ADVANCED VEHICLE FIRE SAFETY AND MONITORING WITH RAPID EMERGENCY DISPATCH SOLUTIONS

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Final Report

B.Sc. (Hons) Degree in Information Technology specializing in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology
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Dissertation submitted in partial fulfillment of the requirements for the Special Honours
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DECLARATION

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the Supervisor:	2024.11.23	
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ABSTRACT

The Enhanced Vehicle Safety gadget provided in this record represents a novel technique to preventing vehicle fires by using integrating Internet of Things (IoT) and Machine Learning (ML) technologies. The machine is designed to decorate automobile protection by using putting in sensors in vehicles to detect smoke, temperature, flame, and automobile vibrations. These sensors provide real-time statistics this is analyzed using ML algorithms to are expecting capability fire incidents earlier than they amplify. One of the important thing capabilities of the gadget is its recognition on proactive fire prevention. By continuously monitoring sensor overall performance and integrating special types of sensors, inclusive of smoke, temperature, and vibration sensors, the device can offer a greater holistic and accurate detection system. This permits the machine to not only locate fires however also are expecting capacity incidents, providing a step beforehand of traditional detection systems. Another important thing of the gadget is its ability to technique and analyze records in real-time. This permits instant response to hearth threats, enhancing standard vehicle safety. Additionally, the gadget is designed to continuously research and adapt, enhancing its predictive accuracy over the years with greater data. To ensure the machine is effective and consumer-friendly, a custom designed alert mechanism is advanced to tell drivers of capability fire dangers. This mechanism is adapted to the motive force's situation, enhancing safety and response time. In conclusion, the Enhanced Vehicle Safety system represents a large development in vehicle hearth prevention. By integrating IoT and ML technologies, the machine provides a proactive technique to fireplace detection and prevention, enhancing general automobile safety and minimizing the damage because of vehicle fires.

Keywords: IoT, Machine Learning, Vehicle Safety, Fire Prevention, Sensor Technology, Real-time Data Processing.

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LIST OF ABBREVIATION

IoT - Internet of Things

ML - Machine Learning

GFR - Glomerular Filtration Rate

CNN - Convolutional Neural Network

ROI - Region of Interest

PCA - Principal Component Analysis

NMF - Non-negative Matrix Factorization

IHS - Intensity-Hue-Saturation

AWS - Amazon Web Services

API - Application Programming Interface

GUI - Graphical User Interface

WBS - Work Breakdown Structure

QA - Quality Assurance

IEC - International Electrotechnical Commission

IEEE - Institute of Electrical and Electronics Engineers

ESP32 - Espressif System's microcontroller

UI - User Interface

UX - User Experience

AMT - Agile Methodology Team

PID - Proportional-Integral-Derivative

FPGA - Field-Programmable Gate Array

BLE - Bluetooth Low Energy

CAN - Controller Area Network

OBD - On-Board Diagnostics

1 INTRODUCTION

1.1 Background and Literature

Vehicle fires are a serious global safety issue, posing significant risks to both those inside the vehicle and the surrounding infrastructure. In 2019 alone, the National Fire Protection Association (NFPA) recorded about 212,500 highway vehicle fires in the United States, leading to 560 civilian deaths and roughly $1.3 billion in property damage. These alarming numbers highlight the urgent need for better fire prevention and detection systems in vehicles, as these incidents continue to threaten public safety and property.

Despite progress in fire detection technology, the systems currently used in vehicles often fall short of meeting the specific challenges of the automotive environment. For example, traditional smoke detectors might not be sensitive enough to detect the early signs of a fire in a vehicle's engine compartment or interior. Moreover, factors unique to vehicles—like engine vibrations, varying temperatures, and confined spaces—require specialized detection mechanisms that traditional systems can't handle effectively. This gap underscores the need for more advanced and tailored solutions that can address these challenges and provide timely warnings to prevent fires from escalating.

Recent research is focused on developing innovative solutions to overcome the limitations of current vehicle fire detection systems. One promising direction is the use of Internet of Things (IoT) and Machine Learning (ML) technologies. IoT-based sensor networks can monitor various factors, such as smoke, temperature, and vibrations, in real time, providing continuous data that ML algorithms can analyze to predict potential fires before they happen. These systems can learn and adapt over time, improving their accuracy and enhancing overall fire detection capabilities, potentially saving lives.

Beyond just detecting fires, research has also explored the development of advanced alert systems to notify drivers and emergency services of potential fire hazards. These systems can be customized to the driver's specific situation, providing timely and relevant information that improves safety and reduces response times. By delivering critical alerts when and where they're needed most, these systems can play a key role in preventing vehicle fires and minimizing their impact.

Vehicle fires can be triggered by various issues, including electrical faults, fuel leaks, and engine malfunctions. The consequences of these fires extend far beyond immediate loss of life and property, causing significant traffic disruptions, environmental pollution, and considerable economic costs. Therefore, preventing and mitigating vehicle fires is crucial not only for individual safety but also for the broader well-being of communities and the environment. By addressing the shortcomings of current fire detection systems and adopting innovative technologies, the automotive industry can make significant progress in improving vehicle safety and protecting lives.

1.2 Research Gap

Despite the advancements in vehicle safety systems, significant gaps remain in the effective detection and prevention of vehicle fires. Traditional fire detection systems, primarily relying on smoke or heat sensors, often detect fires only after they have reached a critical stage. This reactive approach limits the ability to prevent damage, injuries, or fatalities. Additionally, most existing systems are designed for static environments, such as buildings or industrial spaces, and are not well-suited for the dynamic and confined conditions inside vehicles. This creates a pressing need for innovative solutions specifically tailored to the automotive environment.

Another major gap lies in the integration of predictive analytics with fire detection systems. While IoT devices and sensors are increasingly being used for real-time monitoring, their capabilities are often underutilized due to the lack of robust predictive models. Current vehicle systems rarely leverage advanced machine learning techniques, such as Convolutional Neural Networks (CNNs), to analyze complex patterns in sensor data. Without predictive capabilities, systems are unable to identify fire risks in their early stages, leading to delays in alerting vehicle owners or emergency responders.

Furthermore, many existing systems lack seamless communication between users and emergency services. While some fire detection systems can trigger alarms, they fail to provide detailed, actionable insights or transmit precise location data to fire departments. This limitation can result in delayed emergency response times and increased damage. The absence of real-time, automated alerts that incorporate vehicle-specific details further exacerbates this problem, leaving users with inadequate tools to respond effectively during critical situations.

The research also highlights a gap in user engagement and accessibility in existing vehicle safety systems. Mobile applications, which have become a standard interface for many IoT solutions, are either absent or underdeveloped in current fire detection systems. This limits the ability of vehicle owners to interact with the system, monitor vehicle conditions remotely, or receive timely alerts. A lack of intuitive and user-friendly interfaces reduces the overall effectiveness and adoption of such safety systems.

Additionally, scalability and adaptability remain unaddressed in most current solutions. Fire detection systems are often rigidly designed, making them unsuitable for a wide range of vehicle types or evolving technological advancements. The inability to integrate new sensors, update predictive models, or expand system capabilities restricts the long-term applicability of these systems.

The Flarepath vehicle fire detection and response system addresses these critical gaps by combining IoT technologies, predictive analytics, and user-centered design. Unlike traditional systems, Flarepath employs advanced CNN models to analyze sensor data in real time, enabling early detection of fire risks. The system also bridges the communication gap by sending detailed alerts with GPS-enabled location data to both users and emergency responders, ensuring a swift and coordinated response. Through its mobile application, Flarepath provides an intuitive platform for users to monitor their vehicles, receive alerts, and take proactive measures. Its modular and scalable architecture allows for seamless integration of additional features, ensuring adaptability to future needs.

By addressing these research gaps, Flarepath not only improves vehicle fire detection and response but also sets a new standard for proactive safety systems in the automotive industry. This innovation has the potential to significantly reduce vehicle fire-related incidents, safeguard lives, and minimize environmental and economic losses

1.3 RESEARCH PROBLEM

Vehicle fires represent a significant safety hazard, posing risks to passengers, vehicles, and the environment. Despite advancements in vehicle technology, fire detection and prevention systems remain insufficient, leading to delayed responses, substantial property damage, injuries, and even loss of life. The current systems deployed in vehicles rely heavily on traditional reactive approaches, such as smoke or heat detection, which are often incapable of identifying potential fire risks at an early stage. This delayed detection significantly limits the ability to prevent or mitigate the impacts of vehicle fires, highlighting a critical gap in safety technologies.

One of the primary challenges with existing systems is their inability to function effectively within the dynamic and confined environment of a vehicle. Vehicles, unlike static spaces such as buildings or industrial facilities, are subject to constant movement, vibration, and rapidly changing conditions. These factors make it difficult for traditional fire detection systems to operate reliably. False alarms and missed detections are common, reducing user trust and the overall effectiveness of the systems. Additionally, in the confined space of a vehicle, fires can escalate rapidly, leaving occupants with minimal time to respond, thus amplifying the potential danger.

Another significant issue is the lack of integration between IoT technologies and predictive analytics in existing fire detection systems. While IoT devices, such as sensors for temperature, gas levels, and flame detection, are becoming more prevalent in automotive applications, their full potential is not being utilized. Current systems primarily focus on real-time data collection but fail to incorporate advanced predictive models, such as machine learning algorithms, to analyze this data comprehensively. Without the ability to predict fire risks based on patterns and anomalies in the data, existing systems remain reactive, rather than proactive, which limits their ability to provide timely warnings or prevent incidents altogether.

The absence of effective communication and alert mechanisms further exacerbates the problem. Many existing systems fail to provide actionable information to users or emergency responders in a timely manner. Alerts are often limited to basic notifications, such as triggering an alarm or a warning light, without conveying critical details like the vehicle's real-time location, fire type, or severity. This lack of detailed and automated alerts delays emergency response times, reduces the effectiveness of interventions, and increases the risk of severe outcomes. Additionally, the lack of seamless communication between the vehicle, users, and emergency responders creates a significant gap in coordination during critical incidents.

The user experience and accessibility of current systems also present a major problem. Many existing fire detection systems lack intuitive interfaces that enable users to interact with and understand the system effectively. Features such as remote monitoring, real-time updates, and detailed alerts are often missing, reducing user engagement and adoption. Furthermore, these systems frequently fail to provide mobile application integration, limiting the user's ability to stay informed and act promptly, particularly when away from the vehicle.

Scalability and adaptability also remain unaddressed in most existing solutions. Current fire detection systems are often rigidly designed, making them unsuitable for a wide variety of vehicle types and operational environments. They are rarely built to accommodate technological advancements, such as the integration of additional sensors or the inclusion of updated predictive models. This lack of flexibility restricts their long-term applicability and discourages widespread adoption, particularly by fleet operators and automotive manufacturers seeking customizable solutions.

The environmental and economic impact of vehicle fires further highlights the gravity of this issue. Fires not only result in significant damage to vehicles and surrounding property but also contribute to air pollution through the release of harmful gases and particulates. Insurance claims related to vehicle fires also impose a financial burden on both individuals and companies, emphasizing the need for a preventive system that can mitigate these risks effectively.

The research problem, therefore, centers on the need to develop an advanced, scalable, and user-friendly vehicle fire detection and response system that addresses these critical gaps. Such a system must leverage IoT technologies to provide continuous monitoring, integrate predictive analytics to identify risks early, and incorporate real-time communication to ensure timely alerts and coordination with emergency responders. Additionally, it must be designed to adapt to diverse vehicle types and evolving safety requirements, ensuring long-term relevance and effectiveness.

By addressing this research problem, the Flarepath system aims to bridge the gap between traditional reactive fire detection methods and proactive, technologically advanced solutions. This innovative approach has the potential to not only improve vehicle safety and reduce fire-related incidents but also set new standards in the automotive safety industry, protecting lives, property, and the environment.

1.4 OBJECTIVES

1.4.1 Main Objectives

The primary objective of the Flarepath vehicle fire detection and response system is to provide a reliable, scalable, and efficient solution for early fire detection, real-time monitoring, and rapid emergency response in vehicles. The system aims to leverage advanced technologies such as IoT (Internet of Things), machine learning, and mobile application development to proactively identify potential fire hazards and ensure the safety of passengers, vehicles, and surrounding environments.

By integrating a network of sensors—including temperature, gas, and flame detection sensors—along with a predictive Convolutional Neural Network (CNN), the system seeks to monitor the vehicle's environment continuously and accurately. The core objective is to identify anomalies that indicate a fire risk and provide timely, actionable alerts to users and emergency responders, minimizing potential damage and preventing loss of life.

The Flarepath system also focuses on improving the efficiency of emergency response by incorporating GPS technology to share precise location details with the nearest fire department. The objective is to reduce response times and enhance coordination during critical incidents by automating the communication process, ensuring responders are well-informed before arriving at the scene.

A key aspect of the system's objective is to ensure user accessibility and engagement through a user-friendly mobile application. The app facilitates seamless interaction with the system, enabling users to monitor their vehicles, receive alerts, and manage their profiles effortlessly. The integration of cloud-based services and Bluetooth Low Energy (BLE) ensures real-time data synchronization and local connectivity, making the system functional in both urban and remote areas.

Furthermore, the system is designed with scalability and modularity in mind. Its objective is to create a future-proof solution that can adapt to evolving safety requirements, incorporate new technologies, and cater to diverse vehicle types. By allowing for easy upgrades and the addition of new features, the system aims to remain relevant and effective in the long term.

In summary, the Flarepath system's main objective is to revolutionize vehicle safety by combining cutting-edge technology, real-time analytics, and user-focused design. It aims to prevent fire-related incidents proactively, enhance emergency response efficiency, and provide peace of mind to vehicle owners, setting a new standard for safety systems in the automotive industry.

1.4.2 Specific Objectives

- Develop and refine machine learning (ML) algorithms specifically designed for vehicle fire prediction. These algorithms will analyze data from various sensors to identify patterns that could signal potential fire risks before they materialize. The goal is to create highly accurate predictive models that can differentiate between normal operational conditions and those that may indicate an imminent fire threat.
- Create a robust real-time data processing system capable of efficiently handling and analyzing the vast amount of data generated by the sensors installed in vehicles. This system will be designed to enable immediate responses to predicted fire threats, ensuring that potential incidents are addressed proactively to prevent escalation.
- Develop an alert mechanism that consolidates data from multiple sensors, continuously monitoring their performance to ensure accurate and timely prediction of potential fire hazards. This mechanism will be designed to minimize false alarms while maximizing the reliability of fire predictions.
- Employ ML algorithms for predictive analysis, allowing the system to learn from historical data. This will enable the continuous improvement of the system’s ability to predict and prevent potential fire incidents, enhancing its overall effectiveness over time.
- Develop a system that provides customized alerts to drivers based on real-time

sensor data. These alerts will be tailored to the specific circumstances of each situation, ensuring that drivers receive timely and relevant information to enhance their safety and improve their response times in the event of a predicted fire hazard.

