POLYTECHNIC UNIVERSITY OF THE PHILIPPINES

SeekLiyab: An IoT-Integrated Real-Time Fire Detection and Primary Response System

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Billon, Ashlyn Paula I.
Caringal, Jamilah S.
Datu, Dexter Daniel E.
Mazo, Franscine Marie O.
San Juan, Adrian C.

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CHAPTER 1

PROBLEM AND ITS SETTING

1.1 Introduction

Fire incidents in the Philippines remain a pressing issue, causing significant loss of life and property each year. The Bureau of Fire Protection (BFP) recorded 15,900 fire incidents nationwide in 2023, a sharp 21.1% increase from 13,133 cases in 2022. Most of these incidents occurred in residential areas, with the National Capital Region consistently reporting the highest number of cases. Electrical connections, unattended cooking, and other preventable causes were identified as the main triggers. These alarming statistics highlight the need for improved fire safety measures to prevent incidents and minimize their impact.

Currently, many establishments and households rely on conventional Fire Detection and Alarm Systems (FDAS). These systems are primarily designed to identify fire events and trigger alarms within specific zones. A control panel processes data from smoke detectors, heat detectors, and manual call points to localize the general area of the fire and activate an alarm. While these systems are effective in basic fire detection, they often fall short in addressing more complex scenarios, such as distinguishing between actual fires and false alarms caused by environmental factors like steam or dust. Additionally, these systems lack capabilities for real-time analysis, predictive fire occurrence detection, and automated notifications, which are essential for faster response and better safety management.

Given the limitations of current solutions, the need for an advanced system that not only detects fires but also predicts their occurrence has become evident. This is where the essence of SeekLiyab comes in. The proposed system is an IoT-integrated, real-time fire detection and primary response system designed to address the gaps in traditional FDAS. By incorporating Internet of Things (IoT) technology, machine learning, and a notification system, SeekLiyab offers a more robust and reliable approach to fire safety.

The system will utilize multiple sensors, including those for smoke, carbon monoxide (CO), air quality, and temperature, to collect real-time data. A random forest classifier, a machine learning algorithm, will analyze this data to accurately classify fire, maybe fire, and non-fire events while minimizing false alarms. Additionally, SeekLiyab will include predictive capabilities, allowing it to identify patterns that indicate potential fire occurrences based on environmental conditions. Notifications will be sent automatically to key recipients, such as Electrical Engineering Department Chair, building administrators, and the Bureau of Fire Protection, ensuring timely response and coordination.

Through this innovative design, SeekLiyab aims to enhance the accuracy and reliability of fire detection systems and provide a proactive approach to fire safety management. The integration of IoT and machine learning in fire detection represents a significant leap forward in ensuring the safety and well-being of communities in the Philippines.

1.2 Statement of the Problem

The increasing need for reliable fire prevention systems has led to the development of IoT-integrated technologies. However, several concerns remain regarding the overall effectiveness of such devices. This study aims to address the following questions:

1. How reliable is the SeekLiyab system in identifying fire, maybe fire, and non-fire events based on real-time analysis of data from smoke, CO, air quality, and temperature sensors?
2. How consistent is the SeekLiyab system in transmitting SMS alerts to designated recipients, including the electrical engineering department chair, campus administrators, guards, and the Bureau of Fire Protection?
3. To what extent can the SeekLiyab device predict the likelihood of a fire based on environmental factors and data collected from its surroundings?
4. How does the use of IoT and cloud-based storage in SeekLiyab enhance data accessibility and improve decision-making for fire prevention and management?

This investigation will provide insights into the feasibility and limitations of SeekLiyab in ensuring fire safety and prevention. By addressing these questions, the study aims to contribute valuable insights into the design and optimization of IoT-based fire detection systems, paving the way for safer and more reliable implementations in educational settings.

