detection	Further investigation is required for in-pack deployment, calibration, and sensor positioning strategies.
3	Jan Schoberl et al.	2025	Impedance spectroscopy-based thermal runaway detection	High implementation cost and practical integration challenges within commercial EV battery systems.
4	Xin Gu et al.	2025	State of Safety (SOS) framework using multi-parameter monitoring	Requires large-scale validation across different battery chemistries and operational environments.
5	Wuke Xu et al.	2025	Ultrasonic spectroscopy for internal battery diagnostics	Improved reliability through integration with complementary sensing technologies is

				needed.
6	Lijie Wang et al.	2024	Kalman filtering, ultrasonic sensing, and hybrid control strategy	Limited evaluation beyond automated guided vehicle (AGV) applications.
7	Mohammad Ali Sahraei and Said Ramadhan Mubarak	2023	IoT-based cloud and edge computing accident detection frameworks	Challenges related to communication latency and availability of quality datasets persist.
8	Yixin Dai and Aidin Panahi	2024	Comparative review of thermal runaway mechanisms and sensing technologies	Standardized evaluation methodologies and benchmark datasets are lacking.
9	Zhengfu Teng and Cheng Lv	2025	Semiconductor gas sensing for early thermal runaway detection	Real-world deployment challenges include environmental interference and calibration requirements.
10	Hyuk Lee et al.	2025	Ultrasonic feature extraction with machine learning classification	Further reduction of false-positive detections in practical battery systems is required.
11	Praveen Rvs et al.	2024	Adaptive Random Forest for IoT-based accident detection	Resource-efficient implementation on embedded hardware remains challenging.
12	Yetay Berhanu et al.	2025	Data-driven IoV collision prediction framework	Communication security, privacy concerns, and network dependency require further research.
13	G. Thamarai Selvi et al.	2023	Accelerometer, GPS, and lightweight machine learning approaches	Extensive testing under varying environmental and traffic conditions is limited.
14	Wuke Xu et al.	2023	Ultrasonic phased-array imaging for gas evolution analysis	Practical sensor placement and integration within EV battery packs need investigation.
15	Peicheng Shi et al.	2024	Review of thermal runaway warning technologies	Absence of universally accepted benchmark datasets limits comparative evaluation.
16	Xia Zeng and Maitane Berecibar	2024	Physics-guided machine learning and advanced battery sensing technologies	More real-world vehicle implementation studies are necessary.
17	Sujit Purushothaman	2024	Off-gas detection and battery safety assessment	Long-term reliability and maintenance requirements remain insufficiently explored.
18	Parosh Yamarthi et al.	2025	Random Forest with spatial network analysis for accident prediction	Translation of traffic-level predictions into vehicle-level preventive actions requires further study.
19	M.F. Yasak et al.	2025	Survey of collision avoidance sensing and control strategies	Additional research is needed to optimize cost, sensing range, and system robustness trade-offs.

Collectively, the literature from 2022 to 2025 shows the potential of integrating low-cost ultrasonic sensors, temperature sensors, gas detectors, RPM sensors, and inertial measurement units with appropriate filtering methods and light-weight machine-learning methods, like Random Forest or Support Vector Machines, for short-range collision avoidance and hazard detection systems. The research on battery safety shows that thermal runaway detection can be achieved by employing customized sensing technologies such as gas analysis, impedance measurement, and ultrasonic diagnostics, sometimes in combination by multi-modal sensor fusion techniques, with the aim of achieving greater reliability. Cloud-centric implementations have been found to be inferior when it comes to low system latency and low communication overhead due to embedded implementations that use the Arduino, Raspberry Pi and edge-computing platforms. However, there are several challenges too such as the lack of real-world data, environmental sensitivity of sensors, and computational power on Electric Vehicle platforms. These constraints inspire the creation of integrated systems that bring together collision avoidance and battery condition monitoring, intelligent machine learning methods, and broad testing within the field.