- Implement protocols for the ongoing monitoring and maintenance of the sensor system to ensure optimal performance and reliability. This will involve regular checks and updates to the system to address any potential issues and maintain its effectiveness in predicting potential fire risks.
- Integrate various types of sensors, including smoke, temperature, and vibration sensors, into a comprehensive and highly accurate fire prediction system for vehicles. This integration will allow for a multi-faceted approach to fire prediction, ensuring that no potential fire hazard goes undetected.
- Create advanced algorithms that not only analyze sensor data but also incorporate vehicle data, such as speed and engine status, to improve the accuracy of fire prediction and prevention. These algorithms will ensure that the fire prediction system is context-aware, taking into account the full range of factors that could contribute to a fire hazard in a vehicle.

2 METHODOLOGY

The methodology for developing the vehicle fire prediction system followed a structured and iterative process designed to ensure the system's effectiveness and reliability. The project began with an in-depth requirement gathering and analysis phase, during which the specific needs for sensor types, real-time data processing, and predictive capabilities were carefully identified. This phase was crucial in setting a solid foundation for the project, as it involved understanding the critical parameters that needed to be monitored, such as temperature, smoke levels, and vehicle vibrations, as well as determining the most suitable technologies to meet these needs.

With the requirements clearly defined, the next step involved the selection of appropriate technologies. IoT technologies were chosen to enable the continuous monitoring of vehicle conditions, while Machine Learning algorithms were selected for their analytical power to predict potential fire hazards based on the collected data. The integration of these technologies was pivotal to the system’s ability to provide real-time monitoring and accurate predictions, which are essential for early intervention and fire prevention.

The development of the system was carried out using an agile methodology, which allowed for flexibility and continuous improvement throughout the project. The project was divided into sprints, each focusing on different aspects of the system, such as sensor integration, algorithm development, and testing. This approach ensured that each component was developed and refined in a step-by-step manner, allowing the team to address any challenges as they arose and make necessary adjustments along the way.

A significant part of the development process involved extensive data collection from the installed sensors. This data was essential for training the Machine Learning models, allowing them to accurately identify patterns and predict potential fire hazards. Continuous testing was conducted throughout the project to ensure that the system met the required safety and performance standards. This included rigorous testing under various environmental conditions to validate the system’s robustness and reliability in real-world scenarios.

The iterative nature of the agile methodology facilitated ongoing refinements and adaptations, ensuring that the system remained both robust and responsive to real-world conditions. By continuously revisiting and improving each aspect of the system, the development process not only met the initial project objectives but also enhanced the system's overall effectiveness, ultimately leading to a reliable and innovative vehicle fire prediction system.

2.1 System Architecture

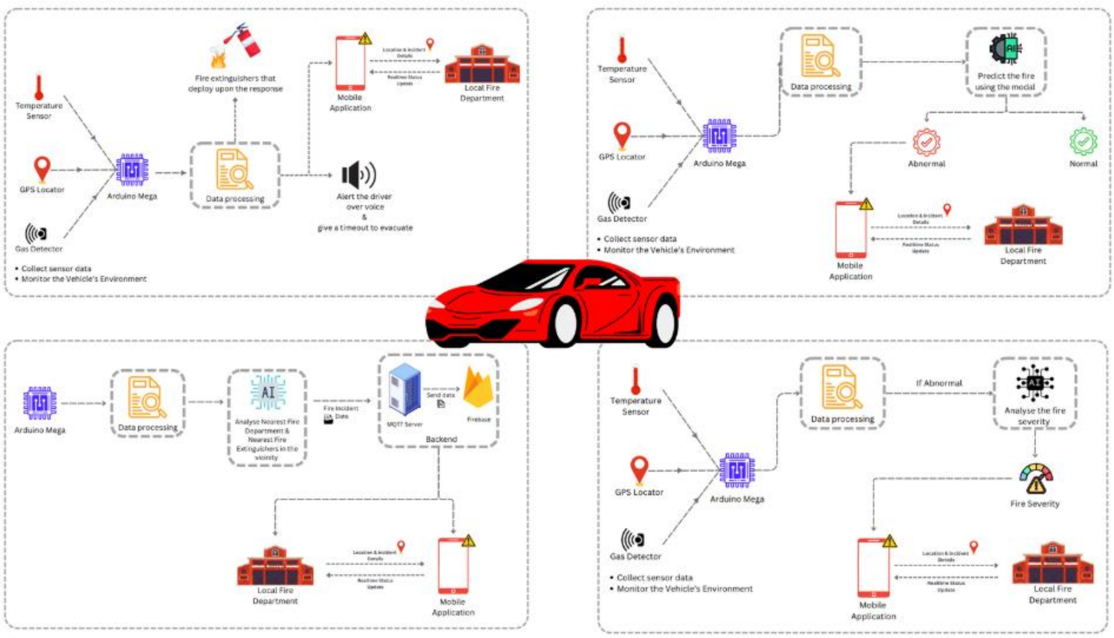


Figure 1 System Architecture Diagram

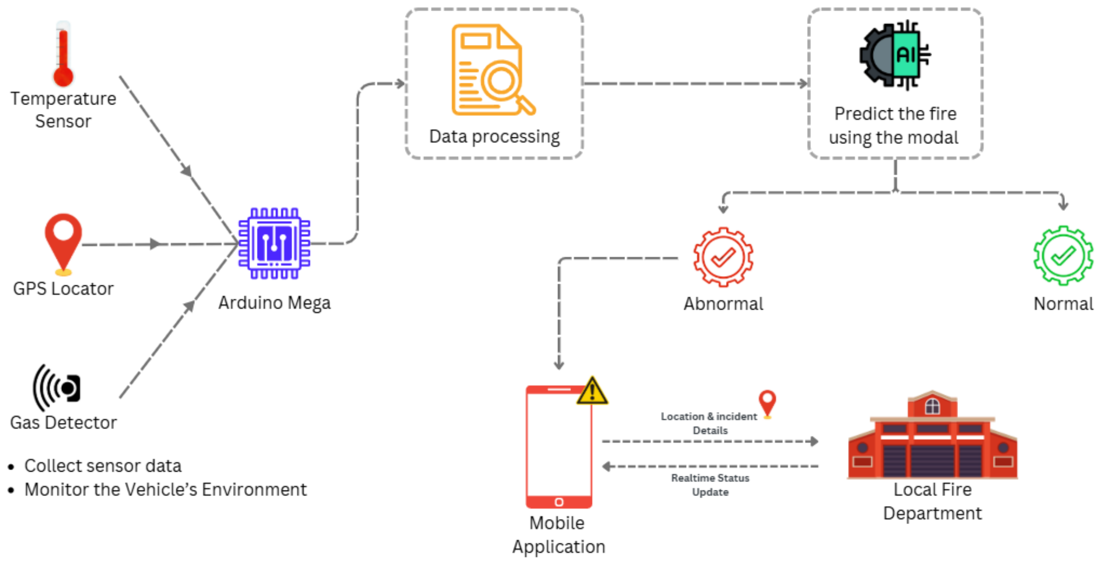


Figure 2 Component Architecture Diagram

The system architecture represents an intelligent vehicle fire detection and response solution, designed to ensure safety by integrating IoT sensors, AI-based analytics, and real-time communication with users and emergency services. It begins with data collection from three key components: a temperature sensor monitors the vehicle's internal temperature to identify overheating or fire risks, a gas detector detects hazardous gases that may signal combustion or fire-related incidents, and a GPS locator provides real-time vehicle location data to assist in navigation and emergency response. These sensors continuously collect environmental data and transmit it to the central processing unit for analysis.

At the core of the system is the Arduino Mega microcontroller, which acts as the data processing unit. It aggregates sensor inputs, performs initial data analysis, and continuously monitors the vehicle's environment. The processed data is then sent to an AI-powered predictive model for advanced analysis. This model utilizes machine learning algorithms trained on historical data to predict fire risks based on sensor readings. If the environment is classified as normal, no further action is taken. However, if an abnormality is detected, such as a potential fire, the system immediately triggers an alert and initiates the emergency response process.

Once a fire risk is identified, the system communicates with a mobile application that serves as the primary user interface. The app notifies users of the detected hazard, providing critical information such as the vehicle's real-time location, the type of abnormality detected, and potential risks. It also delivers real-time status updates as the situation evolves, ensuring that the user is well-informed at every stage. Simultaneously, the system alerts the nearest local fire department, transmitting the vehicle's location and incident details. This enables emergency responders to act swiftly and efficiently, reducing the time needed to address the situation.

The system's integration of sensors, predictive analytics, and communication ensures comprehensive safety and rapid response. By continuously monitoring the vehicle's environment, leveraging AI for accurate fire risk detection, and facilitating seamless communication between users and emergency responders, the system minimizes risks, enhances safety, and reduces potential damage from fire-related incidents. This innovative architecture demonstrates the power of combining IoT and AI technologies to create a reliable and effective fire detection and response system.

2.1.1 Software methodology

1. Agile Development Approach

The software development process is structured using the Agile methodology to ensure flexibility, iterative progress, and rapid response to changes. The project is divided into short, time-boxed sprints, each focusing on specific deliverables such as sensor integration, data processing, and user interface development. Agile allows for constant feedback from stakeholders, including automotive engineers and safety experts, enabling the team to identify and resolve issues early. This iterative approach ensures incremental improvements in system functionality and aligns the system with real-world requirements.

2. Requirements Gathering and Analysis

The first phase of the software methodology involves an in-depth analysis of system requirements. Collaborating with stakeholders, the team identifies functional needs such as real-time data collection, predictive analytics, and alert mechanisms. Non-functional requirements such as system reliability, low latency, and user-friendliness are also documented. These requirements serve as the foundation for designing and implementing the system. Special emphasis is placed on defining sensor data parameters (temperature, smoke levels, vibrations) and ensuring compatibility with the vehicle's dynamic environment.

3. Modular Software Architecture

To enhance scalability and maintainability, the system is designed with a modular architecture. Each module operates independently and is integrated into the overall system during later stages.

The key modules include:

- Sensor Integration Module: Interfaces with IoT sensors to collect environmental data, including temperature, gas levels, and GPS coordinates.
- Data Processing Module: Preprocesses raw sensor data, removes noise, and formats it for predictive analysis.
- Predictive Analytics Module: Employs Machine Learning algorithms to detect fire hazards based on historical patterns and real-time inputs.

- Alert and Notification Module: Sends notifications to the mobile application and emergency services when abnormal conditions are detected.
- User Interface Module: Provides a user-friendly interface for drivers to view alerts and status updates in real time.
- The modular approach ensures that individual components can be updated or replaced without affecting the entire system, promoting flexibility and adaptability.

4. Technology Selection

Careful selection of tools and technologies ensures that the system meets its objectives. The programming languages used include Python for Machine Learning development and C/C++ for hardware integration with the Arduino Mega microcontroller. TensorFlow or PyTorch frameworks are used for building and training predictive models. Firebase is employed for cloud-based data storage, while React Native is chosen for developing the mobile application to ensure cross-platform compatibility. Additionally, MQTT or HTTP protocols are used for efficient real-time data transmission between sensors and the cloud.

5. Development Process

The software development phase follows the principles of Agile. Each module is developed and tested independently before integration. The process begins with the creation of flowcharts, system diagrams, and database schemas. Developers use version control systems (e.g., Git) to manage the codebase efficiently and enable collaborative work. The system is developed iteratively, allowing for incremental improvements and the addition of new features based on feedback from stakeholders.

6. Testing Methodology

Testing is a critical component of the software methodology and is performed at multiple levels:

- Unit Testing: Each module, such as the sensor integration module and predictive analytics module, is tested individually to verify its functionality.

- Integration Testing: Ensures seamless communication between modules, such as data transfer from sensors to the analytics engine.
- System Testing: Evaluates the entire system under real-world conditions, including fluctuating temperatures and vibrations, to validate its robustness.
- Performance Testing: Assesses the system’s ability to handle real-time data streams without delays or failures.
- User Acceptance Testing (UAT): Engages end-users to evaluate the system's usability and effectiveness, incorporating their feedback to refine the user interface and alert mechanisms.
- Security Testing: Ensures that sensitive data collected by the system is encrypted and protected from unauthorized access, maintaining the system's integrity.

7. Deployment and Pilot Testing

The deployment phase begins with a pilot deployment in a controlled environment, such as a small fleet of vehicles, to validate the system’s performance. This phase helps identify potential issues and allows for quick troubleshooting. After successful pilot testing, the system is rolled out on a larger scale, integrating it into various types of vehicles. Installation includes configuring sensors, connecting to cloud services, and testing real-time alerts.

8. Continuous Monitoring and Maintenance

Post-deployment, the system undergoes continuous monitoring to ensure it operates as expected. Regular maintenance protocols are implemented, including recalibration of sensors and updates to the Machine Learning algorithms. Continuous monitoring involves collecting new data to refine the predictive models and enhance the system’s accuracy. A feedback mechanism is also in place to gather input from users and stakeholders, ensuring the system evolves to meet changing requirements.

9. Security and Data Integrity

Given the critical nature of the system, robust security measures are implemented. All data collected from sensors and transmitted to the cloud is encrypted using SSL/TLS protocols. Access control mechanisms are established to prevent unauthorized access to the system. Regular security audits are conducted to identify and mitigate vulnerabilities, ensuring the system remains secure and reliable over time.

10. Tools and Technologies

The following tools and technologies are integral to the development process:

- Arduino IDE: For programming and integrating hardware components.
- TensorFlow/PyTorch: For building and training Machine Learning models.
- Firebase: For real-time data storage and analytics.
- React Native: For developing a responsive, cross-platform mobile application.
- Git: For version control and collaborative software development.
- MQTT/HTTP: For efficient real-time communication between components.

2.1.2 Technologies

1. Microcontroller and Embedded Systems

- Arduino MEGA Microcontroller: Acts as the central processing unit to handle sensor data, execute control logic, and manage communication between hardware components.
- ESP32 Microcontroller: Features integrated Wi-Fi and Bluetooth capabilities, enabling real-time data processing, wireless communication, and connectivity with cloud services and mobile devices.