1.3 Conceptual Framework

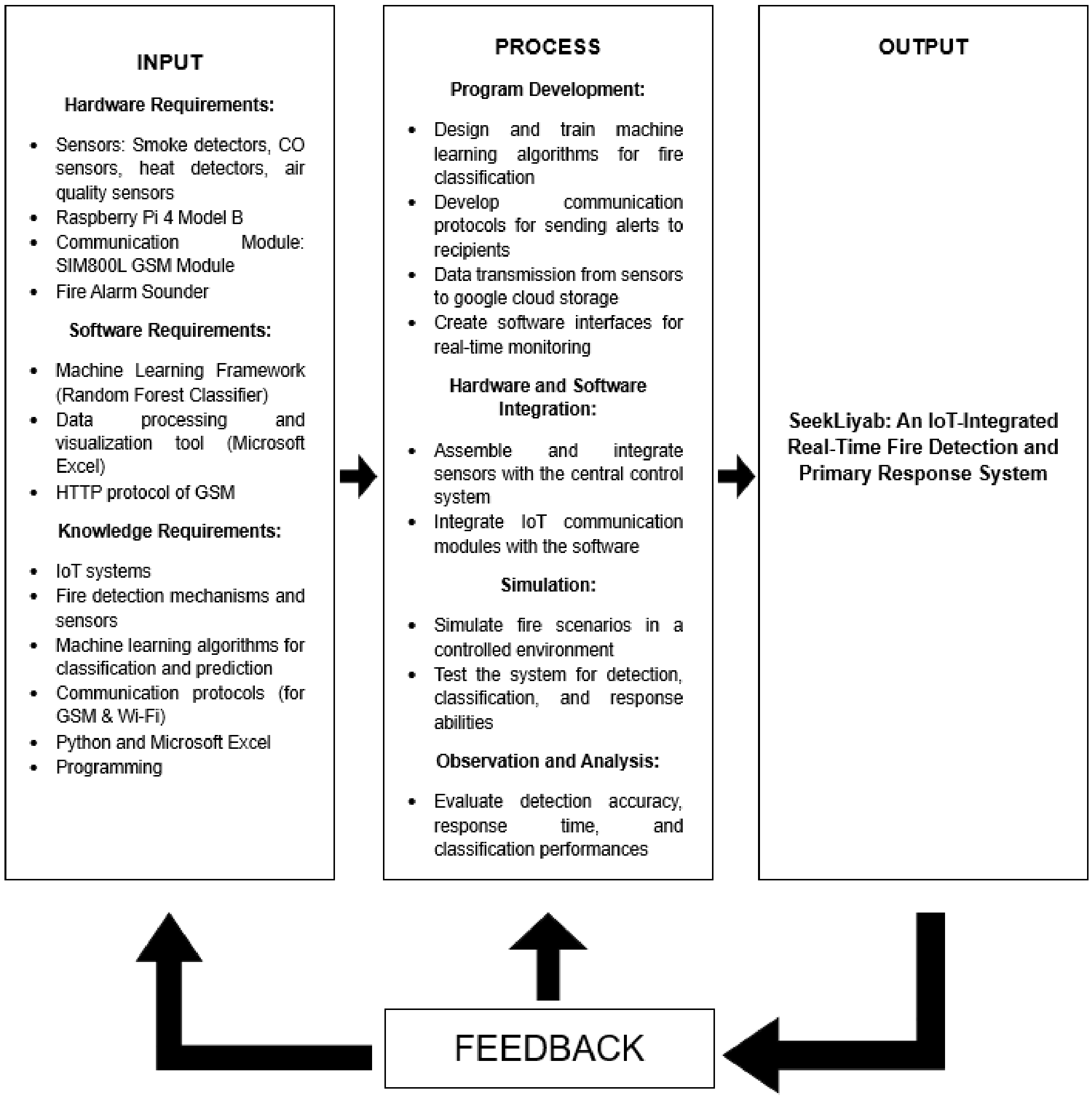

Figure 1. Conceptual Framework

The conceptual framework of the proposed topic follows the Input-Process-Output-Feedback diagram, outlining the systematic flow of the study. The input provides the knowledge, hardware, and software required for the implementation of the IoT-based fire detection and primary response system. Knowledge requirements include IoT systems, fire detection mechanisms, machine learning algorithms, for fire classification and prediction, communication protocols for GSM, Python and Microsoft Excel for data processing and visualization, and programming. The hardware components consist of sensors, such as smoke detectors, CO sensors, heat detectors, and air quality sensors. A central control system using Raspberry Pi 4 Model B, SIM800L GSM module, and a fire alarm sounder. The software requirements include the RFC for machine learning, Python and Microsoft Excel for data processing and visualization, and GSM-based notification systems for real-time alerts.

The process involves program development, including the design and training of machine learning models, development of communication protocols for alerting recipients, transmitting data from the sensors and the creation of real-time monitoring interfaces. This is followed by hardware and software integration, wherein sensors are assembled with the central control system and IoT modules are integrated into the software. The next phase involves simulating fire scenarios in controlled environments to test the system’s detection, classification, and response capabilities, followed by observation and analysis to evaluate system performance and accuracy. The output is the development of the SeekLiyab, an IoT-integrated real-time fire detection and primary response system that utilizes the RFC and SIM800L GSM module to deliver consistent and reliable fire detection and response. The Feedback loop ensures continuous improvement of the system by refining detection algorithms, hardware integration, and communication protocols based on testing results and performance evaluations, ultimately enhancing the system's consistency and reliability.

1.4 Significance of the Study

This study highlights the importance of an IoT-based fire detection and alarm system in improving fire safety protocols. By providing real-time alerts and data, and enhances early fire detection, strengthens emergency response, and promotes a culture of safety, demonstrating the crucial role of technology in mitigating fire hazards and improving safety practices to the following:

For the **Electrical Engineering Department**, this study offers significant benefits to the Electrical Engineering Department, both for students and faculty, by introducing real-time fire detection and alerting services designed to identify early signs of fire hazards. The study promotes a culture of safety and awareness within the department, emphasizing the importance of early fire detection and the role of technology in preventing fire-related incidents

For the **Building Administration**, the implementation of the IoT-based fire detection system empowers building administrators to significantly improve safety protocols within their facilities. By providing timely alerts and detailed information about fire hazards, the system ensures that university staff are quickly notified in the event of a fire. Moreover, administrators can use the data collected by the system to conduct regular safety assessments and improve emergency preparedness plans.

For the **Local Government Units (LGU)**, this study actively promotes fire safety initiatives within the community, equipping local government units with the tools needed to enforce safety regulations and standards more effectively. By utilizing data collected from the fire detection system, local governments can acquire valuable insights into fire hazards within their areas, allowing them to formulate targeted strategies to mitigate these risks and facilitate prompt rescue operations. This preventive approach not only enhances community safety but also fosters a culture of awareness and responsibility regarding fire prevention measures.

For the **Bureau of Fire Protection (BFP)**, the real-time fire detection system provides substantial support to the Bureau of Fire Protection by enabling them to adopt a proactive stance against fire hazards. With immediate alerts and data-driven insights at their disposal, the BFP can respond more swiftly to potential fire incidents, minimizing damage and enhancing public safety. This system allows fire officials to monitor high-risk areas continuously, improving their operational efficiency and effectiveness in mitigating the impacts of fires. Additionally, collaboration with technology can lead to improved training programs and strategic planning for emergency response.

For **future researchers**, the findings from this study lay a crucial foundation for future research endeavors in the realm of IoT applications for safety systems. By highlighting the effectiveness and challenges of implementing real-time fire detection technology, this research encourages future scholars and engineers to explore advancements in both technology and methodologies. The insights gained can inspire innovative solutions that further enhance fire safety and prevention, promoting ongoing improvements in public safety standards and practices. Through continued research, there is significant potential to develop smarter, more efficient systems that adapt to the evolving needs of society.

1.5 Scope and Limitation

This project focuses on designing and implementing wireless FDAS using IoT technology. The system will integrate various sensor technologies to detect smoke and other fire indicators, addressing the limitations and unreliability of conventional battery-operated smoke detectors. Additionally, a predictive analysis feature will be included, continuously monitoring environmental data such as temperature, CO, smoke density, and gas concentration. This feature will assess these conditions to predict the likelihood of a fire, providing early warning and enhancing the system's overall reliability.