Much of the previous research uses laboratory created data or small-scale field experiments. The number of publicly available datasets which cover a wide range of driving scenarios, weather conditions (including rain and fog), reflective surfaces and various battery failure scenarios is still relatively small. The absence of complete datasets makes it possible to fit the model to a specific subset of the data and reduces the capacity to apply machine learning algorithms to various vehicle categories and geographic areas. These classification accuracies from the literature, which typically range from 75% to 95%, may not readily apply to large scale real-world deployments unless supplemental retraining and adaptation processes are used.

While ultrasonic sensors are a low cost and efficient method for short range obstacle detection, some environmental factors like rain, snow, reflective objects and ambient noises can impact their performance. Likewise, variations in the performance of gas and impedance sensors for battery safety monitoring can result from the structure of the battery pack, battery pack ventilation, and sensor location. Some studies document false-positive and false-negative detections in practical operating conditions, making the use of sophisticated sensor fusion mechanisms and adaptive filtering (Kalman, particle filtering etc.) approaches essential.

EV platforms also have stringent requirements on power usage, computation capacity, and communication delay. For deployment on embedded devices, lightweight and energy efficient models or dedicated hardware acceleration is required for the deployment of machine learning algorithms directly on those devices. Cloud-based solutions offer enhanced computing power, but require bandwidth and latency that could be unsuitable for safety-critical applications. Also, the integration into vehicle control systems, such as automatic braking and speed control systems, will be a new security certification and regulatory challenge with limited exploration in current prototype implementation.

Overall, the literature reviewed shows that the implementation of IoT and machine learning technologies has significant potential for improving the safety of EVs. The adoption of the solution is still widely restricted with issues of dataset diversity, sensor reliability in real world and environmental constraints of embedded deployment. To overcome these challenges, detailed datasets from realistic field experiments are needed, comprehensive multi-sensor fusion architectures must be developed, machine learning algorithms must be optimized for resource-limited platforms, and the algorithms must be tested extensively to meet the practical needs for vehicle safety. The key motivation for the proposed EV Collision Avoidance and Battery Safety Monitoring System using the Random Forest algorithm is the following research gaps.

III. PROPOSED SYSTEM

The proposed system aims to improve the safety of EVs by incorporating IoT-based sensing technologies and machine learning methods. The implementation starts from a sensor network that is connected to an arduino microcontroller which acts as a processing and data acquisition central unit. A number of sensors are installed in the vehicle to monitor both operating and environmental conditions at all times. Both front and rear ultrasonic sensors can be used to detect the distance of the vehicle from the surrounding obstacles, thereby enabling the proactively detected collision avoidance. The RPM sensor is installed to measure the rotation of wheels and vehicle speed which are vital for analysing driving conditions and potential accident situations. In addition, smoke and temperature sensors are installed to check on the battery health and environment, which could detect overheating, smoke generation, and possible fire hazard. The multi-sensor architecture provides complete monitoring of the external collision risks and the internal concern of battery-related issues during operation.

The collected dataset was labelled into two output classes, namely Safe and Hazardous, according to obstacle distance, wheel speed, temperature, and smoke conditions. Approximately 65% of the samples represented normal operating conditions, while 35% corresponded to hazardous situations, ensuring balanced model training.