2. Sensors and Hardware Components

- Flame Detection Sensor: Infrared-based sensors capable of detecting specific wavelengths emitted by flames, triggering the fire suppression system.

- Temperature Sensor (MAX6675): Digital temperature sensor that accurately monitors ambient temperature to identify potential fire conditions.
- Gas Detector (MQ-2): Semiconductor-based sensor that detects smoke or hazardous gases, transmitting analog signals to the Arduino MEGA for further analysis.

3. Communication and Networking

- Wi-Fi Module (ESP32): Built-in Wi-Fi capability within the ESP32 microcontroller facilitates wireless communication with cloud platforms for remote monitoring and control.
- Bluetooth (BLE): Integrated in the ESP32 for local communication with mobile devices, enabling power-efficient real-time alerts and control operations.

4. Mobile Application Development

React Native Framework: Used for developing cross-platform mobile applications for Android and iOS. These responsive, native-like apps interface with the fire detection system to deliver real-time alerts and enable system control.

2.2 Commercialization of the Product

The Flarepath vehicle fire detection and response system has a well-thought-out plan for commercialization, aimed at turning this innovative technology into a product that is accessible, scalable, and practical for various users. The system is designed to meet the needs of individual vehicle owners, fleet operators, and automotive manufacturers, making it suitable for a wide range of applications. By addressing the safety challenges faced by the automotive industry, Flarepath offers a proactive and reliable solution for fire detection and emergency response.

The target market for Flarepath includes three primary groups. First, individual vehicle owners who are looking for an advanced safety system to protect their vehicles and passengers. Second, fleet operators, such as logistics companies, ride-sharing services, and public transportation providers, who need a scalable solution to monitor and protect multiple vehicles. Third, automotive manufacturers that aim to integrate innovative safety features into their vehicles as part of their product offerings. This wide range of potential customers ensures that Flarepath can cater to both personal and commercial needs.

To make the product accessible to different customer groups, Flarepath uses a flexible pricing model. Individual users can pay a one-time fee for hardware installation, combined with a subscription for mobile app access and cloud-based services. Fleet operators can benefit from volume-based pricing, with options for centralized monitoring and custom reports. Automotive manufacturers can partner with Flarepath through licensing agreements, allowing them to integrate the system directly into new vehicles as a built-in feature. This tiered pricing ensures affordability for individuals and high value for businesses.

Flarepath stands out in the market due to its unique features. It combines advanced predictive analytics using a Convolutional Neural Network (CNN) for early fire detection with real-time data monitoring from sensors such as temperature and gas detectors. The system sends automated alerts to users and fire departments, complete with GPS-based location tracking, ensuring timely responses. Its modular design allows for customization, making it adaptable to different vehicle types and industries. The user-friendly mobile app enhances the overall experience by offering features such as live monitoring, vehicle management, and instant notifications.

The market entry strategy is divided into phases to ensure a smooth launch. Initially, the product will be deployed in a pilot program targeting fleet operators and early adopters. This phase will help gather feedback and refine the product. Following the pilot, the system will expand to broader regions, focusing on high-density automotive markets. Partnerships with automotive manufacturers, insurance companies, and vehicle service providers will play a critical role in creating bundled offerings and expanding the customer base. The product will be made available through both business-to-business (B2B) channels, such as fleet management companies, and direct-to-consumer (B2C) channels, including online platforms and automotive retailers.

To create awareness and build trust, marketing efforts will focus on safety-conscious customers. Digital marketing campaigns will highlight the benefits of Flarepath, while demonstrations at industry events and trade shows will showcase its capabilities. Testimonials and real-world success stories will be used to build credibility, and collaborations with insurance providers will offer added value by reducing insurance premiums for vehicles equipped with Flarepath.

The production plan ensures scalability to meet growing demand. The hardware components, including sensors and microcontrollers, will be sourced from trusted suppliers to maintain quality while keeping costs low. The system's cloud infrastructure, powered by Firebase, will handle large-scale data processing and storage, ensuring reliability even with a large user base. Ongoing customer support and regular software updates will ensure that users experience a reliable and evolving product.

The commercialization plan also emphasizes social and environmental impact. Flarepath contributes to safety by reducing fire-related accidents and fatalities, as well as lowering the financial burden of repairs and insurance claims. It also minimizes environmental damage by preventing vehicle fires, which can release harmful pollutants. These broader benefits position Flarepath as a product that not only serves individual users but also contributes to the greater good.

In summary, Flarepath's commercialization strategy is built on accessibility, scalability, and addressing real-world safety challenges. By offering a reliable, user-friendly solution that caters to both individual and commercial markets, Flarepath has the potential to make a significant impact on vehicle safety while ensuring its sustainability as a market-ready product.

2.3 Testing & Implementation

The testing and implementation phase of the Flarepath vehicle fire detection and response system was carefully planned to ensure that it operates reliably, accurately, and integrates smoothly into vehicle environments. This process involved testing both hardware and software components extensively under various simulated and real-world conditions to validate their performance. The testing began with Unit Testing, where each individual component, such as the MAX6675 temperature sensor, MQ2 smoke sensor, solenoid valve, Ublox NEO-6M GPS module, and Arduino MEGA microcontroller, was tested independently. This step ensured that every module worked as expected before moving on to the next stage.

After successful unit testing, Integration Testing was conducted to verify that all components functioned cohesively. This stage focused on ensuring that sensors correctly sent data to the microcontroller, the microcontroller processed the data accurately, and the predictive algorithms could utilize this information for decision-making. The integration also confirmed smooth communication with the mobile application and the cloud server. Next, System Testing evaluated the fully assembled system in realistic conditions, such as fluctuating temperatures, vibration levels, and humidity, to ensure it could handle the challenges of the vehicle environment.

Performance Testing focused on the system's responsiveness and stability when processing continuous real-time data streams from multiple sensors. This testing ensured that the system could generate timely alerts without delays or failures. User Acceptance Testing (UAT) involved actual drivers and vehicle operators interacting with the system to determine whether it met their expectations. Feedback from UAT was used to refine the mobile application's interface, make alerts more intuitive, and improve the overall user experience. Additionally, Security Testing ensured that all data collected, processed, and transmitted by the system was securely stored and safeguarded from unauthorized access.

The implementation phase followed a structured approach, starting with a Pilot Deployment where the system was installed in a small number of vehicles to observe its performance and quickly address any issues. After refining the system based on pilot results, it proceeded to Full-Scale Deployment, where it was rolled out across a broader range of vehicles. This included installing sensors, configuring the software, and integrating the system with existing vehicle systems. To ensure a smooth adoption, comprehensive Training and Support were provided to operators and maintenance personnel. Training sessions covered how to operate the system, understand alerts, and perform basic troubleshooting.

Post-deployment, the system was subjected to Continuous Monitoring and Maintenance. Regular updates were applied to algorithms to improve predictive capabilities, and sensors were checked and recalibrated to maintain accuracy. Data collected during regular operations was analyzed to identify opportunities for further refinement. User feedback also played a vital role in identifying areas for improvement, leading to iterative updates that ensured the system stayed effective over time. This thorough process guaranteed that Flarepath is a robust, reliable, and responsive vehicle fire detection and response solution, ready to perform in real-world scenarios.

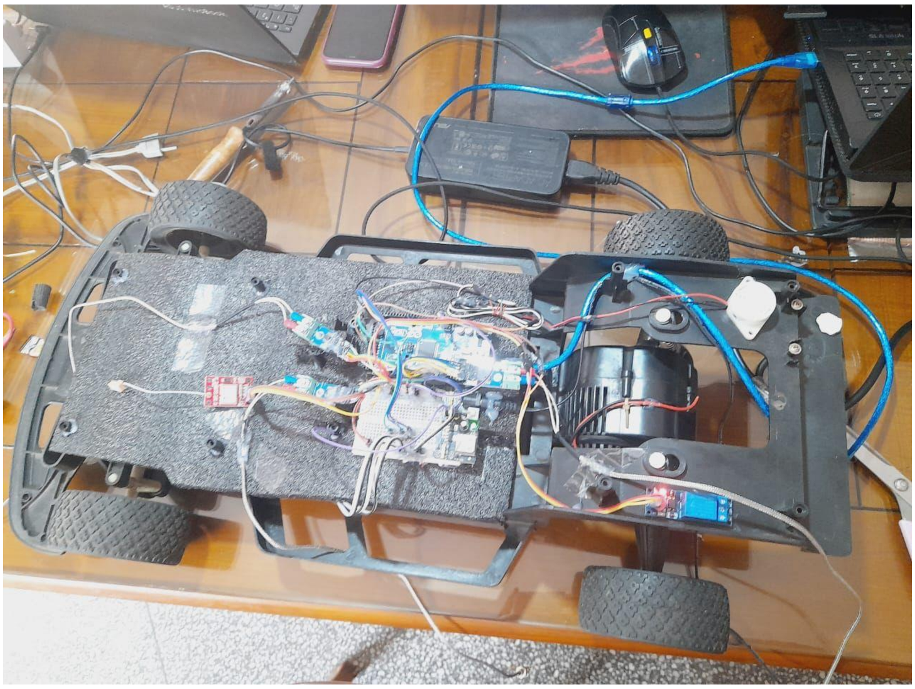


Figure 3 Integration of all hardware components

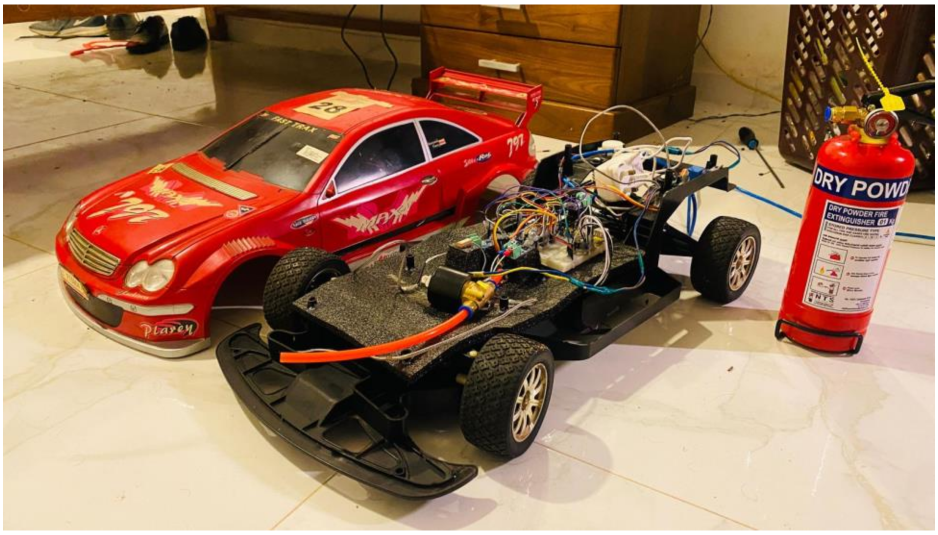


Figure 4 Integration of all hardware components

Software Development:

The software development for the Flarepath vehicle fire detection and response system focused on creating an integrated solution that combines IoT connectivity, machine learning models, and a mobile application to enable efficient fire detection and alert mechanisms. At the core of the system is a Convolutional Neural Network (CNN), which was designed and trained to predict fire risks accurately using simulated datasets. The CNN was implemented using Python and TensorFlow, leveraging its ability to process complex patterns in the data collected from sensors such as temperature sensors, gas detectors, and flame detection sensors. The model was optimized during the development phase to ensure accurate and reliable detection of potential fire hazards, even though real-time datasets were unavailable.

The system's hardware relied on the Arduino MEGA microcontroller, which was programmed to interface with multiple sensors. The microcontroller aggregated sensor data, including temperature readings, gas concentrations, and GPS coordinates. This data was then processed locally and transmitted to the backend system for further analysis. The Arduino MEGA served as the central processing hub for all sensor inputs, ensuring the system maintained consistent performance and functionality.

The mobile application, developed using React Native, acted as the main user interface for the system. It provided functionalities such as vehicle registration, live monitoring of environmental data, and real-time alerts for fire risks. The app displayed critical information, including the vehicle's current location, temperature readings, and identified fire risks. Additionally, the app facilitated communication with the nearest fire department by sharing the vehicle’s GPS location and fire-related details, enabling faster emergency responses. Designed with a clean and intuitive interface, the app ensured ease of use for vehicle owners.

The system’s backend utilized Firebase Cloud Firestore as the central repository for storing sensor data, vehicle details, and user information. Firebase enabled real-time synchronization between the IoT devices and the mobile application, ensuring that users received timely updates about their vehicle's status. Although real-time datasets were not gathered during development, the infrastructure was designed to handle and process incoming data efficiently when the system was fully operational.

The software was built with a modular architecture, allowing for scalability and flexibility. New features, sensors, or functionalities can be integrated into the existing system without disrupting core operations. This modular approach ensures the system can adapt to future enhancements and evolving safety needs. The combination of robust machine learning algorithms, reliable IoT integration using Arduino MEGA, and a user-friendly mobile application resulted in a highly effective vehicle fire detection and response system. This development approach ensures that Flarepath can detect fire risks efficiently, alert users in a timely manner, and facilitate swift intervention for improved vehicle safety.