Furthermore, the researcher will integrate SMS messaging for real-time alerts, transmitting notifications wirelessly to concerned authorities, such as fire departments, building administrators, and/or emergency response teams.

However, the project will not integrate control over external factors that may affect Wi-Fi signals or mobile data availability, such as network congestion, signal interference, or service outages. Additionally, the researcher will not determine the duration of the device's operation when using a battery as its primary source of energy. Factors such as battery capacity, device usage patterns, and environmental conditions will influence battery life, but these aspects are outside the scope of the current research and will not be analyzed in this study.

CHAPTER 2

REVIEW OF RELATED LITERATURE AND STUDIES

2.1 Related Literature and Studies

Internet of Things (IoT)

This chapter presents a review of related literature that explores key technologies relevant to the utilization of IoT in real-time detection and response for fire safety enhancement. The review covers IoT and its integration with fire detection and alarm systems, highlighting the role of wireless sensor networks in enhancing system efficiency. Additionally, it delves into the application of machine learning techniques in improving fire detection accuracy and predictive capabilities. By synthesizing these fields, the chapter provides a comprehensive understanding of the current advancements and challenges in implementing a reliable and effective fire safety system. Al-Sakran et al. (2019) discusses the design and implementation of a fire alarm system utilizing Internet of Things (IoT) technologies. Presented at the Third World Conference on Smart Trends in Systems, Security, and Sustainability (WorldS4), the study outlines how the system integrates sensing nodes, mesh networking, and the MQTT protocol to ensure reliable fire detection and user notification. The authors emphasize the scalability, reliability, and user-centric design of the system, showcasing its potential to enhance safety and responsiveness in fire emergencies.

Fire Detection and Alarm System (FDAS)

Previous research papers discussed IoT-based fire alarm detection systems that leverage wireless sensor networks and cloud connectivity for real-time fire monitoring and alerting. These systems integrate a variety of sensors—such as smoke, temperature, and gas detectors—into an ad-hoc network of nodes connected to microcontrollers like Raspberry Pi or ESP8266. By using MQTT or similar protocols, these systems aim to provide efficient, low-cost solutions for detecting fire outbreaks and sending immediate alerts to authorities and residents. It discusses the integration of advanced technologies in FDAS to enhance fire prevention and response. Gragain et al. (2024) emphasize the use of GSM modules, temperature, and smoke sensors for real-time alerts and monitoring, highlighting their affordability and adaptability. Vidyadhari et al. (2023) explore an IoT-based system combining Arduino boards, flame sensors, and GSM modules for remote alerts, offering flexibility and integration with home automation. Thakkar et al. (2022) introduce a Random Forest Algorithm for fire detection and prediction, leveraging environmental data to identify fire risks with high accuracy. Similarly, Li et al. (2022) refine smoke detection using sub-pixel mapping and random forest results for better spatial details and dynamic monitoring. These studies collectively demonstrate the potential of integrating Raspberry Pi, GSM, and RFCs to develop scalable, efficient, and accurate fire detection systems for diverse applications.

In terms of FDAS, recent developments have centered on the use of GSM modules for real-time detection, response, and notification capabilities for fire safety. The GSM SIM800L module is widely used in FDAS for its affordability and efficiency. It integrates with Arduino Uno and sensors like temperature and smoke detectors for instant SMS alerts. GSM-based systems can detect flames and send SMS or call notifications, proving their flexibility and reliability over traditional alarms.

Wireless Sensor Network (WSN)

When combined with WSNs, machine learning significantly extends the capabilities of FDAS. WSNs provide real-time data collection, while ML processes this data, recognizing patterns that indicate early-stage fires and improving response times. These networks rely on efficient communication protocols and energy-saving strategies to extend their operational lifespan. Studies by Islam et al. (2019) and Banđur et al. (2019) emphasize how optimized deployment and power management significantly impact the network's reliability and effectiveness in various IoT-driven environments, including smart agriculture and industrial monitoring.

Moreover, the related literature on WSNs emphasizes their critical role in enhancing FDAS. WSNs contribute significantly to real-time data monitoring and transmission, enabling early fire detection and swift response in FDAS applications. The literature also discusses network coding techniques that enhance the reliability and security of fire detection systems, ensuring resilient data transfer even during communication disruptions. Hence, WSNs are shown to be highly adaptable, providing a secure, reliable foundation for modern FDAS by efficiently managing data flow, energy consumption, and real-time fire response.

Random Forest Classifier (RFC)

On the side of Machine Learning (ML), it offers diverse algorithms—primarily supervised, unsupervised, and reinforcement learning—that convert data into actionable insights, which are crucial for decision-making across various fields, especially in the context of Industry 4.0. By enabling automated data analysis and prediction, ML has transformed applications such as fire detection, where early identification of hazards is essential for minimizing risk. This integration of ML algorithms like Support Vector Machines (SVM), Decision Trees, Random Forests, and Neural Networks allows systems to identify and assess potential threats with high accuracy, further enhancing the effectiveness of FDAS.

RFC significantly improves fire detection accuracy by processing diverse sensor inputs. It achieves low error rates in predicting forest fires and enhances smoke detection accuracy. This confirms its effectiveness for FDAS applications. The GSM module ensures reliable alerts, while Random Forest processes data to identify fire incidents accurately. Systems combining these technologies enhance response times and reliability. Ahmad et al. (2018) compared machine learning algorithms—Support Vector Machine (SVM), Random Forest (RF), and Extreme Learning Machine (ELM)—for intrusion detection. Using the NSL-KDD dataset, a benchmark for evaluating intrusion detection systems, they tested these algorithms on datasets of varying sizes.

Results showed that ELM outperformed others in accuracy, precision, and recall for large datasets (65,535 samples). However, SVM performed better on smaller datasets. The study concluded that ELM is more effective for analyzing large-scale network intrusion data, with potential for further exploration in feature selection and transformation. Gupta et al. (2021), studied that the system integrates with algorithms like Support Vector Machine (SVM), Random Forest, Decision Tree, and Neural Networks to predict fire onset. With 1,441 labeled instances for training and testing, Random Forest achieved the highest accuracy of 98.5%, precision of 98.6%, and recall of 98.6%. The system provides real-time alerts to authorities, enabling faster responses, improved resource management, and minimized environmental and property damage.