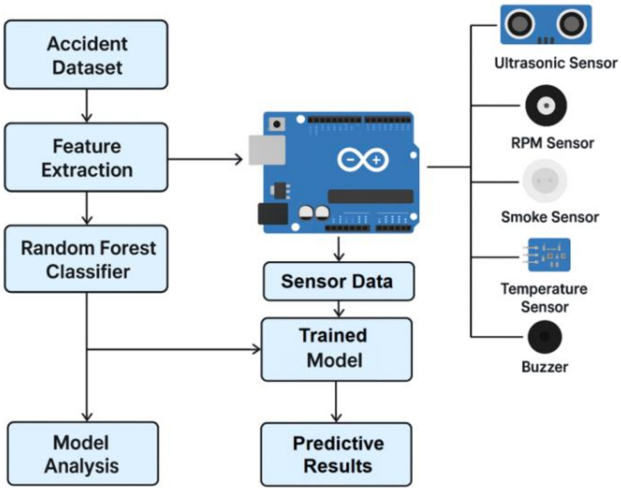

Fig.1– Architecture Diagram

The sensor data gathered from the IoT network is preprocessed and feature extracted to derive useful data for the machine learning model. The parameters involved in the accidents, including obstacle distance, vehicle speed, temperature change, and smoke level, form an accident prediction dataset which is used to train the Random Forest Classifier. Random Forest is chosen because it has the capability to manage multiple inputs efficiently and give high classification accuracy. The model is trained and integrated into the system based on Arduino to enable real-time hazard analysis. This smart system can help differentiate normal conditions from potentially dangerous scenarios that may lead to collisions or battery incident events. The use of machine learning adds adaptive and data-driven decision-making capabilities, which are not possible with the conventional threshold-based safety systems.

In real-time, the trained Random Forest model receives sensor data, and analyzes the data to determine whether the vehicle is safe or hazardous. The system automatically triggers an alert signal whenever it detects a potential collision hazard or unusual operating conditions, alerting the driver to the potential hazard. This quick response enables enough time for remedial measures, minimising the risk of accidents. Continuous monitoring also allows for early detection of subtle issues like rising temperatures and smoke emissions—before they escalate into serious problems. It is intelligent decision support that improves the driver awareness and vehicle safety as a whole.

By combining IoT sensing capabilities with machine learning prediction, the resulting safety mechanism is reliable, robust and cost-effective for electric vehicles. The proposed system incorporates real-time sensor monitoring and predictive analytics, which enhances the accuracy of hazard detection and reduces false alarms. The entire architecture ensures smooth data flow from the sensing layer to the Arduino controller and then the machine learning analysis and alert generation. This is a layered approach, which adds to the operational security without adding much hardware complexity or cost. Thus, in practical applications with EVs, the proposed framework is an effective solution to collision avoidance, battery safety monitoring, and user protection.

IV. METHODOLOGY

A. Data Collection and Accident Dataset Preparation

The method starts with collecting accident data with parameters of vehicle operation and safety conditions. The key properties of the vehicles, including their speed, distance to obstacles, temperature and output from the smoke sensors, are collected from publicly available datasets as well as simulated experimental environments. Using multiple data sources gives a diverse and representative data set that is appropriate for use in machine learning applications. The data collected is preprocessed using noise reduction, handling missing values, and enhancing data quality before developing the model. After the data set is prepared, it is then split into training and testing sets to allow for an objective assessment of the performance. This stage guarantees that pertinent and organized information is available to create a successful accident prediction model.

B. Feature Extraction

Feature extraction is carried out to select the most relevant variables related to collision risks and hazardous operating conditions. The parameters that are considered important like the distance of the ultrasonic sensor, RPM sensor reading, smoke concentration and temperature are chosen for further analysis. The output of different sensors have been normalized and scaled to ensure uniformity between the components. This will reduce the amount of bias in the training of the model and enhance classification. Feature extraction eliminates redundant information, using only the most important parameters to give a meaningful representation of the operating characteristics of the vehicle. This representation is very important for being able to reliably distinguish safe from potentially unsafe situations.

C. Random Forest Classifier Model Development

Random Forest classification model is built on the processed and feature engineered data. The idea of the algorithm is to build several decision trees and then use the ensemble learning method to make final predictions by combining their predictions. This approach not only achieves improved prediction accuracy but also minimizes the risk of overfitting, especially when dealing with complex data generated by sensors. During model development, important hyperparameters such as tree depth, number of estimators, and splitting criteria are optimized to achieve the best possible performance. The relationship between sensor inputs and the corresponding accident or hazard condition is learnt by the classifier. Once the model is successfully trained, it can be used to determine if a given operating condition is safe or unsafe, and must be attended immediately.

