UNIVERSITY of RWANDA

ACEIoT

Website: www.aceiot.ur.ac.rw
Mail: aceiot@ur.ac.rw

College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

Research Thesis Title: A Smart Approach with AI-IoT Synergy to Enhance Educational Spaces: A Real-Time Air Pollution Monitoring System, A Case Study: UR-NYARUGENGE Campus

A dissertation submitted in partial fulfillment of the requirements for the award of the Master of Science degree on the Internet of Things: Embedded Computing Systems

Submitted by: NIYOMUGABO Eric
Registration Number: 217154220

Supervised by: Dr. Gaspard GASHEMA
Dr. Eric HITIMANA

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Declaration

I NIYOMUGABO Eric, Master's student from the African Center of Excellence in the Internet of Things: Embedded Computing Systems, at the University of Rwanda. I declare that this research thesis is my original work and has not been presented anywhere in the world.

NIYOMUGABO Eric

Ref: 217154220

Signed: ………………………….

Date: ……/……/……

Bonafide certificate

This is to certify that this submitted Research Thesis work report is a record of the original work done by NIYOMUGABO Eric (**Ref. No:** 217154220), Masters in IoT-Embedded Computing Systems Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in the Internet of Things, the Academic year 2022/2024.

This work has been submitted under the supervision of Dr. Gaspard GASHEMA
and Dr. Eric HITIMANA

Main Supervisor: Dr. Gaspard GASHEMA   Co-Supervisor: Dr. Eric HITIMANA

Date: Date:

Signature: Signature:

The Head of Masters and Training

Dr. James RWIGEMA

Date:

Signature…………………

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Abstract

Rapid urbanization and climate change pose serious environmental issues to cities such as Kigali, with considerable air pollution. Public health, safety, and quality of life are all significantly impacted by this problem, especially in educational settings where students and staff are Fragile. Conventional monitoring methods, which are frequently more reactive than proactive, are insufficient to successfully handle these issues. Highlighting the University of Rwanda (UR) at the NYARUGENGE Campus (College of Science and Technology (CST)), this study proposes an Internet of Things (IoT)-enabled air pollution monitoring system specifically made for educational settings. The system seeks to enhance the campus environment by collecting and analyzing air quality data in real-time by using random forest. It consists of setting up an IoT sensor network throughout the NYARUGENGE Campus to track air quality continuously. These sensors send their data to a central system, where time series machine learning algorithms are used to receive, process, and evaluate it. This method makes it possible to spot abnormalities, identify trends, and forecast future circumstances. The incorporation of an SMS warning mechanism that promptly alerts students and campus administrators when air quality standards are surpassed is a crucial component of this system. This guarantees prompt and efficient reactions to possible threats, protecting the campus community's health and well-being. Technology promotes data-driven campus planning, environmental sustainability, and public health outcomes by enabling real-time data collection and predictive analysis. The installation of this IoT- and machine learning using time series algorithm and random forest-based air pollution monitoring system at NYARUGENGE Campus opens the door for more intelligent, secure, and sustainable learning environments by providing a scalable model for other educational institutions dealing with comparable environmental issues.

Keywords: *AI-IoT Synergy, environmental monitoring, real-time data, urban sustainability, machine learning.*

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List of Abbreviations

ACEIoT: African Center of Excellence in Internet of Things

ADC: Analog-to-Digital Converters

AI: Artificial Intelligent

AQI: Air Quality Index

CO_2: Carbon dioxide

CSS: Cascading Style Sheets

CST: College of Science and Technology

GSM: Global System for Mobile Communications

HTML: Hypertext markup language

I/O pins: Input and Output

IDE: Integrated Development Environment

IoT: Internet of Things

LCD: Liquid Crystal Display

NodeMCU: Microcontroller unit

PHP: Hypertext Processor

PM2.5 and PM10: Parameter matter

SMS: Short Message Service

SPI: Serial peripheral interface

UART: Universal asynchronous receiver/transmitter

UR: University of Rwanda

VOC: Volatile organic compounds

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CHAPTER I: GENERAL INTRODUCTION

1.1 Background

Global urbanization, industrialization, and climate change have led to serious environmental challenges for metropolitan areas, including increased flood risks, temperature fluctuations, water contamination, and, notably, declining air quality [1]. These issues strain urban infrastructure and pose significant threats to public health. Kigali, the capital city of Rwanda, faces these challenges as a city with significant economic growth. To ensure sustainable development and the well-being of its citizens, managing its environmental impact is crucial [2].