GSM Module

Another, the body of literature on notification systems demonstrates their essential role in improving emergency response across various settings, with clear applications in fire detection and alert systems relevant to institutional environments. Lowu and Noé (2023) provides an innovative approach to home security, with a significant focus on the application of the GSM module. The GSM module is effectively utilized as a core component for real-time notifications, enabling seamless communication between the system and the homeowner. By leveraging SMS and email services, the system ensures timely alerts about intrusions or security breaches, making it a reliable tool for remote monitoring. This use of the GSM module highlights its versatility in modern security systems, offering a cost-effective and easily deployable solution. Gragasin et al. (2024) highlights the integration of a GSM module for real-time communication in fire detection systems. The GSM module facilitates the transmission of SMS alerts to users' smartphones upon detecting fire hazards. This ensures timely notifications and enhances emergency response coordination. The study demonstrates the module's reliability in providing instant alerts, addressing limitations of traditional fire alarms. While the system effectively combines affordability and adaptability, future enhancements could improve its integration with advanced technologies like machine learning.

Notification systems for vehicle accident detection also underscore the potential of automated alerts for emergency response teams. Chang et al. (2019) and Bhakat et al. (2021) discuss systems that detect vehicle crashes using sensors and send alerts to emergency contacts and authorities. These approaches could be relevant for broader applications where swift responses are required, such as alerting university guards or the BFP in a campus setting. The adaptable aspects of these systems, which focus on fast, targeted notifications, provide a basis for creating fire detection systems in university environments that instantly alert internal and external emergency responders.

Furthermore, systems like Mamamayan (Rey et al., 2022) and those presented by Prakash et al. (2023) and Adetunji et al. (2023) illustrate effective methods for broad-based emergency notifications within communities. These systems use mobile apps or dual-activation mechanisms to alert emergency teams and community responders, supporting coordinated and timely responses. By integrating these principles, a fire detection and notification system on a campus could promptly inform the department chair, guards, utility staff, and BFP in real time. Overall, these studies highlight how IoT, AI, and mobile technologies facilitate automated notifications across diverse scenarios, offering a foundation for developing a comprehensive, institution-based fire detection and alert system.

2.2 Theoretical Framework

Related literature underscores the pivotal role of emerging technologies in enhancing FDAS. The integration of IoT, WSN, and ML, specifically the RFC, demonstrates significant potential in improving real-time fire detection and response. IoT-based systems, utilizing wireless sensor networks and Google cloud connectivity, provide a scalable and efficient framework for fire monitoring. These systems employ various sensors—smoke, temperature, air quality and gas detectors—interconnected through protocols to ensure seamless data transmission and alert generation. Machine learning algorithms, such as RFC, process diverse sensor input costs to enhance detection accuracy, while GSM module-based notification systems enable timely alerts to relevant stakeholders. Collectively, these technologies form a robust foundation for developing advanced FDAS that are reliable and cost-effective.

Building on this foundation, the researchers aim to address the limitations of current FDAS by integrating IoT, WSNs, ML, and GSM-based notification systems into a cohesive framework. The growing incidence of fire incidents and the unreliability of traditional alarm systems necessitate an innovative approach to fire safety. By synthesizing these advanced technologies, the proposed system seeks to enhance fire detection accuracy and primary response through immediate communication with emergency responders. This integrated system is designed to overcome challenges in data reliability, response times, and alert dissemination, thereby providing a more effective solution for fire safety management across various environments, including residential, industrial, and institutional settings.

The significance of this study lies in its potential to revolutionize fire safety systems through the integration of IoT, WSNs, ML, and GSM modules. This comprehensive approach offers enhanced real-time detection, predictive capabilities, and rapid notification, ultimately aiming to minimize fire-related damage and casualties. By leveraging the strengths of these technologies, the study proposes a scalable, adaptable, and efficient solution that addresses the critical need for improved fire safety measures. The findings contribute to the body of knowledge by presenting a model that not only advances technological applications in FDAS but also establishes a new standard for proactive fire management strategies.

CHAPTER 3

RESEARCH DESIGN AND METHODOLOGY

This chapter presents the research design and methodology employed in this study, emphasizing the prototype testing design used to evaluate the system's performance and functionality. The chapter outlines the process involved in designing, developing, and testing the prototype, detailing the methods and criteria used for assessment. It includes the description of the research framework, testing environment, performance metrics, and data collection procedures to ensure the system meets its intended objectives. By providing a systematic approach to prototype evaluation, this chapter aims to highlight the rigor and validity of the methodology used in achieving the study’s goals.

3.1 Research Design

The researchers will develop a prototype of an IoT-integrated fire detection and alarm system, integrating various wireless sensor networks, machine learning algorithm, fire alarm sounder, and notification mechanism, for real-time monitoring and improving primary response systems.

The research aims to design, develop, and evaluate an improved fire detection and alarm system through various testing under control conditions for enhanced reliability and reduced false alarms.

The independent variables in this research include the type of sensors used, machine learning algorithm implemented, environmental conditions, and the notification mechanism employed. The dependent variables will be measured outcomes such as detection accuracy, classification performance, and response time.