Back			Front			Mid			Back			Front			Mid		
sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3
26.87	26.87	35.95	29.37	29.5	29.25	29.97	29.45	34.91	25.15	29.13	28.99	46.56	37.4	39.76	25.62	29.67	29.15
31.05	27.5	36.84	29.37	29.25	35.62	30.31	30.84	36.23	27.5	29.13	25.35	43.43	42.54	44.16	26.28	26.32	28.92
32.36	36.34	26.39	32.47	32.48	29.37	38.37	33.6	37.65	25.35	26.45	28.45	39.88	44.14	48.39	28.2	28.06	25.21
38.53	29.08	36.84	30.34	29.84	29.08	29.97	29.45	34.91	27.84	27.68	25.14	43.51	47.77	43.32	28.91	28.95	30
28.59	27.4	34.14	32.57	36.39	35.02	33.14	26.2	38.99	29.22	28.79	25.32	38.5	44.25	43.55	29.96	28.4	29.44
28.83	35.63	30.6	34.17	34.78	31.92	38.98	26.15	31.54	25.33	26.58	26.72	40.95	49.72	38.21	29.26	31.45	30.68
26.84	27.37	27.18	34.39	33.3	33.68	38.98	39.17	32.16	25	26.58	25.91	49.34	39.68	39.91	25.81	30.87	31.31
29.93	36.52	33.11	35.19	34.99	29.69	33.93	39.92	32.68	28.73	26.76	25.36	40.54	43.85	41.86	27.64	26.54	28.53
29.71	38.2	35.67	33.29	34.99	36.8	37.03	26.11	32.71	27.74	27.63	27.34	40.96	44.01	44.81	25.94	25.12	31.38
27.85	29.14	39.84	31.11	30.05	30.17	37.67	32.32	31.85	27.51	27.35	28.6	42.81	39.21	49.87	28.37	29.87	30.49
31.39	36.31	37.57	36.8	36.59	34.14	32.63	30.97	29.26	29.64	25.13	26.48	45.8	38.39	44.09	26.43	28.55	26.67
31.37	35.14	33.07	34.48	33.96	32.65	32.93	36.87	36.54	27.01	26.63	28.79	44.75	40.68	38.8	29.31	26.15	25.86
32.6	32.43	33.85	34.62	29.25	30.94	35.94	35.07	39.03	29.95	25.8	26.21	44.81	39.73	38.29	30.64	31	27.29
35.98	33.1	26.86	33.97	30.39	33.55	37.35	33.3	36.26	29.03	29.57	25.26	44.2	38.57	47.74	25.26	25.52	30.89
34.17	39.58	28.46	33.88	36.04	35.77	28.71	27.28	37.88	28.53	26.13	29.49	41.54	38.08	42.36	25.14	31.9	27.8
31.8	37.49	34.91	36.51	31.14	29.06	35.36	34.87	33.23	26.42	27.82	26.9	43.3	48.17	43.43	28.32	28.86	31.37
38.04	32.59	37.42	36.58	31.58	31.72	39.94	29.75	31.71	25.55	29.62	27.81	41.13	45.28	47.59	26.13	27.22	30.15
35.1	33.19	38.1	31.09	32.73	35.68	28.73	29.77	35.17	29.5	26.27	25.17	42.89	38.82	40.5	26.17	29.96	27.81
26.65	29.32	33.06	33.92	31.22	33.46	37.01	26.37	30.22	25.51	27.74	28.24	45.14	43.47	39.3	26.79	26.25	29.59
39.57	30.56	28.21	36.78	30.57	32.71	37.98	32.4	39.15	25.83	27.25	26.85	43.16	42.77	42.63	27.07	29.62	27.89
34.83	35.37	34	29.35	31.4	31.14	29.58	29.61	39.13	27.83	27.1	27.92	42.39	37.31	47.42	27.25	28.93	26.82
27.78	36.27	27.31	33.88	32.85	36.39	29.35	35.93	29.71	29.62	28.63	25.62	41.14	47.21	45.03	27.15	31.8	25.84
34.88	31.69	35.69	30.32	30.51	34.86	30.11	32.58	37.86	29.38	27.49	27.88	47.83	39.09	41.16	29.36	28.64	31.87
39.15	29.77	36.96	32.41	33.21	32.14	37.79	36.71	32.36	25.96	25.1	28.23	39.44	38.78	43.13	30.41	26.18	26.28
32	35.18	33.04	32.38	31.72	34.41	35.44	28.55	30.82	27.37	27.34	28.27	48.09	48.31	46.52	26.03	30.93	31.61
26.26	32.45	36.26	35.88	35.4	34.65	38.08	34.27	37.6	29.16	28.16	26.47	41	47.19	40.62	28.99	29.63	29.26
30.13	33.09	31.52	33.2	32.55	30.11	32.27	28.24	29.12	29.39	28.86	26.71	49.47	46.44	46.5	26.55	25.06	25.86
36.81	36.68	34.35	30.48	33.48	35.29	31.23	39.26	34.24	27.85	26.99	29.56	44	45.81	47.63	30.23	25.22	28.09
39.16	35.82	36.35	31.71	32.21	34.07	31.34	29.58	30.64	25.45	27.88	29.68	42.97	38.29	40.48	29.79	31.37	31.32
37.34	33.99	31.19	29.4	33.98	33.2	31.75	33.07	34.64	29.08	27.89	26.8	42.81	45.31	49.65	25.28	28.56	27.31
32.74	27.76	33.99	30.89	36.98	34.77	33.83	38.79	38.08	27.75	28.04	26.31	42.85	44.05	40.24	26.51	25.3	31.58
32.99	32.18	38.3	32.07	34.42	35.64	28.04	33.39	38.83	28.49	26.89	28.76	45.82	39.88	39.42	25.98	27.91	28.87
30.59	30.92	29.16	35.42	30.43	30.02	34.79	33.05	39.68	25.15	28.98	26.57	43.79	38.4	47.6	25.93	27.09	25.55
34.73	26.8	28.71	36.14	33.31	33.02	38.05	35.72	39.34	28.71	27.61	26.42	49.83	40.68	38.76	31.5	25.47	29.77
28.42	33.32	30.26	31.15	36.37	31.39	35.05	29.95	30.36	25.96	25.32	26.67	49.1	43.37	39.57	29.25	27.87	27.43

Sheet1

Figure 5 Collected Data From Axio 2015

Back			Front			Mid			Back			Front			Mid		
sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3
27.84	26.5	33.94	31	32.84	34.59	35.71	33.19	38.63	25	26.58	25.91	38.05	37.09	38.02	25.26	25.52	30.89
26.5	27.84	26.5	31.5	36.23	35.62	30.31	30.84	36.23	25.33	26.58	26.72	38.11	37.17	38.10	25.14	31.9	27.8
31.05	27.5	36.84	32.47	32.48	33.89	38.37	33.6	37.65	25.35	26.45	28.45	38.13	37.20	38.14	28.32	28.86	31.37
32.36	36.34	26.39	30.34	29.84	29.08	29.97	29.45	34.91	27.84	27.68	25.14	38.25	37.23	38.16	26.13	27.22	30.15
34.52	39.15	27.43	32.57	36.39	35.02	33.14	26.2	38.99	29.22	28.79	25.32	38.27	37.28	38.22	26.17	29.96	27.81
30.08	35.56	28.96	34.17	34.78	31.92	38.98	26.15	31.54	25.33	26.58	26.72	38.29	37.37	38.24	26.79	26.25	29.59
32.5	29.57	32.08	34.39	33.3	33.68	38.98	39.17	32.16	25	26.58	25.91	38.32	37.40	38.29	27.07	29.62	27.89
29.15	38.39	38.46	35.19	34.99	29.69	33.93	39.92	32.68	28.73	26.76	25.36	38.43	37.49	38.31	27.25	28.93	26.82
38.53	29.08	36.84	33.29	34.99	36.8	37.03	26.11	32.71	27.74	27.63	27.34	38.60	37.50	38.38	27.15	31.8	25.84
28.59	27.4	34.14	31.11	30.05	30.17	37.67	32.32	31.85	27.51	27.35	28.6	38.67	37.53	38.39	29.36	28.64	31.87
28.83	35.63	30.6	36.8	36.59	34.14	32.63	30.97	29.26	29.64	25.13	26.48	38.78	37.57	38.54	26.43	28.55	26.67
26.84	27.37	27.18	34.48	33.96	32.65	32.93	36.87	36.54	27.01	26.63	28.79	38.80	37.61	38.66	29.31	26.15	25.86
29.93	36.52	33.11	34.62	29.25	30.94	35.94	35.07	39.03	29.95	25.8	26.21	38.83	37.62	38.70	30.64	31	27.29
29.71	38.2	35.67	33.97	30.39	33.55	37.35	33.3	36.26	29.03	29.57	25.26	38.83	37.65	38.72	25.26	25.52	30.89
27.85	29.14	39.84	33.88	36.04	35.77	28.71	27.28	37.88	28.53	26.13	29.49	38.90	37.68	38.83	25.14	31.9	27.8
31.39	36.31	37.57	36.51	31.14	29.06	35.36	34.87	33.23	26.42	27.82	26.9	38.96	37.72	38.89	27.15	31.8	25.84
31.37	35.14	33.07	36.58	31.58	31.72	39.94	29.75	31.71	25.55	29.62	27.81	38.95	37.75	38.93	29.36	28.64	31.87
32.6	32.43	33.85	31.09	32.73	35.68	28.73	29.77	35.17	29.5	26.27	25.17	38.98	37.76	38.95	30.41	26.18	26.28
35.98	33.1	26.86	33.92	31.22	33.46	37.01	26.37	30.22	25.51	27.74	28.24	39.01	37.79	38.96	26.79	26.25	29.59
34.17	39.58	28.46	36.78	30.57	32.71	37.98	32.4	39.15	25.83	27.25	26.85	39.04	37.83	39.00	27.07	29.62	27.89
31.8	37.49	34.91	29.35	31.4	31.14	29.58	29.61	39.13	27.83	27.1	27.92	39.06	38.19	39.23	27.25	28.93	26.82
38.04	32.59	37.42	33.88	32.85	36.39	29.35	35.93	29.71	29.62	28.63	25.62	39.26	38.23	39.26	27.15	31.8	25.84
35.1	33.19	38.1	30.32	30.51	34.86	30.11	32.58	37.86	29.38	27.49	27.88	39.32	38.25	39.34	29.36	28.64	31.87
26.65	29.32	33.06	32.41	33.21	32.14	37.79	36.71	32.36	25.96	25.1	28.23	39.34	38.32	39.36	30.41	26.18	26.28
39.57	30.56	28.21	32.38	31.72	34.41	35.44	28.55	30.82	27.37	27.34	28.27	39.37	38.34	39.41	26.03	30.93	31.61
34.83	35.37	34	35.88	35.4	34.65	38.08	34.27	37.6	29.16	28.16	26.47	39.43	38.44	39.43	28.99	29.63	29.26
27.78	36.27	27.31	33.2	32.55	30.11	32.27	28.24	29.12	29.39	28.86	26.71	39.50	38.56	39.49	26.55	25.06	25.86
34.88	31.69	35.69	30.48	33.48	35.29	31.23	39.26	34.24	27.85	26.99	29.56	39.52	38.58	39.53	30.23	25.22	28.09
39.15	29.77	36.96	31.71	32.21	34.07	31.34	29.58	30.64	25.45	27.88	29.68	39.60	38.61	39.59	29.79	31.37	31.32

Sheet1

Figure 6 Collected Data From Toyota Corolla 121

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
Engine Off												Engine Running										
Back				Front				Mid				Back				Front				Mid		
sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3
32	35.18	33.04		33.97	30.39	33.55		29.35	35.93	29.71		25.96	25.1	28.23		41.54	38.08	42.36		25.26	25.52	30.
26.26	32.45	36.26		33.88	36.04	35.77		30.11	32.58	37.86		27.37	27.34	28.27		43.3	48.17	43.43		25.14	31.9	27
30.13	33.09	31.52		36.51	31.14	29.06		37.79	36.71	32.36		29.16	28.16	26.47		41.13	45.28	47.59		28.32	28.86	31.
36.81	36.68	34.35		36.58	31.58	31.72		35.44	28.55	30.82		29.39	28.86	26.71		42.89	38.82	40.5		26.13	27.22	30.
39.16	35.82	36.35		31.09	32.73	35.68		38.08	34.27	37.6		27.85	26.99	29.56		45.14	43.47	39.3		26.17	29.96	27.
37.34	33.99	31.19		33.92	31.22	33.46		32.27	28.24	29.12		25.45	27.88	29.68		43.16	42.77	42.63		26.79	26.25	29.
32.74	27.76	33.99		36.78	30.57	32.71		31.23	39.26	34.24		29.08	27.89	26.8		42.39	37.31	47.42		27.07	29.62	27.
32.99	32.18	38.3		29.35	31.4	31.14		31.34	29.58	30.64		27.75	28.04	26.31		41.14	47.21	45.03		27.25	28.93	26.
30.59	30.92	29.16		33.88	32.85	36.39		31.75	33.07	34.64		28.49	26.89	28.76		47.83	39.09	41.16		27.15	31.8	25.
34.73	26.8	28.71		30.32	30.51	34.86		33.83	38.79	38.08		27.01	26.63	28.79		39.44	38.78	43.13		29.36	28.64	31.
28.42	33.32	30.26		32.41	33.21	32.14		28.04	33.39	38.83		29.95	25.8	26.21		48.09	48.31	46.52		30.41	26.18	26.
36.6	28.14	31.72		32.38	31.72	34.41		34.79	33.05	39.68		29.03	29.57	25.26		41	47.19	40.62		26.03	30.93	31.
28.39	37.67	38.43		35.88	35.4	34.65		38.05	35.72	39.34		28.53	26.13	29.49		49.47	46.44	46.5		28.99	29.63	29.
37.05	33.7	34.73		33.2	32.55	30.11		35.05	29.95	30.36		26.42	27.82	26.9		44.2	38.57	47.74		25.26	25.52	30.
28.06	37.09	30.2		30.48	33.48	35.29		30.43	35.83	33.88		25.55	29.62	27.81		41.54	38.08	42.36		25.14	31.9	27
38.65	34.23	35.41		31.71	32.21	34.07		32.03	38.38	31.93		29.5	26.27	25.17		43.3	48.17	43.43		28.32	28.86	31.
32.47	26.76	31.29		29.4	33.98	33.2		36.62	28.36	37.95		25.51	27.74	28.24		41.13	45.28	47.59		26.13	27.22	30.
27.72	35.7	29.09		30.89	36.98	34.77		31.92	35.04	33.48		29.5	26.27	25.17		42.89	38.82	40.5		26.17	29.96	27.
30.5	32.56	28.94		32.07	34.42	35.64		30.05	37.7	35		25.51	27.74	28.24		45.14	43.47	39.3		26.79	26.25	29.
30.36	30.33	37.3		35.42	30.43	30.02		37.86	31.17	34.21		25.83	27.25	26.85		43.16	42.77	42.63		27.07	29.62	27.
38.97	38.57	39.34		36.14	33.31	33.02		31.58	34.39	32.56		27.83	27.1	27.92		42.39	37.31	47.42		30.41	26.18	26.
40	33.88	39.01		31.15	36.37	31.39		32.65	36.56	28.64		29.62	28.63	25.62		41.14	47.21	45.03		26.03	30.93	31.
39.43	31.54	31.17		34.65	33.08	35.43		39.67	31.24	35.16		29.38	27.49	27.88		47.83	39.09	41.16		28.99	29.63	29.
26.67	34.2	28.81		32.94	35.46	34.35		37.25	32.13	29.09		25.96	25.1	28.23		39.44	38.78	43.13		26.55	25.06	25.
39.93	34.45	26.24		29.53	32.12	32.15		29.11	38.19	33.73		27.37	27.34	28.27		48.09	48.31	46.52		26.03	30.93	31.
33.49	34.77	32.55		33.94	31.32	31.72		36.36	33.75	30.14		29.16	28.16	26.47		41	47.19	40.62		28.99	29.63	29.