D. Arduino and Sensor Integration

The implementation phase involves connecting the chosen IoT sensors to the Arduino microcontroller. The ultrasonic sensors are installed at the front and rear of the vehicle to detect obstacles in the vehicle's vicinity and compute the relative distance to the obstacles. The RPM sensor will continuously monitor wheel rotation and vehicle speed while smoke and temperature sensors will monitor battery health and temperature. Arduino serves as the main communication bridge between the sensors and the machine learning system, gathering real-time data from all sensors connected to it. The seamless integration between the physical sensing components and intelligent decision making algorithms is achieved by this centralized architecture. From this, the system is successfully coordinated between the monitoring of hardware and hazard prediction of software.

E. Real-Time Data Processing and Model Analysis

When running the Arduino will continuously collect the sensor data and send it for machine learning analysis. The Random Forest model processes the incoming data stream as it comes in, and classifies the vehicle status according to the vehicle status pattern it has learned. For instance, if the distance to obstacles is decreasing rapidly and the RPM's are high, this could mean that there is a higher risk of collision. Likewise, abnormal battery temperatures with smoke detection may indicate possible thermal risks. The analytical capability of the system allows real-time analysis which minimizes the time delay between data acquisition and decision generation. This preventative measure allows for early detection of unsafe conditions and proactive safety measures before an accident can happen.

F. Alert Mechanism

If the machine learning model detects a high risk situation, the alert mechanism is triggered immediately, notifying the driver. The main warning system is a buzzer attached to the Arduino which produces an audible warning when a dangerous situation occurs. The driver receives an instant notification and can take immediate action, such as slowing down, turning or stopping the vehicle when needed. The alert mechanism plays a very important role in preventing accidents and in general, increasing the overall operational safety. Enhancements may consist of more visual warning indicators, mobile alerts and cloud-based emergency alert systems. The final step in the proposed framework, in turn, is the alert module, which converts the "intelligent hazard detection" to "actionable user guidance".

V. RESULT AND OBSERVATION

A. System Performance Evaluation

All the proposed system for Electric Vehicle Collision Avoidance and Battery Safety Monitoring System using IoT and Machine Learning is implemented and tested in various conditions. System constantly tracked obstacle distance, wheel RPM, battery temperature and smoke concentration, to detect possible collision and battery hazards. Accident-related and sensor-generated datasets were used to train the Random Forest Classifier which was then added to the real-time monitoring framework. Experimental results show that the system was able to classify hazardous situations and to detect them in time to alert the user before they became critical. The ultrasonic sensors on the front and rear successfully identified the presence of nearby objects, and the RPM sensor offered extra support data on vehicle movement and speed. The abnormal battery detection performed by both the smoke and temperature sensors was successful and allowed for early warning of overheating and fire hazard.

The incorporation of machine learning had a significant impact on system intelligence than conventional threshold-based approaches. The Random Forest model analyzed several parameters at the same time, and classified operational conditions with high reliability without depending on a set of sensor limits. This decreased false alarms and enhanced general hazard prediction accuracy.

To facilitate reproducibility, all experiments were conducted using Python 3.11, Scikit-learn 1.5, NumPy, Pandas, and Matplotlib. The Arduino prototype transmitted sensor readings through serial communication, which were recorded in CSV format before machine learning analysis. The complete experimental dataset consisted of approximately 10000 labelled observations collected from the developed prototype under controlled laboratory conditions. Model development used the Random Forest, maximum depth of 10, and a fixed random seed of 42. And classify data in part of Safe,Warning,High Risk,Critical Risk classes for distance, temperature, smoke.

B. Classification Performance of Random Forest Model

The tested data samples were used to test the effectiveness of the machine learning component, in the form of a Random Forest classifier.