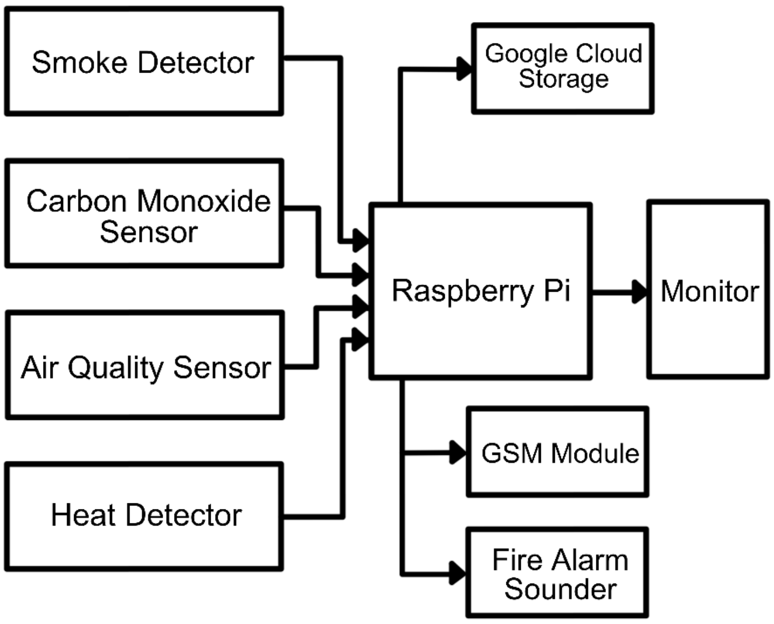

Figure 2. *Block Diagram*

Figure 2 illustrates the interaction and connectivity among the system components. At the core is the Raspberry Pi, which serves as the central processing unit. It receives inputs from four sensors, which are smoke, carbon monoxide, air quality, and heat detectors. These sensors continuously monitor environmental conditions and send real-time data to the Raspberry Pi for processing.

Both raw and processed data are displayed on a monitor for real-time observation and stored in Google Cloud Storage for record-keeping. Raspberry

Pi sends processed data to a GSM module for SMS notifications to predefined recipients. A fire alarm sounder is also activated to alert occupants during a fire event. This integration ensures accurate detection, effective communication, and reliable system performance.

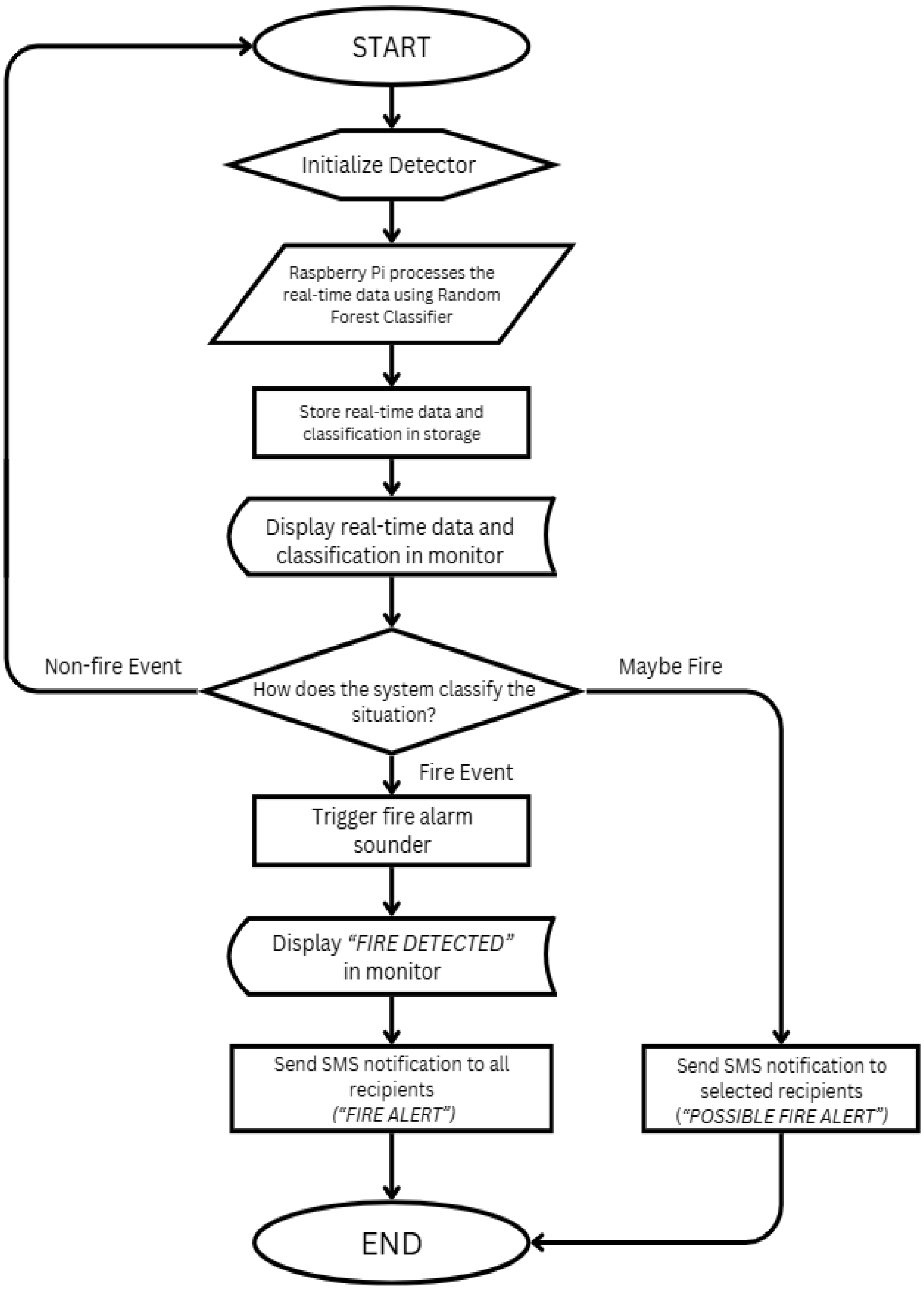

Figure 3. *System Flow Chart*

Figure 3 outlines the operational flow of the fire detection system. The process starts with the initialization of the detector, which activates the system components. Real-time data collected from sensors is processed using a Random Forest Classifier. The classified data is stored and displayed on a monitor for real-time observation. Based on the system's classification, the event is categorized as either a "Non-fire Event," "Maybe Fire," or "Fire Event."