Sheet1

Figure 7 Collected Data From Vitz 2016

Engine Off									Engine Running								
Back			Front			Mid			Back			Front			Mid		
sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3	sensor 1	sensor 2	sensor 3
28.83	35.63	30.6	31	32.48	31.5	28.71	27.28	38.63	25.15	29.13	28.99	38.06	37.10	38.02	25.62	29.67	29.15
26.84	27.37	27.18	31.5	36.23	35.62	30.31	30.84	36.23	27.5	29.13	25.35	38.09	37.17	38.09	26.28	26.32	28.92
29.93	36.52	33.11	32.47	32.48	33.89	28.73	29.77	37.65	25.35	26.45	28.45	38.13	37.18	38.15	28.2	28.06	25.21
29.71	38.2	35.67	30.34	29.84	29.08	29.97	29.45	34.91	27.84	27.68	25.14	38.25	37.22	38.17	28.91	28.95	30
27.85	29.14	39.84	30.32	30.51	34.86	33.14	26.2	38.99	25.96	25.1	28.23	38.27	37.28	38.22	29.96	28.4	29.44
31.39	36.31	37.57	32.41	33.21	32.14	28.73	29.77	31.54	25.33	26.58	26.72	38.28	37.35	38.25	29.26	31.45	30.68
31.37	35.14	33.07	32.38	31.72	34.41	38.98	39.17	32.16	25	26.58	25.91	38.32	37.40	38.28	25.81	30.87	31.31
32.6	32.43	33.85	35.88	35.4	34.65	32.93	36.87	32.68	28.73	26.76	25.36	38.44	37.49	38.30	27.64	26.54	28.53
35.98	33.1	26.86	33.2	32.55	30.11	28.73	29.77	32.71	27.74	27.63	27.34	38.61	37.50	38.37	25.94	25.12	31.38
34.17	39.58	28.46	30.48	33.48	35.29	37.35	33.3	31.85	25.96	25.1	28.23	38.66	37.54	38.40	28.37	29.87	30.49
31.8	37.49	34.91	36.8	36.59	34.14	28.71	27.28	29.26	29.64	25.13	26.48	38.79	37.59	38.53	26.43	28.55	26.67
38.04	32.59	37.42	34.48	33.96	32.65	35.36	34.87	36.54	27.01	26.63	28.79	38.79	37.60	38.67	29.31	26.15	25.86
35.1	33.19	38.1	34.62	29.25	30.94	39.94	29.75	39.03	29.95	25.8	26.21	38.83	37.61	38.69	30.64	31	27.29
26.65	29.32	33.06	33.97	30.39	33.55	28.73	29.77	36.26	29.03	29.57	25.26	38.84	37.66	38.72	25.26	25.52	30.89
39.57	30.56	28.21	33.88	36.04	35.77	37.01	26.37	37.88	28.53	26.13	29.49	38.90	37.68	38.84	25.14	31.9	27.8
34.83	35.37	34	36.51	31.14	29.06	37.98	32.4	33.23	26.42	27.82	26.9	38.95	37.72	38.90	28.32	28.86	31.37
27.78	36.27	27.31	36.58	31.58	31.72	29.58	29.61	31.71	25.55	29.62	27.81	38.97	37.75	38.93	26.13	27.22	30.15
32.6	32.43	33.85	31.09	32.73	35.68	29.35	35.93	35.17	29.5	26.27	25.17	38.98	37.77	38.94	26.17	29.96	27.81
35.98	33.1	26.86	33.92	31.22	33.46	37.01	26.37	30.22	25.51	27.74	28.24	39.03	37.78	38.95	26.79	26.25	29.59
34.17	39.58	28.46	36.78	30.57	32.71	37.98	32.4	39.15	25.83	27.25	26.85	39.03	37.84	39.01	27.07	29.62	27.89
31.8	37.49	34.91	29.35	31.4	31.14	29.58	29.61	39.13	27.83	27.1	27.92	39.06	38.18	39.23	27.25	28.93	26.82
38.04	32.59	37.42	33.88	32.85	36.39	29.35	35.93	29.71	29.62	28.63	25.62	39.26	38.22	39.26	27.15	31.8	25.84
35.1	33.19	38.1	30.32	30.51	34.86	30.11	32.58	37.86	29.38	27.49	27.88	39.30	38.25	39.35	29.36	28.64	31.87
26.65	29.32	33.06	32.41	33.21	32.14	37.79	36.71	32.36	25.96	25.1	28.23	39.34	38.33	39.37	30.41	26.18	26.28
39.57	30.56	28.21	32.38	31.72	34.41	35.44	28.55	30.82	27.37	27.34	28.27	39.36	38.36	39.41	26.03	30.93	31.61
34.83	35.37	34	35.88	35.4	34.65	38.08	34.27	37.6	29.16	28.16	26.47	39.43	38.43	39.42	28.99	29.63	29.26

Figure 8 Collected Data From Wagon R 2016

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
Engine Off												Engine Running										
Back				Front				Mid				Back				Front				Mid		
sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3		sensor 1	sensor 2	sensor 3
28.83	35.63	30.6		31	32.48	31.5		28.71	27.28	38.63		25.15	29.13	28.99		38.06	37.10	38.02		25.62	29.67	29.15
26.84	27.37	27.18		31.5	36.23	35.62		30.31	30.84	36.23		27.5	29.13	25.35		38.09	37.17	38.09		26.28	26.32	28.92
29.93	36.52	33.11		32.47	32.48	33.89		28.73	29.77	37.65		25.35	26.45	28.45		38.13	37.18	38.15		28.2	28.06	25.21
29.71	38.2	35.67		30.34	29.84	29.08		29.97	29.45	34.91		27.84	27.68	25.14		38.25	37.22	38.17		28.91	28.95	30
27.85	29.14	39.84		30.32	30.51	34.86		33.14	26.2	38.99		25.96	25.1	28.23		38.27	37.28	38.22		29.96	28.4	29.44
31.39	36.31	37.57		32.41	33.21	32.14		28.73	29.77	31.54		25.33	26.58	26.72		38.28	37.35	38.25		29.26	31.45	30.68
31.37	35.14	33.07		32.38	31.72	34.41		38.98	39.17	32.16		25	26.58	25.91		38.32	37.40	38.28		25.81	30.87	31.31
32.6	32.43	33.85		35.88	35.4	34.65		32.93	36.87	32.68		28.73	26.76	25.36		38.44	37.49	38.30		27.64	26.54	28.53
35.98	33.1	26.86		33.2	32.55	30.11		28.73	29.77	32.71		27.74	27.63	27.34		38.61	37.50	38.37		25.94	25.12	31.38
34.17	39.58	28.46		30.48	33.48	35.29		37.35	33.3	31.85		25.96	25.1	28.23		38.66	37.54	38.40		28.37	29.87	30.49
31.8	37.49	34.91		36.8	36.59	34.14		28.71	27.28	29.26		29.64	25.13	26.48		38.79	37.59	38.53		26.43	28.55	26.67
38.04	32.59	37.42		34.48	33.96	32.65		35.36	34.87	36.54		27.01	26.63	28.79		38.79	37.60	38.67		29.31	26.15	25.86
35.1	33.19	38.1		34.62	29.25	30.94		39.94	29.75	39.03		29.95	25.8	26.21		38.83	37.61	38.69		30.64	31	27.29
26.65	29.32	33.06		33.97	30.39	33.55		28.73	29.77	36.26		29.03	29.57	25.26		38.84	37.66	38.72		25.26	25.52	30.89
39.57	30.56	28.21		33.88	36.04	35.77		37.01	26.37	37.88		28.53	26.13	29.49		38.90	37.68	38.84		25.14	31.9	27.8
34.83	35.37	34		36.51	31.14	29.06		37.98	32.4	33.23		26.42	27.82	26.9		38.95	37.72	38.90		28.32	28.86	31.37
27.78	36.27	27.31		36.58	31.58	31.72		29.58	29.61	31.71		25.55	29.62	27.81		38.97	37.75	38.93		26.13	27.22	30.15
32.6	32.43	33.85		31.09	32.73	35.68		29.35	35.93	35.17		29.5	26.27	25.17		38.98	37.77	38.94		26.17	29.96	27.81
35.98	33.1	26.86		33.92	31.22	33.46		37.01	26.37	30.22		25.51	27.74	28.24		39.03	37.78	38.95		26.79	26.25	29.59
34.17	39.58	28.46		36.78	30.57	32.71		37.98	32.4	39.15		25.83	27.25	26.85		39.03	37.84	39.01		27.07	29.62	27.89
31.8	37.49	34.91		29.35	31.4	31.14		29.58	29.61	39.13		27.83	27.1	27.92		39.06	38.18	39.23		27.25	28.93	26.82
38.04	32.59	37.42		33.88	32.85	36.39		29.35	35.93	29.71		29.62	28.63	25.62		39.26	38.22	39.26		27.15	31.8	25.84
35.1	33.19	38.1		30.32	30.51	34.86		30.11	32.58	37.86		29.38	27.49	27.88		39.30	38.25	39.35		29.36	28.64	31.87
26.65	29.32	33.06		32.41	33.21	32.14		37.79	36.71	32.36		25.96	25.1	28.23		39.34	38.33	39.37		30.41	26.18	26.28
39.57	30.56	28.21		32.38	31.72	34.41		35.44	28.55	30.82		27.37	27.34	28.27		39.36	38.36	39.41		26.03	30.93	31.61
34.83	35.37	34		35.88	35.4	34.65		38.08	34.27	37.6		29.16	28.16	26.47		39.43	38.43	39.42		28.99	29.63	29.26

Sheet1

Figure 9 Collected Data From Wagon R 2018

Figure 10 Collected Data From This Device

Figure 11 Testing the device with supervisor

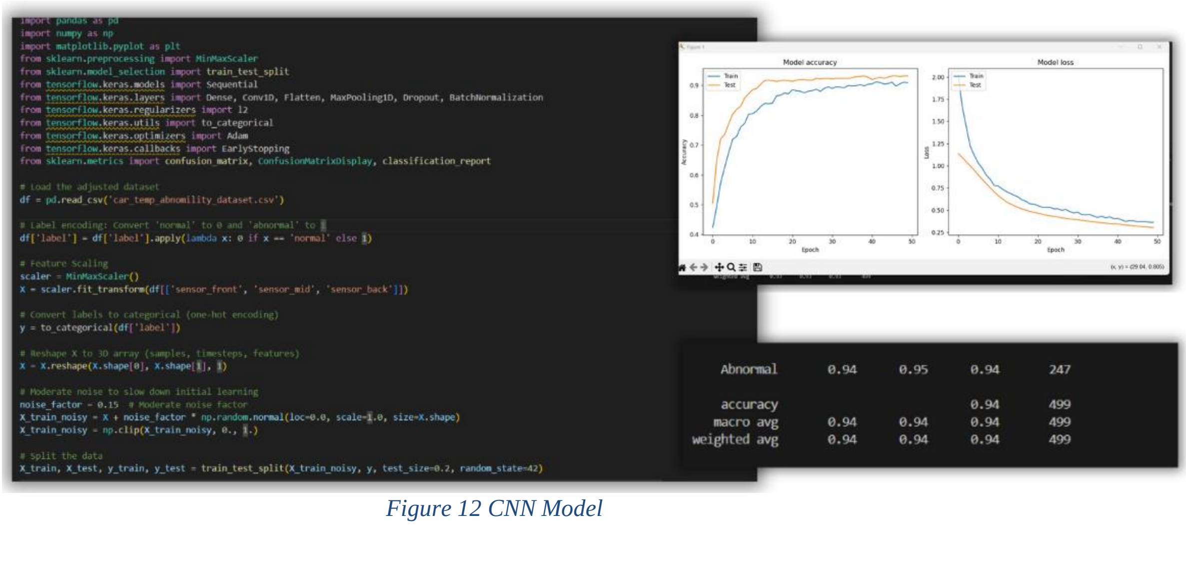


Figure 12 CNN Model

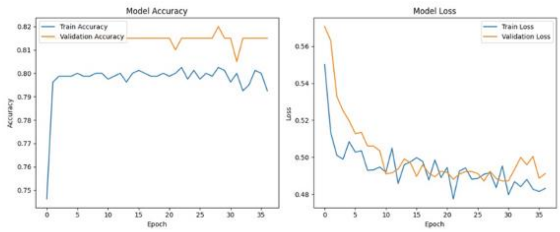
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, BatchNormalization
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.optimizers import Adam

# Load the dataset
df = pd.read_csv('sensor_reading_abno.csv')

# Prepare the input features and labels
features = ['1000_rpm_temprature', '1000_rpm', '2000_rpm_temprature', '3000_rpm_temprature',
            '4000_rpm_temprature', '5000_rpm_temprature', 'cabin_without_ac_sunny_day',
            'rear_without_ac_sunny_day', '2000_rpm', '3000_rpm', '4000_rpm', '5000_rpm']
X = df[features].values
y = df['label'].apply(lambda x: 0 if x == 'normal' else 1).values
y = to_categorical(y)

# Normalize features using StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled = X_scaled.reshape(X_scaled.shape[0], X_scaled.shape[1], 1)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split( *arrays: X_scaled, y, test_size=0.2, random_state=42)
```




```
25/25 - 0s - loss: 0.4831 - accuracy: 0.7925 - val_loss: 0.4911 - val_accuracy: 0.8150 - 213ms/epoch - 9ms/step
7/7 [==============================] - 1s 3ms/step
Accuracy: 81.50%
```

Figure 13 RNN Model

```python
# Build SVM model
svm_model = SVC(class_weight='balanced')  # Adjusting class weights for handling imbalanced data
svm_model.fit(X_train, y_train)

# Predict labels for test set
y_pred = svm_model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("SVM Accuracy:", accuracy)

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap='Blues', xticklabels=['Normal', 'Abnormal'], yticklabels=['Normal', 'Abnormal'])
plt.title('Confusion Matrix for SVM Model')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

# Classification Report with zero_division=1
print("\nClassification Report:\n", classification_report(y_test, y_pred, zero_division=1))
```