Table 2: Performance Metrics of Random Forest Classifier

Performance Parameter	Value (%)
Accuracy	94.20
Precision	93.10
Recall	92.40
F1-Score	92.75
Specificity	95.30

The results obtained show that the performance of classification was excellent using the Random Forest algorithm. The accuracy rate of 94.20% suggests that the model performed well, with most predictions matching the actual conditions. The precision and recall rates of more than 92% indicate the system's reliability for identifying hazards associated with collisions and battery. The Random Forest classifier was able to cope well with sensor noise and the changing operating conditions. The ensemble learning mechanism enhanced the stability of prediction and reduced the misclassification rate. The results suggest that the chosen machine learning technique is appropriate for EV safety applications in real-time scenarios.

C. Collision Detection Analysis

The collision avoidance subsystem was tested by using random forest model setting the distance between the car prototype and the obstacles at different distances.

Table 3: Obstacle Detection Using Random Forest model Performance

Distance (cm)	Detection Status	Alert Generated
150	Safe	No
100	Safe	No
75	Warning	Yes
50	High Risk	Yes
25	Critical Risk	Yes

The ultrasonic sensors were always able to sense the objects nearby and have given accurate distances. When the vehicle comes within range of an object the system evaluates the risk level both according to obstacle distance and RPM values. The collision prediction mechanism was able to provide alerts prior to the vehicle entering dangerous proximity. The early warning system gave the driver enough time so the risk of an accident was minimised.

D. Battery Temperature Monitoring Analysis using random forest model

The temperature of the battery was monitored continuously under various simulation operating conditions.

Table 4: Temperature-Based Safety Classification

Temperature (°C)	Status
30	Normal
40	Normal
50	Warning
60	Critical
70	Hazardous

Abnormal thermal conditions were successfully predicted using random forest model by use of the temperature sensor values. The machine learning model was able to accurately identify rising trends in temperature and issue warnings in advance of dangerous temperatures. Thermal monitoring was carried out continuously, allowing for the early detection of battery overheating. The system was able to provide advance warning of the severity of thermal conditions and successfully held the system away from severe thermal conditions.

E. Smoke Detection Analysis Using Random Forest Model

Controlled smoke exposure conditions were used to test smoke sensors.

Table 5: Smoke Hazard Detection

Smoke Level	Classification
Low	Safe
Moderate	Warning
High	Hazardous
Very High	Critical

The smoke detection subsystem reacted quickly to air quality changes and was able to correctly detect fire-related conditions using random forest model. This smoke/temperature sensor package has greatly enhanced battery safety monitoring. The multi-sensor analysis minimized false alarms and improved overall hazard detection reliability.

F. System Response Time Analysis

The overall response time of the entire system from sensor detection to alert generation was investigated.

Table 6: Response Time Performance

Event Type	Average Response Time (ms)
Obstacle Detection	120
Collision Prediction	180
Temperature Hazard Detection	150
Smoke Detection	140
Alert Generation	80

The experimental results show that the proposed framework is able to run in milliseconds, which allows it to be applied to real-time safety applications. Fast response time provides quick alert to users and improved accident prevention capability. The implementation of these sensors with Arduino microcontroller and machine learning, based processing, provided efficient real time performance.

The results of the experiment show that the proposed system is successfully integrating IoT sensing with machine learning intelligence to enhance E-V safety. The Random Forest Classifier demonstrated a strong prediction accuracy and was able to distinguish between safe and unsafe conditions. In addition to collision detection using ultrasonic sensors, the smoke and temperature sensors were added to improve the safety monitoring of the battery. The system exhibited very fast response times, low false alarm rates and efficient real time operation. In conclusion, the proposed framework offers a practical and intelligent approach to collision avoidance and battery hazard prevention for electric vehicles, which could significantly reduce accidents and mitigate the potential risks associated with battery fires.