If a fire is detected, the system triggers the fire alarm sounder, displays a "FIRE DETECTED" message on the monitor, and sends SMS notifications labeled "FIRE ALERT" to all designated recipients. For a "Maybe Fire" scenario, SMS notifications labeled "POSSIBLE FIRE ALERT" are sent to selected recipients for further monitoring. If no fire is detected, the system continues monitoring. This iterative process ensures real-time detection and response, emphasizing accuracy and reliability.

3.2 FDAS Schematic Diagrams

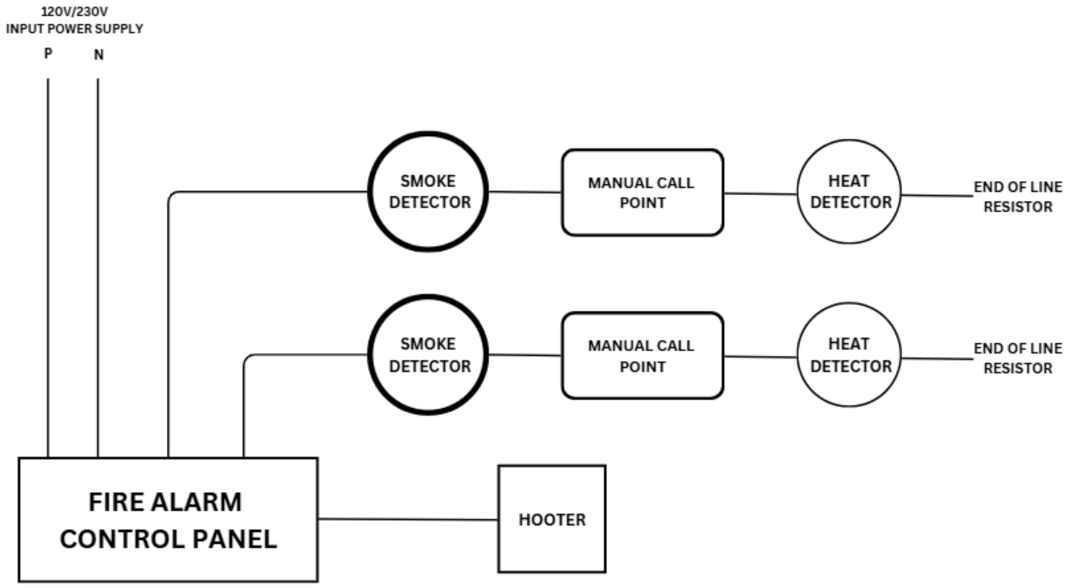

Figure 4. *Conventional FDAS Schematic Diagram*

Figure 4 illustrates the conventional fire detection and alarm system, which relies on a wired network of smoke detectors, manual call points, and heat detectors connected to a central fire alarm control panel. Upon detecting signs of fire, such as smoke or heat, the system triggers the fire alarm sounder to alert nearby people. While effective in localized environments, this setup is limited by its reliance on manual intervention via manual call points and its inability to provide remote monitoring or notifications to external stakeholders.

Furthermore, Figure 5 shown below represents the IoT-integrated Fire Detection and Alarm System (FDAS), which enhances conventional designs through advanced sensor networks and cloud-based technologies. The proposed system incorporates multiple sensors, including CO, air quality, smoke, and heat detectors. These components wirelessly transmit data to a centralized monitoring panel via Google cloud storage. Unlike the conventional system, the IoT-based FDAS automatically analyzes real-time data using machine learning algorithms, differentiating between fire and non-fire events with higher precision. Additionally, it activates fire alarms and sends SMS notifications to key personnel, including the Electrical Engineering department chair, campus administrators, and the Bureau of Fire Protection.

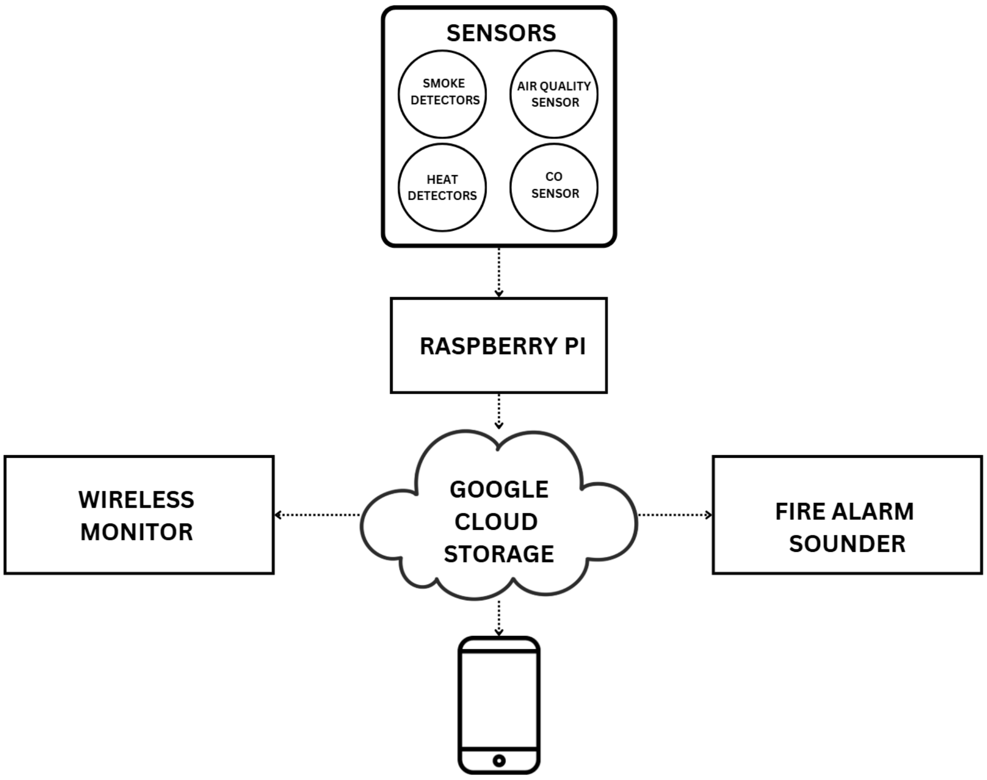

Figure 5. *IoT-Integrated FDAS Schematic Diagram*

By leveraging IoT and cloud computing, the proposed system ensures improved situational awareness, remote accessibility, and enhanced decision-making capabilities, addressing the limitations of traditional FDAS designs.