In this endeavor, air pollution monitoring is essential, especially in educational settings where staff and students are in close contact with problems related to air quality. These risks can be considerably reduced by installing specialized air pollution monitoring systems on sites like the University of Rwanda (UR)-Nyarugenge Campus in Kigali [3]. As part of this system, IoT sensors would be placed across the campus to continually monitor the quality of the air. A specific Machine learning algorithm would be used to analyze the gathered data to spot any anomalies, forecast possible threats, and find trends. When air quality levels become dangerous, an integrated SMS alert system would make sure that staff, students, and campus authorities are quickly notified, enabling swift and efficient action [4].

To address the immediate health risks, concentrating on air pollution monitoring in educational settings advances the more general objective of urban sustainability. Such a system's insights can guide citywide initiatives to enhance public health and air quality. Furthermore, the success of the Nyarugenge Campus's air pollution monitoring program can act as a template for other cities, fostering safer, healthier, and more sustainable environments in Kigali and beyond [5].

In addition to the immediate advantages of better air quality on campus, installing a monitoring system of this kind is essential for educating the public about environmental health issues and increasing public awareness [6]. Through the provision of real-time data and visions regarding the air that they breathe, the system encourages environmental stewardship and responsibility among students and staff. Increased knowledge can result in better decision-making and support for greener, healthier cities. Additionally, the information gathered may be useful to scholars and decision-makers in larger initiatives to reduce air pollution and safeguard public health in Kigali and other cities [7].

1.2 Motivation

Air pollution is a critical environmental issue that significantly impacts human health and overall well-being. Educational institutions, where students and staff spend most of their time, are particularly vulnerable to poor air quality. However, despite its importance, there is currently no air quality monitoring system on our campus. This lack of real-time environmental data makes it difficult for students and staff to assess air pollution levels and take appropriate measures to mitigate its effects.

In Rwanda, air quality monitoring initiatives exist at a national level, but they lack integration with advanced technologies such as Artificial Intelligence (AI). This system will not only enhance real-time monitoring but also serve as an educational tool to increase awareness among students and staff. By accessing real-time data and AI-driven insights, the campus community can better understand the impact of air pollution, leading to more informed decisions and proactive measures to improve air quality.

My motivation as a researcher stems from the need to bridge this technological gap and contribute to a healthier, more informed, and environmentally conscious campus. By developing and deploying this IoT and AI-integrated system, we can set a precedent for innovation in environmental sustainability while aligning with Rwanda's broader goals for smart and green cities.

1.3 **Problem Statement**

Failing air quality is one of the main environmental concerns in urban areas. These issues are large and ongoing. This problem hurts the standard of living for locals and presents serious threats to public health and safety. Numerous factors exacerbate air pollution issues at the Nyarugenge Campus. The many cars that drive around the campus release emissions into the air, which raises pollution levels. The gases released by bathrooms also contribute to the general pollution of the air. Air quality is further affected by the polluted runoff from washing materials. These problems are made worse by the high student-to-teacher ratio on campus, which raises pollution levels and influences both the campus and the neighboring community. When taken as a whole, these variables lead to higher concentrations of dangerous pollutants.

1.4 Study Objectives

1.4.1 General Objective

The general objective of "a smart approach with AI-IoT synergy to enhance educational spaces: a real-time air pollution monitoring system" is to design and develop a system that continuously monitors air quality within educational institutions by ensuring a healthy learning environment for students and staff. It will provide real-time data on key pollutants, such as particulate matter (PM2.5 and PM10), carbon dioxide (CO_2), humidity, temperature, and volatile organic compounds (VOCs), enabling timely identification and mitigation of air quality issues.