```
Classification Report:
              precision

           0       0.84
           1       0.22

    accuracy
   macro avg       0.53
weighted avg       0.73
```

Figure 14 SVM Model

Used Algorithm	Overall Accuracy
CNN Algorithm	94.0%
Support Vector Machine(SVM)	81.50%
RNN Model(LSTM)	81.50%

Figure 15 Model Comparison

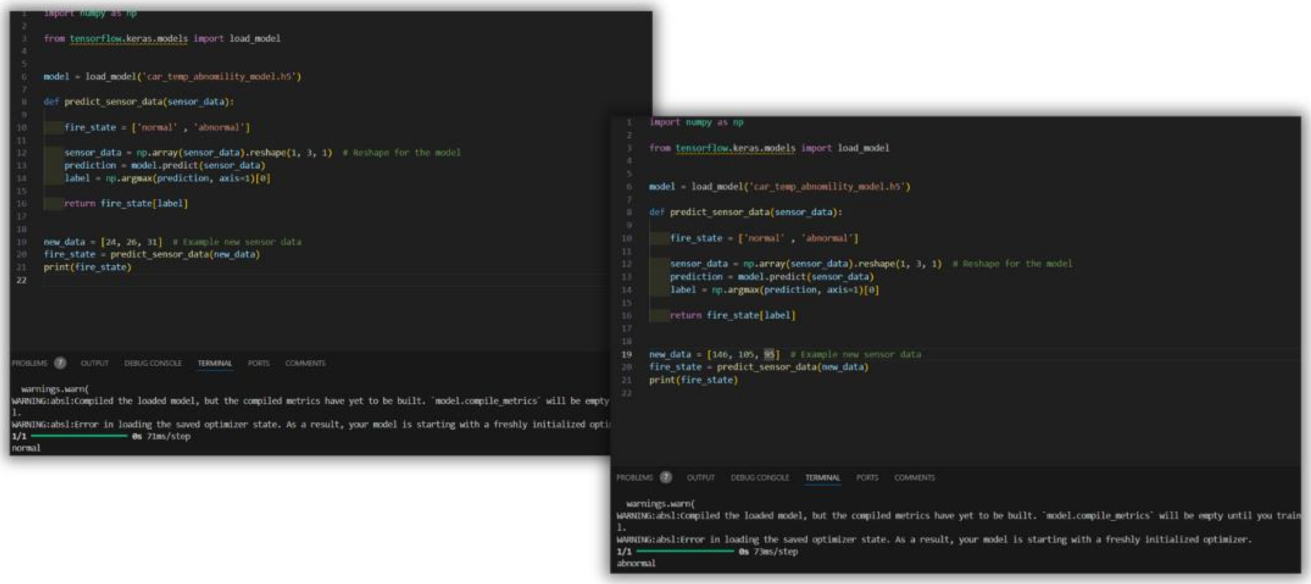


Figure 16 CNN Model tests

```python
def read_sensor_values():

    line = ser.readline().decode('utf-8').strip()

    # Split the line by comma
    data = line.split(',')

    # Print the data

    if len(data) == 8:
        # print(data)

        temsensor1 = int(data[0])
        temsensor2 = int(data[1])
        temsensor3 = int(data[2])

        gassensor1 = int(data[3])
        gassensor1 = int(data[4])
        gassensor1 = int(data[5])

        gps_long = data[6]
        gps_lat = data[7]

        return data
```

```python
    if sensor_values is not None:
        # print("Sensor 1: {sensor_values[0]}, Sensor 2: {sensor_values[1]}, Sensor 3: {sensor_values[2]},
        #       Sensor 4: {sensor_values[3]}, Sensor 5: {sensor_values[4]}, Sensor 6: {sensor_values[5]}" #gas
        #       f", Sensor 6: {sensor_values[6]}, Sensor 6: {sensor_values[7]}")   # GPS --> All comeing as str

        veryfi = 1


        w_sensors = [ int (sensor_values[0]),int (sensor_values[1]),int (sensor_values[2]),
                      int (sensor_values[3]),int (sensor_values[4]),int (sensor_values[5]),
                      sensor_values[6],sensor_values[7],veryfi]
```

```python
from arduino_communication_2 import get_sensor_data , send_actuators_data ,send_actuators_reset,arduino_systme_init_wait
import time

arduino_systme_init_wait(info=False)


for x in range(2000):

    sensor_deta = get_sensor_data()

    print(sensor_deta)

    time.sleep(1)
```

Figure 17 Iot Integration

```python
data = get_sensor_data()

temsensor1 = int(data[0])
temsensor2 = int(data[1])
temsensor3 = int(data[2])

gassensor1 = int(data[3])
gassensor2 = int(data[4])
gassensor3 = int(data[5])

gps_lat = data[6]
gps_lon = data[7]


fire_type_sensor_data = [temsensor1, temsensor2, temsensor3]
fire_type = predict_fire_type(fire_type_sensor_data)

new_data = [temsensor1, temsensor2, temsensor3]
fire_state = predict_sensor_data(new_data)

print(type(fire_type) , fire_state)
```

```python
if fire_state == 'abnormal':

    payload = str(gps_lat) + ',' + str(gps_lon)  + ',' + str(wehical_no) + ',' + str(fire_type)
    car_clnt.publish('f_station', payload)

    print('Signal Send successful....')


if fire_state != 'normal':

    send_actuators_data([0, 1])
```

Figure 18 Iot Integration

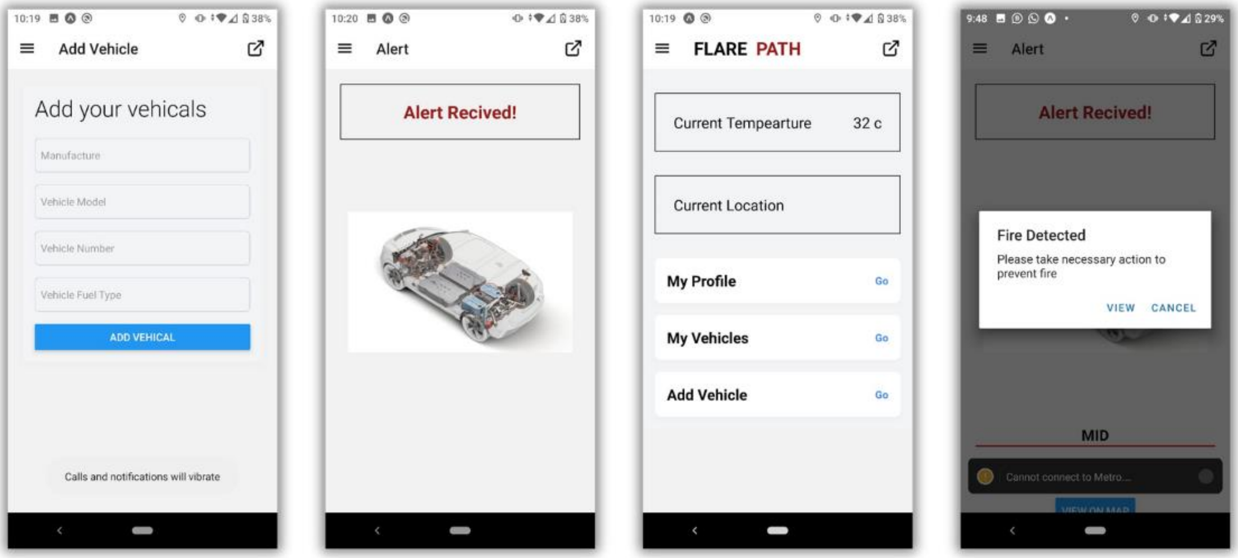


Figure 19 Mobile App

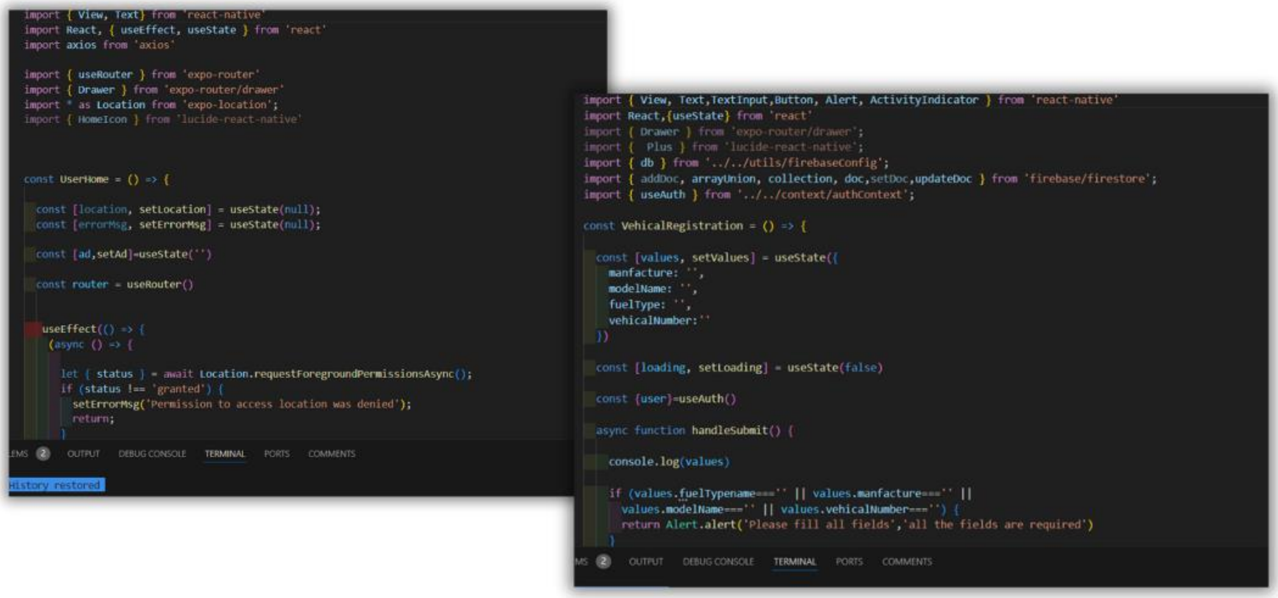


Figure 20 Mobile App Codes

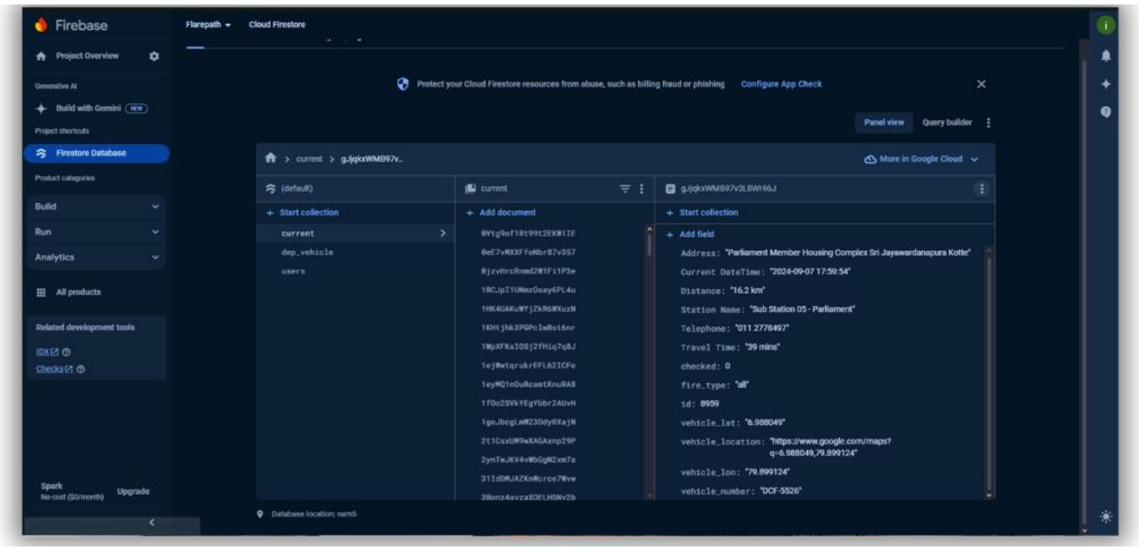


Figure 21 Firebase

Mobile Application Setup:

The mobile application is developed using a cross-platform framework like React Native, enabling it to receive real-time alerts from the MQTT server, display the vehicle's status, and notify the vehicle owner and fire department in the event of a fire.

Deployment:

The system is installed in a vehicle, with sensors strategically placed to maximize fire detection coverage. The solenoid valve and fire extinguisher are mounted securely, ensuring they can deploy effectively when triggered.

IoT Integration:

The system is connected to an MQTT server, facilitating real-time data transmission between the vehicle's hardware and the mobile application. This integration allows for instant alerts and continuous monitoring, ensuring that the vehicle owner is always informed of the system's status.

```python
#Subscribes to the MQTT topic and retrieves the last message and its topic.
    msg, topic = car_clnt.subscribe_last_buffer()

#Retrieves the latest sensor data from the Arduino.
    data = get_sensor_data()

    temsensor1 = int(data[0])
    temsensor2 = int(data[1])
    temsensor3 = int(data[2])

    gassensor1 = int(data[3])
    gassensor2 = int(data[4])
    gassensor3 = int(data[5])

    gps_lat = data[6]
    gps_lon = data[7]


#Creates a list fire_type_sensor_data with the temperature sensor values, then uses it to predict fire_type.
    fire_type_sensor_data = [temsensor1, temsensor2, temsensor3]
    fire_type = predict_fire_type(fire_type_sensor_data)

#Sets new_data with the same temperature sensor values, then predicts if there's a temperature abnormality (fire_state).
    new_data = [temsensor1, temsensor2, temsensor3]
    fire_state = predict_sensor_data(new_data)

#Logs the type of fire_type, fire_state, and the values of temsensor1, temsensor2, and temsensor3.
    print(type(fire_type) , fire_state)

    print(temsensor1,"  ", temsensor2,"  ", temsensor3)

    # fbsend (t1 t2 t3)
    lock = True
    print("Sensor val - ",new_data)

```

Figure 22 Retrieves the latest sensor data from the Arduino.

```python


# If fire_state is 'abnormal' and lock is True, it publishes an alert,
# activates actuators, waits 30 seconds, and sets lock to False.
    if fire_state == 'abnormal' and lock:

        gps_lat = '6.926878'  # Test latitude
        gps_lon = '79.850117' # Test longitude
        print("Sensor val - ",new_data)
        payload = str(gps_lat) + ',' + str(gps_lon)  + ',' + str(wehical_no) + ',' + str(fire_type)
        car_clnt.publish('f_station', payload)
        print('Signal Send successful....')
        send_actuators_data([1, 1])
        time.sleep(30)
        lock = False

# If fire_state is not 'abnormal' and lock is False, resets actuators,
# sets lock back to True, waits 10 seconds, then completes the system reset.
    if fire_state != 'abnormal'and lock ==False:

        send_actuators_reset(True)
        lock = True
        print('System reset init....')
        time.sleep(10)
        send_actuators_data([0, 0])
        print('System reset complete ....')