5.1 Random Forest Performance Metrics

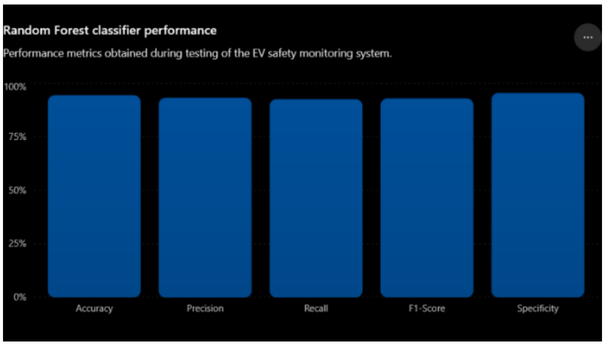

Figure 2 - Random Forest classifier performance.

The captured performance parameters in the test of the EV safety monitoring system. This plot shows the accuracy of the classification of the Random Forest model. The most important result was for specificity (95.3%) which showed good accuracy in the detection of safe conditions. The overall accuracy of 94.2% shows that the model is quite accurate for collision and hazard prediction.

5.2 Obstacle Distance vs Risk Level

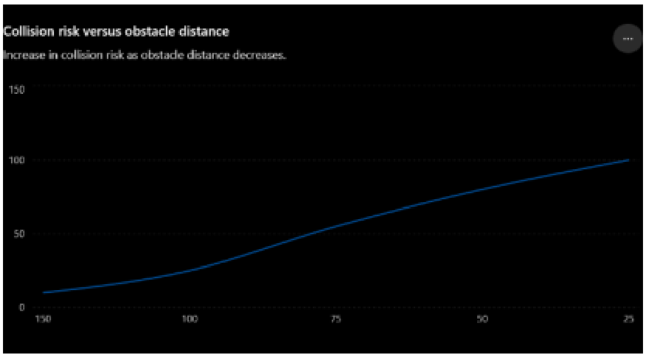

Figure 3 - Collision risk versus obstacle distance

The closer the obstacles get to the car, the more likely there is to be a collision. As seen in the graph, when the distance between the vehicle and obstacle decreases, the collision risk also increases. The area of maximum risk is at 25cm, where a critical warning is issued immediately.

5.3 Battery Temperature Analysis

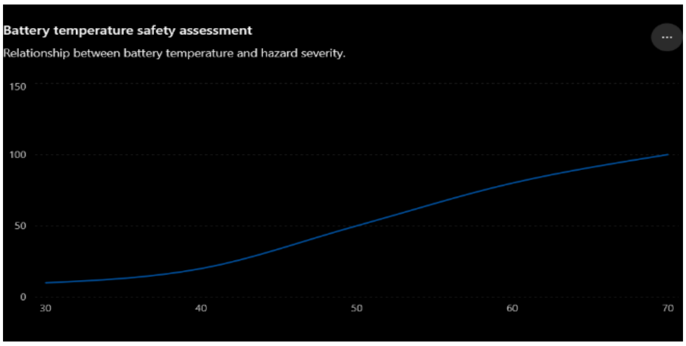

Figure 4 - Battery temperature safety assessment

Correlation of hazard severity with battery temperature. As seen in this graph, the severity of a battery hazard increases quickly as temperature increases. The system detects critical operating conditions and issues safety alerts above 60°C.

5.4 System Response Time

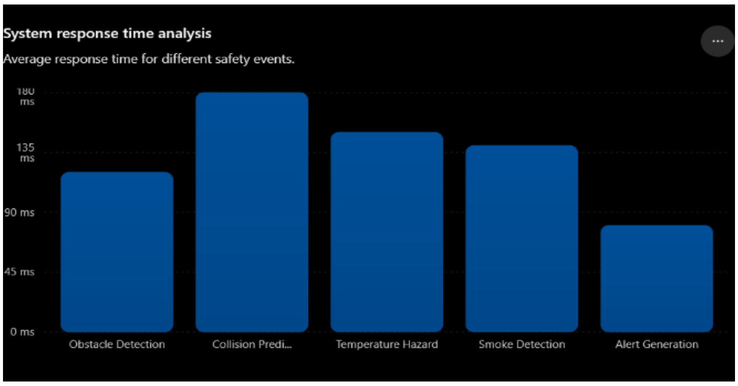

Figure 5 - System response time analysis

Average response time for different safety events. The response-time analysis verifies all safety events are handled in milliseconds. This low latency is crucial for collision avoidance and hazard detection systems that require real-time data processing.