3.3 Materials and Equipment

1. **Sensors**
   a. **MQ2 Smoke Detector:** For detecting smoke
   b. **ME2-CO CO Sensor:** Monitoring of CO Level
   c. **MQ 135 Air Quality Sensor:** For assessing environmental condition
   d. **MCP9808 Heat Detector:** For detection of change in temperature

2. **Control and Monitoring System**

   a. **Custom built Monitoring System:** For real-time monitoring of data from the sensors

   b. **Raspberry Pi 4 Model B:** For integrating sensors and processing of data

3. **Communication Modules**

   a. **SIM800L GSM Module:** For sending notification alerts and to enable communication between sensors and control panel

4. **Software Tools**

   a. **Random Forest Classifier:** For classification of environmental situation

   b. **Microsoft Excel:** for data analysis and visualization

3.4 Experimental Setup

The test environment for this study is specifically designed to simulate indoor conditions where fire incidents may occur. A controlled testing area will be set up to replicate various scenarios, incorporating environmental factors such as temperature changes, the presence of smoke, air quality variations, carbon monoxide levels, and visible flames. This setup will recreate realistic situations that will simulate fire, maybe fire, and non-fire events, such as cooking, candle and trash burning, cigarette or vape smoking, barbecue grilling, and igniting of spilled combustible materials. Additionally, these simulations will assess the system's ability to distinguish between actual fire incidents and false alarms. By enabling control over environmental variables, this setup ensures rigorous testing of the prototype to evaluate its consistency, reliability, and real-world applicability.

Moreover, the hyperparameter tuning process for this fire detection system is designed to optimize its performance in accurately identifying fire, maybe fire and non-fire events while ensuring reliable alert mechanisms. The key parameters include sensor thresholds, such as smoke sensitivity, temperature levels, CO detection levels, and air quality. RFC parameters are also optimized, the number of input features, learning rates, and training to improve classification accuracy. This comprehensive tuning process focuses on enhancing key performance metrics such as true positive rates, false positive rates, precision, recall, and ensuring the system's robustness and reliability in practical applications.

Sensor calibration will involve establishing baseline responses under both normal and fire-risk conditions to ensure precise detection capabilities. The machine learning algorithm will undergo training to accurately differentiate between fire, maybe fire and non-fire events, ensuring reliable classification for early fire detection. Lastly, the notification mechanism will be fine-tuned to deliver reliable and consistent alerts based on sensor data and classification results.

3.5 Experimental Procedure

The experimental procedure consists of four phases: Baseline Testing, Fire Event Testing, and Non-Fire Event Testing. In Baseline Testing, the system operates in a controlled environment under normal indoor conditions, such as standard temperature and the absence of smoke or flames, to establish baseline sensor outputs. This ensures that the sensors and machine learning algorithms are calibrated to classify non-fire events accurately without triggering false alarms.

FACTOR	VALUE RANGE FROM TESTING
Smoke Density (ppm)	
Carbon Monoxide Level (ppm)	
Dust Level (µg/m³)	
Temperature (°C)	

Table 1. *Conditions Table for Baseline Testing*

In Fire Event Testing, the ability of the system to detect fire scenarios is evaluated by simulating controlled fire conditions using heat sources, smoke, flames and necessary components for simulation of fire. During this phase, the sensors and ML classification are monitored to ensure all the data acquired and transmitted are recorded for setting the value range.

FACTOR	VALUE RANGE FROM TESTING
Smoke Density (ppm)	
Carbon Monoxide Level (ppm)	
Dust Level (µg/m³)	
Temperature (°C)	

Table 2. *Conditions Table for Fire Event Testing*

In Non-Fire Event Testing, the system's capacity to differentiate fire events from non-fire scenarios like steam or dust is assessed by introducing these non-fire conditions into the testing area. This phase focuses on real-life situations where some levels are average, but no fire is still present and detected.

FACTOR	VALUE RANGE FROM TESTING
Smoke Density (ppm)	
Carbon Monoxide Level (ppm)	
Dust Level (µg/m³)	
Temperature (°C)	

Table 3. *Conditions Table for Non-Fire Event Testing*

Trial No.	Smoke Density (ppm)	CO Level (ppm)	Dust Level ($\mu g/m^3$)	Temperature (°C)	Classification

Table 4. *Training Data Table*

This table represents the training dataset utilized to train the Random Forest Classifier for accurate situational classification and predictive capabilities. The classifier is designed to categorize scenarios into three distinct classifications: Fire Event, Non-fire Event, and Maybe Fire Event. The table includes data collected across multiple trials, featuring the following parameters:

- **Smoke Density (ppm):** Represents the concentration of smoke particles in parts per million, providing an indicator of potential fire activity;
- **CO Level (ppm):** Denotes the carbon monoxide concentration in parts per million, an important factor in fire detection;
- **Dust Level ($\mu g/m^3$):** Measures the quantity of dust particles in the air, which may influence the event classification;
- **Temperature (°C):** Captures the ambient temperature, aiding in identifying heat-related anomalies; and
- **Classification:** Specifies the resultant categorization (Fire Event, Non-fire Event, or Maybe Fire Event) based on the input parameters. This

training data is critical in developing the Random Forest Classifier's ability to recognize patterns and reliably predict fire-related events with precision.

3.6 Data Gathering Procedure

The data collected from the IoT-based Fire Detection and Alarm System (FDAS) will include smoke concentration, measured in parts per million (ppm) using smoke sensors, and carbon monoxide levels, also recorded in ppm through CO sensors. Air quality metrics, such as the presence of volatile organic compounds (VOCs) and particulates, will be monitored using air quality sensors and measured in micrograms per cubic meter (µg/m³). Heat sensors will capture temperature levels in degrees Celsius (°C) to detect changes indicative of fire hazards.