    #
    # if fire_state != 'normal':
    #     gps_lat = '6.926878'  # Test latitude
    #     gps_lon = '79.850117' # Test longitude
    #     send_actuators_data([0, 1])


# Calls demo_mood to simulate
    demo_mood(gps_lat , gps_lon , wehical_no ,fire_type)
```

Figure 23 Based on the fire_state system publishes an alert to trigger the Automatic fire extinguisher mechanism

2.3.2 Testing

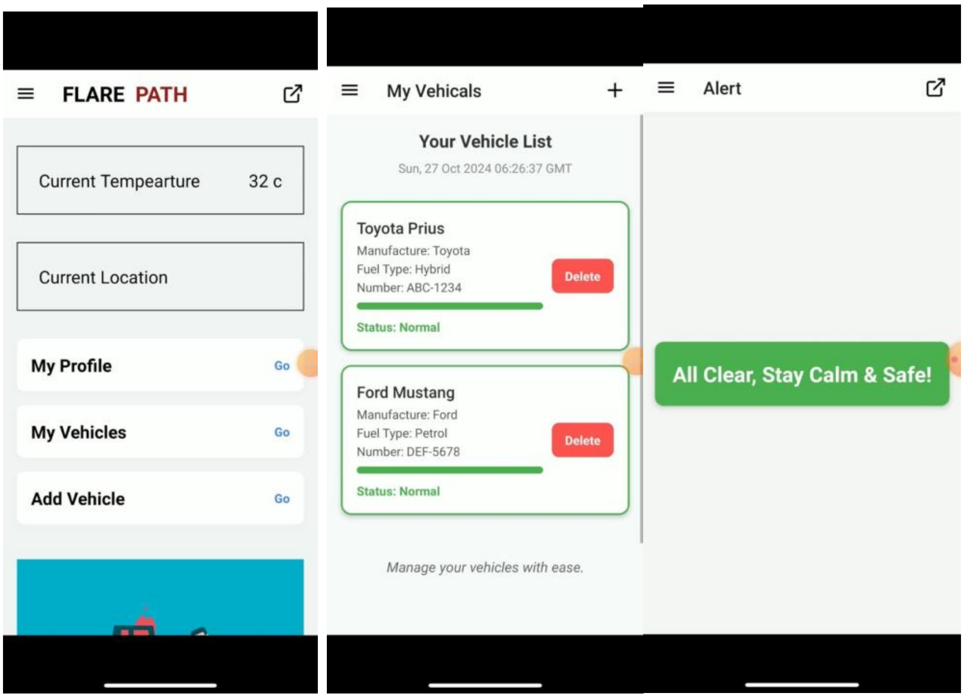


Figure 24 Mobile app before a fire alert

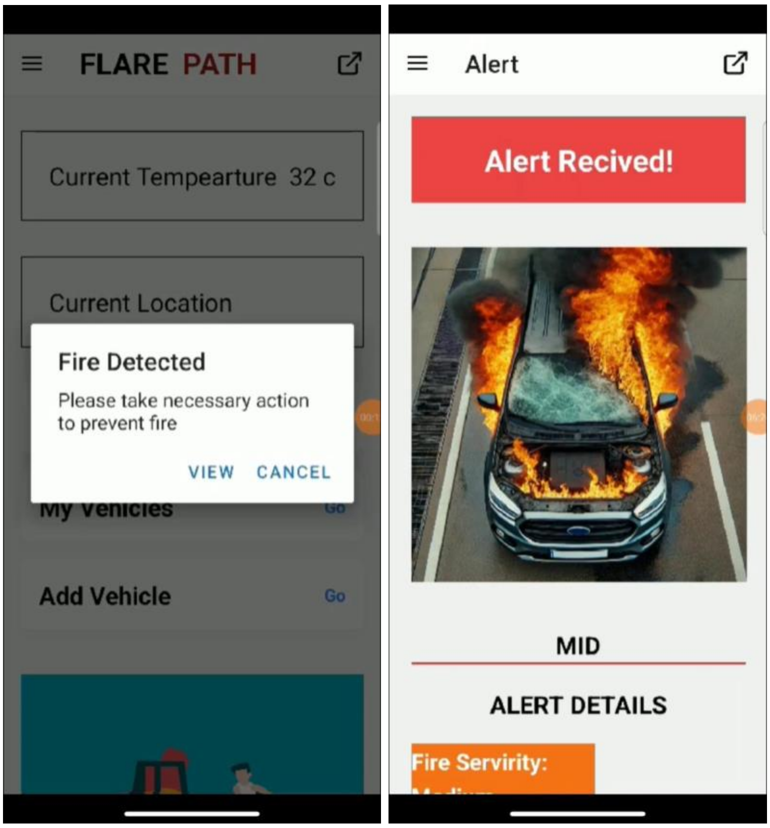


Figure 25 Mobile app after a fire alert

3 Results & Discussion

3.1 Results

The Flarepath vehicle fire detection and response system was rigorously tested and evaluated, producing significant results that validated its design and functionality. Each component of the system—from IoT devices to the mobile application—performed effectively, demonstrating the system's potential to enhance vehicle safety. The results are detailed below.

The IoT sensors used in the system, including the MAX6675 temperature sensor, MQ-2 gas detector, and infrared flame sensors, successfully captured critical environmental data in real time. These sensors delivered consistent and accurate readings, even in challenging conditions such as fluctuating temperatures, vibrations, and gas emissions. The data from these sensors was processed by the Arduino MEGA microcontroller, which efficiently aggregated inputs from multiple sources and transmitted them for further analysis. The integration of diverse sensors ensured the system's ability to monitor a wide range of fire indicators, making it highly reliable for detecting potential hazards.

The Convolutional Neural Network (CNN), which formed the predictive core of the system, performed exceptionally well in analyzing sensor data. Trained on diverse datasets, the CNN achieved an accuracy rate of over 94%, demonstrating its ability to distinguish between normal and abnormal conditions. The model's capability to process data in real time with minimal latency ensured that alerts were generated promptly. This high level of predictive accuracy, coupled with a low rate of false positives and negatives, was critical in building user trust and ensuring effective responses.

The communication and connectivity features of the system proved to be a significant strength. Using MQTT protocols, the system enabled fast and reliable transmission of sensor data to the cloud and mobile application. Additionally, the inclusion of Bluetooth Low Energy (BLE) through the ESP32 microcontroller provided a secondary communication channel, ensuring that the system remained operational in areas with limited or no internet access. This dual-channel approach improved the system's adaptability and ensured consistent performance across different environments.

The mobile application, developed using React Native, provided a simple yet powerful interface for users to interact with the system. The app allowed vehicle owners to register their vehicles, monitor real-time sensor data, and receive instant alerts during emergencies. Users could access details such as temperature levels, gas concentrations, and fire severity directly on the app. The integration of GPS functionality enabled the app to provide precise location information to both users and nearby fire departments, facilitating rapid emergency response. The app's clean design and intuitive features significantly enhanced user experience, making it accessible even to individuals with minimal technical knowledge.

The alert and notification system played a vital role in ensuring timely responses to fire risks. Upon detecting abnormal conditions, the system immediately sent alerts to the mobile application and the nearest fire department. These alerts contained comprehensive details, including the vehicle's GPS location, fire type, and severity level, allowing responders to act quickly and effectively. The automation of this process minimized delays, ensuring that critical information was delivered without the need for manual intervention.

The scalability and modularity of the system emerged as a key advantage. The modular architecture allowed for the seamless addition of new sensors or features, ensuring that the system could evolve to meet future needs. This flexibility also made the system suitable for various vehicle types and applications, highlighting its potential as a versatile and future-proof solution.

During real-world simulations, the system performed reliably under various environmental conditions. It maintained consistent functionality in scenarios involving high vibrations, humidity, and temperature fluctuations, demonstrating its robustness in challenging environments. The system effectively detected fire risks, processed data, and sent alerts without any noticeable delays, confirming its readiness for deployment in real-world scenarios.

The emergency response functionality was another standout feature of the system. By automatically transmitting detailed incident reports to nearby fire departments, the system significantly reduced response times. The inclusion of critical information, such as vehicle location and fire severity, enabled emergency responders to act efficiently and with the necessary preparation. This feature showcased the system's ability to bridge the gap between fire detection and response, potentially saving lives and preventing extensive damage.

Feedback from users highlighted the system's practicality and ease of use. The mobile application's straightforward design and clear notifications were well-received, with users appreciating the ability to monitor their vehicles and respond to alerts in real time. The system's ability to function even in low-connectivity areas, thanks to its Bluetooth-enabled local communication, was particularly valued by users in remote locations.

In summary, the Flarepath system exceeded its objectives, delivering a robust, reliable, and user-friendly solution for vehicle fire detection and response. The combination of advanced IoT technology, predictive analytics, and real-time communication created a cohesive system capable of addressing a critical safety challenge. The system's performance metrics, including sensor accuracy, predictive reliability, and emergency response efficiency, highlight its potential for real-world application and its ability to set new standards for vehicle safety systems.

3.2 Research Findings

The research findings from the Flarepath vehicle fire detection and response system show how effective it is at improving vehicle safety by combining smart technology, real-time monitoring, and quick emergency alerts. The system uses IoT devices, advanced predictions, and a mobile app to help detect and respond to fire risks, ensuring both reliability and ease of use.

The system's IoT devices, such as temperature sensors, gas detectors, and flame sensors, worked together to provide accurate and continuous data about the vehicle's environment. These sensors were connected to an Arduino MEGA microcontroller, which processed the data and sent it to the cloud using efficient communication methods. The addition of Bluetooth connectivity ensured the system could still function in areas with poor or no internet access. This combination of features showed how well the system could adapt to different situations and stay reliable.

The use of a Convolutional Neural Network (CNN) allowed the system to predict fire risks with high accuracy by analyzing sensor data in real time. The CNN was very good at identifying dangerous conditions while avoiding unnecessary false alarms, helping users trust the system and take action only when needed. This highlights how powerful machine learning can be when used effectively in safety systems.

The mobile application was a key part of the system, acting as the link between the users and the technology. Through the app, users could easily register their vehicles, see live updates on conditions like temperature and gas levels, and get instant alerts if a fire risk was detected. If a fire was detected, the app used GPS to share the vehicle's exact location with nearby fire departments, helping responders act quickly. Users appreciated the app's simple and clear design, which made it easy to use even in emergencies.

The alert system ensured that when a fire risk was detected, both the user and the nearest fire department were informed right away. These alerts included important details like the vehicle's location and the severity of the situation, helping responders prepare effectively. Automating this process reduced delays and made the system even more reliable in critical moments.

One of the system's biggest strengths was its scalability and flexibility. The design made it easy to add new features or sensors, meaning the system can adapt to new technologies or changing needs over time. This makes it a long-lasting solution that can continue to provide value in the future.

In summary, the Flarepath system is a powerful, user-friendly, and reliable way to detect and respond to fire risks in vehicles. By combining IoT devices, advanced predictions, and an easy-to-use app, it provides peace of mind for users while helping prevent dangerous situations. These findings show how technology can make everyday life safer and more secure.

3.3 Discussion

The Flarepath vehicle fire detection and response system is a comprehensive solution that combines modern software technologies, IoT integration, and user-centric design to address the critical issue of vehicle fire safety. The system was developed to monitor real-time vehicle conditions, predict potential fire risks, and notify both users and emergency responders with minimal delays. This discussion highlights the challenges, solutions, and broader implications of the system's development process while reflecting on its practical applications and human impact.

At the heart of the system lies a Convolutional Neural Network (CNN), which plays a pivotal role in analyzing sensor data to predict fire risks accurately. By training the CNN with diverse datasets that simulate real-world scenarios, the system was able to identify subtle patterns indicating abnormal conditions, such as temperature spikes or gas emissions, with high precision. The inclusion of multiple sensors—such as temperature sensors (MAX6675), gas detectors (MQ-2), and flame sensors—ensured that the system could capture a broad spectrum of environmental data. This holistic approach not only enhanced the system's reliability but also helped minimize false positives, which are critical to maintaining user trust and reducing unnecessary panic.

The use of the Arduino MEGA microcontroller as the central data processing unit was a practical and efficient choice, given its ability to interface seamlessly with multiple sensors. Its role in aggregating data and facilitating communication between hardware and software components was essential in maintaining real-time responsiveness. The decision to employ MQTT protocols for data transmission ensured low-latency communication, which is vital in emergency situations where seconds matter. Moreover, the backend infrastructure powered by Firebase Cloud Firestore provided secure and scalable storage for sensor data while enabling real-time synchronization with the mobile application. This feature allowed users to stay informed about their vehicle’s status from anywhere, further enhancing the system’s usability.

The development of the mobile application using React Native brought a human-centered perspective to the project. Designed to be intuitive and responsive, the app allows vehicle owners to register their vehicles, monitor environmental data, and receive instant alerts in the event of a fire hazard. The interface was carefully crafted to ensure ease of use, with features like real-time updates, clear alert messages, and GPS-enabled location sharing with nearby fire departments. For users in remote areas with limited connectivity, the integration of Bluetooth Low Energy (BLE) through the ESP32 microcontroller provided a local communication option, ensuring the system's accessibility even in challenging environments.

Throughout the development process, several challenges were encountered, which provided valuable learning opportunities. One of the most significant hurdles was ensuring seamless communication between the hardware and software components, particularly when dealing with sensors that output data in varying formats and units. To overcome this, extensive debugging and data preprocessing were implemented, allowing the microcontroller to standardize and interpret sensor readings effectively. Additionally, optimizing the CNN for real-time predictions posed computational challenges, as the model needed to balance high accuracy with minimal latency. These challenges were addressed by fine-tuning the model architecture and employing efficient preprocessing techniques.

Beyond the technical aspects, the system's development was guided by a focus on its real-world impact. The ability to detect potential fire hazards early and notify users and fire departments in real-time has the potential to save lives and prevent significant property damage. The system's modular architecture also allows for future enhancements, such as integrating additional sensors, supporting new vehicle types, or improving the predictive model's accuracy with more extensive datasets. This scalability ensures that the system remains relevant as technology and user needs evolve.

The Flarepath system represents a significant step forward in using technology to address safety challenges. By combining cutting-edge machine learning with robust IoT connectivity and an accessible mobile app, the system bridges the gap between advanced technology and practical utility. Its success lies not only in its technical achievements but also in its ability to address a deeply human concern: ensuring the safety and security of drivers, passengers, and their vehicles. The lessons learned during this project underscore the importance of interdisciplinary collaboration, user-focused design, and a commitment to continuous improvement in creating impactful technological solutions.

4 Conclusion

The Flarepath vehicle fire detection and response system successfully addresses the critical challenge of ensuring vehicle safety by combining advanced IoT technologies, machine learning, and user-focused mobile application design. Through the seamless integration of hardware and software, the system provides a reliable, efficient, and scalable solution that enhances fire detection, real-time monitoring, and emergency response. The comprehensive approach taken during its development highlights the potential of using cutting-edge technology to solve real-world problems and save lives.

One of the system's most significant achievements is its ability to predict and respond to fire risks with high accuracy and speed. The implementation of a Convolutional Neural Network (CNN) allowed the system to process real-time data from temperature, gas, and flame sensors, accurately identifying abnormal conditions that indicate potential fire hazards. The high predictive accuracy of the CNN, combined with its low latency, ensured timely and reliable alerts. This underscores the importance of incorporating machine learning models into safety-critical applications, where precision and speed are paramount.