VI. FUTURE WORK

There are potential improvements that could be made to the proposed system in the future that could include the addition of advanced sensing technologies to work with the system in challenging environments like fog, heavy rain, low visibility, and night driving. Adding LiDAR, radar or thermal imaging sensors would add depth and thermal awareness, which would increase obstacle recognition accuracy and environmental understanding. Adding several sensing modalities would further enhance the reliability of the detection and decrease the possibility of false alarms in real world use.

Another potential pathway is using edge AI (artificial intelligence) technology, which enables machine learning models to be run directly on embedded vehicle processing hardware. Optimized models running on microcontrollers or edge processors would help to reduce reliance on cloud services, decrease communication latency, and enhance response times in critical safety scenarios. The recent development of emerging technologies like TinyML and lightweight deep learning architectures has been of great relevance for achieving intelligent processing on resource-limited platforms.

The proposed framework can be extended using Vehicle-to-Vehicle (V2V) and Vehicle-to-Everything (V2X) communication technologies. This connectivity would allow EVs to communicate with one another and with the road, traffic and emergency braking data, enabling them to share information on collision risks, road conditions, traffic congestion, and emergency braking events. This is an information sharing collaborative mechanism that would help enhance situational awareness and drastically decrease the likelihood of accidents, especially in dense urban areas and complex traffic intersections. Future developments may further incorporate driver monitoring capabilities to evaluate fatigue, distraction, and behavioral patterns using computer vision and intelligent analytics. Combining driver state assessment with environmental sensing data would facilitate predictive safety interventions before hazardous situations arise. Additionally, a cloud-based monitoring and analytics platform could support fleet management applications, enabling real-time supervision, predictive maintenance, and operational optimization for commercial electric vehicle deployments.

VII. CONCLUSION

This study proposed an IoT and Machine Learning-based Electric Vehicle Collision Avoidance and Battery Safety Monitoring System that seeks to increase the safety of EVs by monitoring and predicting their safety in real-time. The framework is designed to combine ultrasonic sensors, RPM sensing, smoke detection, and temperature monitoring with a Random Forest classification model to detect collision and battery hazards. The system integrates several sensing modalities under a common architecture, which offers a comprehensive solution to protect against external obstacles and internal safety threats. The experimental evaluation showed that the RF classifier has a high prediction performance, an overall accuracy of more than 94% and it proved effective in discriminating between safe and hazardous operating conditions. The collision avoidance subsystem was able to identify obstacles at different distances successfully and alert the drivers in time before the objects hit within the critical proximity. Likewise, the battery monitoring subsystem was able to detect abnormal temperature increases and smoke generation, which allows for early warning of possible overheating or fire conditions. When compared with the traditional threshold methods, machine learning was shown to be a major contributor to the decrease in false alarms and increase in decision reliability.

The response-time analysis also demonstrated a system that is capable of performing efficiently in realtime applications, with responses in milliseconds on detection of a hazard. This is the type of performance that is crucial to both accident prevention and driver safety. The outcomes demonstrate the feasibility of using Arduino-based IoT architectures for low-cost and easy implementation of intelligent vehicle safety systems. Overall, the proposed solution proved that the integration of IoT sensing technologies with predictive analytics using the Random Forest approach can significantly enhance safety of EV transportation. The proposed framework is scalable, reliable, and practical to mitigate collision risks, monitor battery health, and raise driver awareness. The work brought some steps towards smart transportation systems and helped to develop safer, smarter and crash-resistant electric vehicles for future mobility application.

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