All sensor outputs will be recorded electronically using data acquisition modules connected to a Google cloud storage system for real-time monitoring and data management. This ensures efficient logging of smoke, CO, air quality, and heat sensor outputs, providing continuous access to environmental data.

The data will be recorded at a frequency suitable for real-time monitoring to ensure the responsiveness and reliability of the system. Sensor readings, including smoke concentration, CO levels, air quality metrics, and temperature, will be sampled every second during testing. This high-frequency sampling will capture rapid changes in environmental conditions, ensuring real-time detection of fire, maybe fire and non-fire scenarios.

3.7 Data Analysis

This section provides a comprehensive discussion of how the collected data will be evaluated to assess the performance and reliability of the proposed FDAS. The analysis primarily focuses on the classification performance of the random forest classifier, a machine learning algorithm employed to differentiate between fire, maybe fire, and non-fire events, and even to predict fire occurrences. The classifier's effectiveness will be analyzed using F-1 Score, which is a crucial metric in evaluating the performance of classification models. The F1-score is the harmonic mean of precision and recall. It provides a single metric that captures both false positives and false negatives, making it particularly useful when dealing with imbalanced datasets. The formula for Precision, Recall, and F-1 Score is given respectively as,

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Precision measures the accuracy of positive predictions. It is defined as the number of true positives divided by the sum of true positives and false positives. High precision indicates that when the model predicts a fire, it is likely correct. While Recall measures the ability of a model to find all true positives. It is defined as the number of true positives divided by the sum of true positives and false negatives. High recall indicates that most actual fire occurrences are detected by the model.

The analysis will also assess the reliability of individual sensors by examining their consistency across repeated scenarios and under varying environmental conditions. This will include the analysis of sensor outputs during controlled fire simulations, normal indoor activities, and stress tests. Any discrepancies or anomalies in sensor behavior will be documented and evaluated to determine their potential impact on overall system performance.

	Predictive Positive (Fire)	Predictive Negative (No Fire)
Actual Positive (Fire)		
Actual Negative (No Fire)		

Table 5. *Confusion Matrix*

Additionally, Table 5 presents the confusion matrix derived from the evaluation of the Random Forest Classifier utilized in the IoT-based Fire Detection and Alarm System (FDAS). This matrix is a vital analytical tool that enables researchers to assess the model's performance in accurately predicting fire occurrences based on sensor data. The confusion matrix is organized to display four key outcomes of the classification process:

- **True Positives (TP)**: This value represents the number of instances where the model correctly identified a fire occurrence. A high TP count indicates effective detection capabilities, suggesting that the model is proficient at recognizing actual fire events.

- **False Negatives (FN)**: This metric indicates the number of actual fire occurrences that were incorrectly classified as non-fire by the model. A significant FN value highlights potential weaknesses in detection, as these missed detections can pose serious safety risks. Reducing FN is crucial for enhancing the reliability of the FDAS.

- **False Positives (FP)**: This count reflects instances where the model incorrectly predicted a fire when there was none. While a low FP value is desirable to minimize unnecessary alarms, it is essential to balance this with recall to ensure that actual fires are not overlooked.

- **True Negatives (TN)**: This value shows the number of instances where the model correctly identified non-fire situations. A high TN count reflects the model's ability to accurately discern safe conditions, contributing to overall system reliability.

By analyzing the values presented in Table 6, researchers can identify which parameters and features of the model are performing well (overperforming) and which ones require further optimization (underperforming). By understanding how different parameters influence TP, FP, FN, and TN counts, researchers can make informed decisions on which hyperparameters to adjust to enhance model performance.

To facilitate this analysis, software tools such as Python and Microsoft Excel will be used for data visualization and the evaluation of machine learning performance metrics, including precision, recall, and F1 scores derived from the confusion matrices. Python will also aid in automating the interpretation of sensor data and refining the classification model. Meanwhile, Excel will be utilized for organizing raw data, generating descriptive statistical summaries, and comparing performance metrics.

Parameters	**Smoke Density (ppm)**	**CO Level (ppm)**	**Dust Level (µg/m³)**	**Temperature (°C)**
Smoke Density (ppm)	1.00			
CO Level (ppm)		1.00		
Dust Level (µg/m³)			1.00	
Temperature (°C)				1.00

Table 6. *Collinearity Matrix of Parameters*

Table 7 presents a correlation matrix that evaluates the multicollinearity among four critical sensor parameters used in the IoT-based Fire Detection and Alarm System (FDAS): **Smoke Density**, **CO Level**, **Dust Level**, and **Temperature Level**. This assessment is essential for understanding the relationships between these parameters and identifying potential redundancies that may impact the model's performance and interpretability. By analyzing the correlations presented in Table 7, researchers can determine which parameters exhibit significant redundancy. Reducing redundancy among parameters can lead to a more robust design for the FDAS, improving model interpretability and reducing the risk of multicollinearity issues during regression analysis. The insights derived from this multicollinearity assessment can guide decisions on feature selection and model design, ensuring that the FDAS remains efficient while maintaining high predictive accuracy in fire detection scenarios.

These rigorous data analysis methods aim to ensure that the FDAS is robust, accurate, and reliable in identifying fire events while minimizing false alarms. By providing a detailed evaluation framework, this analysis will establish the system’s applicability in real-world fire safety scenarios.

3.8 Reliability and Validity

The researchers will test the FDAS extensively, going through multiple design iterations to ensure its dependability. Each phase, including baseline, fire event, and non-fire event was carefully calibrated and repeated to refine the system’s ability to distinguish between fire, maybe fire, and non-fire scenarios accurately. Through these iterative tests, adjustments were made to enhance sensor accuracy, optimize the machine learning algorithm’s performance, and ensure consistency in notification responses. Validity was reinforced by establishing controlled conditions that replicate real-life fire and non-fire events, thus allowing the system to be validated against potential real-world applications. This approach aimed to provide a reliable prototype that can effectively respond in diverse and challenging environments, hence supporting the study’s goal of developing an innovative, dependable, and precise FDAS.

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