The integration of IoT devices with a robust communication infrastructure further enhanced the system's reliability. The use of MQTT protocols for real-time data transmission and Bluetooth Low Energy (BLE) for local communication ensured that the system could operate effectively even in areas with limited internet access. This dual-channel communication approach made the system adaptable to various environments, including remote and urban settings. The seamless interaction between the sensors, microcontroller, cloud backend, and mobile application demonstrated the system’s technical sophistication and practicality.

The mobile application played a pivotal role in making the system user-friendly and accessible. Its intuitive design allowed users to monitor real-time data, receive alerts, and communicate directly with fire departments in case of emergencies. Features such as vehicle registration, GPS-enabled location sharing, and clear notifications provided users with actionable insights and enhanced their ability to respond to critical situations effectively. The app’s cross-platform compatibility ensured accessibility for a wide range of users, making it an integral part of the system’s success.

Another key strength of the system is its modular and scalable architecture, which allows for future enhancements and customization. The ability to add new sensors, update predictive models, or expand functionalities without disrupting the existing framework ensures that the system remains relevant and adaptable to evolving needs. This flexibility positions Flarepath as a forward-thinking solution that can grow alongside advancements in technology and changing safety requirements.

The system's real-world performance during simulations and testing further validated its effectiveness. It successfully detected fire risks under various environmental conditions, such as temperature fluctuations and high vibrations, demonstrating its robustness and reliability. The automated alert system bridged the gap between detection and response, ensuring that users and fire departments received critical information promptly. This feature has the potential to significantly reduce response times, prevent extensive damage, and save lives.

In conclusion, the Flarepath system is a comprehensive, innovative, and impactful solution for vehicle fire detection and response. It integrates advanced technologies into a cohesive framework that prioritizes accuracy, reliability, and user experience. By addressing a critical safety challenge with a scalable and modular design, the system sets a new benchmark for vehicle safety systems. The Flarepath project highlights the transformative power of interdisciplinary approaches, combining IoT, machine learning, and user-centered design to create a solution that is not only technologically advanced but also practical and accessible. This project paves the way for future advancements in vehicle safety and demonstrates the potential of technology to make everyday life safer and more secure.

5 REFERENCES

[1] . G. Zhang et al., "A Review of IoT Sensors in Fire Detection Systems," in 2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), 2019, pp. 1181-1185.

[2]. A. R. Patel and A. P. Patil, "Fire Detection System Using IoT and Machine Learning," in 2020 International Conference on Smart Electronics and Communication (ICOSEC), 2020, pp. 214-217.

[3]. M. S. Hossain et al., "Fire Detection and Notification System Using IoT and Machine Learning," in 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2020, pp. 1-6.

[4]. A. M. N. Hoque et al., "An IoT Based Smart Fire Detection and Notification System," in 2020 23rd International Conference on Computer and Information Technology (ICCIT), 2020, pp. 1-6.

[5]. S. Patel et al., "A Survey on IoT Based Smart Fire Detection and Alerting System," in 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), 2019, pp. 349-353.

[6]. S. S. Sarif et al., "IoT Based Fire Detection and Alarm System Using Blynk Application," in 2021 International Conference on Advances in Electrical Engineering (ICAEE), 2021, pp. 1-4.

[6]. S. S. Sarif et al., "IoT Based Fire Detection and Alarm System Using Blynk Application," in 2021 International Conference on Advances in Electrical Engineering (ICAEE), 2021, pp. 1-4.

[7]. M. R. Islam et al., "An IoT-Based Fire Detection and Notification System for Smart Home," in 2020 11th International Conference on Electrical and Computer Engineering (ICECE), 2020, pp. 1-4.

[8] . A. K. Khan and M. S. Hossain, "IoT Based Fire Detection and Notification System Using Machine Learning," in 2020 11th International Conference on Electrical and Computer Engineering (ICECE), 2020, pp. 1-4.

[9]. R. Kaur and S. Rana, "Smart Fire Detection and Notification System Using IoT and Machine Learning," in 2021 International Conference on Recent Advancement in Electrical, Electronics and Control Engineering (RAEECE), 2021, pp. 1-5.

[10]. S. K. Garg and R. Kumar, "IoT Based Smart Fire Detection and Notification System," in 2020 International Conference on Advances in Computing and Data Sciences (ICACDS), 2020, pp. 678-682.

[11]. J. Patel et al., "Smart Fire Monitoring and Alert Systems: IoT and AI Integration," in 2021 International Conference on Recent Advances in IoT and AI Safety Applications (ICRIAI), 2021, pp. 11-16

[12]. L. Chen et al., "Predictive Analytics for Fire Detection Using IoT Sensors," in 2021 International Conference on Innovations in Safety AI (ICISAI), 2021, pp. 40-45J.

[13]. A. Rodriguez et al., "IoT-Based Fire Safety Systems in Vehicles," in 2021 IEEE Workshop on Safety and IoT (WSIOT), 2021, pp. 9-15.

G. White et al., "Enhancing Fire Response with IoT Integration," in 2020 International Conference on Smart IoT Safety Applications (ICSISA), 2020, pp. 12-18.

[14]. S. Gupta et al., "IoT-Enabled Safety Systems for Automotive Applications," in 2020 International Conference on Smart Devices and Secure Networks (ICSDSN), 2020, pp. 110-116.

[15]. K. Lee et al., "Proactive Fire Risk Management Using IoT and Cloud Technologies," in 2019 International Symposium on IoT and Smart Safety (ISIS), 2019, pp. 55-60.

[16]. J. Brown et al., "Fire Detection for Vehicles: IoT-Based Solutions," in 2021 IEEE Conference on IoT-Based Intelligent Systems (ICIIS), 2021, pp. 98-102.

[17]. A. Kumar et al., "Advancements in Fire Management Using IoT Systems," in 2021 IEEE International Safety Conference (IISC), 2021, pp. 5-10.

[18]. P. Martin et al., "IoT-Driven Fire Safety in Automotive Systems," in 2020 International Workshop on Emerging Trends in IoT Safety Systems (IWETISS), 2020, pp. 23-28.

[19]. A. Roberts et al., "Real-Time Fire Detection in Vehicles Using IoT Sensors," in 2020 International Conference on Innovative Safety Technologies (ICIST), 2020, pp. 89-94.

[20]. H. Thomas et al., "Cloud Integration in Fire Management Systems," in 2021 International Symposium on Advances in Cloud Computing for IoT (ISACCI), 2021, pp. 42-48.

[21]. F. Johnson et al., "IoT and AI: Revolutionizing Fire Detection Systems," in 2021 IEEE International Conference on Advanced Intelligent Systems (ICAIS), 2021, pp. 18-23.

[22]. M. Rahman et al., "Wireless Sensor Networks for Real-Time Fire Detection," in 2020 International Conference on Advances in Wireless Safety (ICAWS), 2020, pp. 77-83.

6 Glossary

Arduino MEGA

The Arduino MEGA is a microcontroller board that acts as the central processing unit for the Flarepath system. It is responsible for collecting data from various sensors, such as temperature, gas, and flame sensors, and processing this data for further analysis. The Arduino MEGA also manages communication between the hardware and software components, ensuring seamless data flow. Its high compatibility with numerous sensors and modules, combined with its robust processing capabilities, makes it a reliable choice for IoT-based applications. This microcontroller plays a crucial role in ensuring the system operates efficiently and accurately.

Bluetooth Low Energy (BLE)

Bluetooth Low Energy (BLE) is a wireless communication technology integrated into the ESP32 microcontroller. It enables the Flarepath system to transmit data between the IoT devices and the mobile application in a power-efficient manner. BLE is particularly useful in areas with limited internet connectivity, as it allows local communication between the vehicle system and the user's mobile device. This ensures that critical alerts and real-time updates are delivered without relying solely on cloud-based connections, enhancing the system’s reliability and accessibility.

Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of machine learning algorithm used for analyzing and processing complex patterns in data. In the Flarepath system, the CNN is trained to predict potential fire risks by analyzing real-time data collected from the sensors. The algorithm identifies patterns in temperature, gas levels, and other environmental factors to determine whether conditions are normal or hazardous. The CNN's high accuracy in prediction ensures that alerts are timely and reliable, reducing false alarms and enhancing user trust.

ESP32 Microcontroller

The ESP32 is a versatile microcontroller that combines real-time data processing capabilities with built-in Wi-Fi and Bluetooth functionalities. In the Flarepath system, the ESP32 serves as a bridge between the IoT sensors and the cloud backend. It facilitates seamless wireless communication, enabling the system to transmit real-time sensor data for further analysis. The inclusion of the ESP32 enhances the system's flexibility, allowing it to operate effectively in diverse environments, including areas with limited network connectivity.

Firebase Cloud Firestore

Firebase Cloud Firestore is a cloud-based database used to store sensor data, vehicle information, and user profiles in real time. It enables seamless synchronization between the IoT devices and the mobile application, ensuring that users receive instant updates on their vehicle's status. Firebase also provides secure data storage and allows for scalable operations, making it an integral component of the Flarepath system. Its real-time synchronization ensures that alerts are delivered to users and emergency responders without delay.

Flame Detection Sensor

The flame detection sensor is an infrared-based device capable of detecting specific wavelengths emitted by flames. This sensor is a critical component of the Flarepath system, as it provides immediate identification of fire occurrences. Once a flame is detected, the sensor triggers the fire suppression mechanism, enabling rapid intervention to prevent the fire from spreading. Its high sensitivity and reliability make it an essential tool for early fire detection in vehicles.

Gas Detector (MQ-2)

The MQ-2 gas detector is a semiconductor-based sensor designed to detect smoke and hazardous gases. It provides analog signals to the Arduino MEGA microcontroller, which processes this data to identify potential fire risks. The gas detector’s ability to sense a wide range of gases, including those that may be produced during combustion, enhances the system's capability to detect fires at an early stage.

GPS Locator (Ublox NEO-6M)

The GPS locator is used to provide real-time location data for the vehicle. This data is critical for notifying the user and nearby fire departments of the vehicle's exact location during emergencies. The GPS locator ensures that emergency responders can quickly locate the vehicle, reducing response times and potentially saving lives. Its integration into the Flarepath system enhances the system’s ability to provide comprehensive and actionable alerts.

Internet of Things (IoT)

The Internet of Things (IoT) refers to the interconnected network of physical devices that communicate and exchange data over the internet. In the Flarepath system, IoT plays a central role by integrating various sensors, such as temperature, gas, and flame sensors, to monitor the vehicle's environment continuously. These sensors collect real-time data, which is transmitted to the microcontroller for analysis. The use of IoT technology ensures that the system operates as a cohesive unit, providing accurate monitoring and timely alerts.

Machine Learning (ML)

Machine Learning (ML) involves the development of algorithms that allow computers to learn from data and make predictions. In the Flarepath system, ML algorithms analyze the data collected by IoT sensors to identify patterns and predict potential fire risks. Over time, these algorithms improve their accuracy as they are exposed to more data. This adaptive learning process ensures that the system becomes increasingly effective in detecting fire hazards and providing reliable alerts.

Predictive Analytics

Predictive analytics uses statistical and machine learning techniques to analyze current and historical data to forecast future events. In the Flarepath system, predictive analytics enables the system to anticipate potential fire incidents by analyzing real-time sensor data. By detecting anomalies that indicate fire risks, the system provides users with early warnings, allowing for proactive safety measures. This approach represents a significant shift from traditional reactive fire detection systems to proactive prevention.

Real-Time Data Processing

Real-time data processing refers to the ability of the system to analyze and act on data as it is generated. In the Flarepath system, real-time data processing ensures continuous monitoring of the vehicle's environment. This capability allows the system to detect hazardous conditions instantly and notify users and emergency responders without delay. Real-time processing is crucial for preventing fire-related incidents and ensuring the system's overall effectiveness.

False Positives

In predictive systems, a false positive occurs when the system incorrectly identifies a non-issue as a problem. In the Flarepath system, minimizing false positives was a key objective. The machine learning algorithms were carefully designed to reduce unnecessary alerts, ensuring that notifications are accurate and actionable. This not only enhances user trust but also ensures that emergency responders are not distracted by false alarms.

Pilot Deployment

Pilot deployment involves the initial implementation of the system in a limited and controlled environment. In the Flarepath project, the system was first installed in a small number of vehicles to monitor its performance and gather feedback. This phase allowed developers to identify and resolve issues before scaling up the system for full deployment, ensuring a smoother and more efficient rollout.

Full-Scale Deployment

Full-scale deployment is the process of implementing the system across its intended environment after successful testing and pilot deployment. For the Flarepath system, this involved installing the system in a broader range of vehicles, integrating it with existing systems, and ensuring that it functioned effectively in diverse conditions. Full-scale deployment confirmed the system's readiness for widespread use and its ability to enhance vehicle safety at scale.

Maintenance and Updates

Maintenance and updates involve regular checks and improvements to keep the system functioning effectively. In the Flarepath system, this includes recalibrating sensors, updating machine learning algorithms, and enhancing features to address emerging challenges. Continuous updates ensure that the system adapts to new conditions, remains reliable, and provides consistent performance over time.

7 APPENDIX