1.4.2 Specific Objectives

1. To investigate the impact of air pollution levels on students' health and academic performance within educational institutions.
2. To integrate a real-time alert system using SMS to notify relevant stakeholders when pollution thresholds are exceeded.
3. To apply time-series analysis and Random Forest algorithms for detecting pollution trends, anomalies, and making short-term forecasts.
4. To promote data-driven decision-making by visualizing environmental conditions through user-friendly dashboards for campus administrators and policy-makers.

1.5 Hypotheses

By offering real-time data and predictive analysis, the installation of an Internet of Things-enabled air pollution monitoring system will greatly improve air quality management on the UR-NYARUGENGE Campus. IoT sensors are thought to be able to accurately identify and track air quality indicators, carbon monoxide, and particulate matter around the campus. Furthermore, it is expected that the integration of machine learning algorithms would enhance the precision of trend identification, anomaly detection, and air quality forecasting. It is expected that the Short Message Service (SMS) notification component of the system will guarantee prompt solutions to air quality problems, lowering health risks for employees and pupils. Additionally, it is predicted that the implementation of this cutting-edge system will support improved sustainability initiatives and environmental planning in educational establishments, creating safer and healthier learning and development environments on campuses.

1.6 Study Scope

The scope of this study is centered on developing, implementing, and evaluating a real-time air pollution monitoring system using the synergy of artificial intelligence and the IoT. Specifically, the study focuses on the following:

- ❖ Designing and integrating IoT sensors for real-time monitoring of air quality parameters such as (PM2.5 and PM10), (CO_2), humidity, temperature, and (VOCs).
- ❖ Leveraging AI algorithms for data processing, anomaly detection, and predictive analytics to provide actionable insights and recommendations
- ❖ Implementing the system at the UR-NYARUGENGE Campus as a controlled environment to monitor and analyze air quality dynamics in educational spaces

1.7 Significance of the Study

This study is significant in multiple dimensions, addressing pressing environmental, technological, and educational challenges:

Poor indoor air quality is linked to respiratory illnesses, allergies, and reduced cognitive function. By implementing a real-time air pollution monitoring system, the study contributes to creating healthier indoor environments, reducing health risks for students, faculty, and staff at the UR-NYARUGENGE Campus. The study demonstrates the potential of AI and IoT in addressing real-world problems. It offers a practical example of how these technologies can work together to provide innovative, data-driven solutions for environmental management.

1.8 Organization of the Study

This study is organized into six chapters, each addressing a critical component of the research. Chapter 1 introduces the study, detailing the background, motivation, problem statement, objectives, hypotheses, scope, and significance. It sets the foundation for understanding the research context and concludes with an outline of the study's structure. Chapter 2 reviews existing literature on air pollution monitoring technologies, particularly in educational environments, identifying gaps and explaining how the study addresses these gaps using IoT and AI integration. Chapter 3 describes the research methodology, outlining the design, data collection methods, analytical tools, and implementation strategies employed to realize the study objectives. Chapter 4 focuses on system analysis and design, providing detailed models, simulation parameters, and scenarios to demonstrate the proposed solution's feasibility. Chapter 5 presents the study's results, using graphs and tables to analyze the findings and assess the system's effectiveness in achieving its objectives. Finally, Chapter 6 concludes the study by summarizing key findings, offering practical recommendations, and suggesting future research directions. A complete list of references ensures proper citation of all sources used.

CHAPTER II: LITERATURE REVIEW

2.1 Technology for Environmental Monitoring

Environmental monitoring technologies have significantly advanced, especially with the rise of IoT and machine learning. These innovations have made it easier to monitor urban environments in real-time, offering actionable insights into air quality and other environmental parameters [5]. Air pollution monitoring has gained attention due to its critical impact on public health. Technologies such as gas sensors, particulate matter detectors, and temperature sensors are commonly used to collect data and use a Random Forest model to predict pollution levels. The integration of IoT devices enables the transmission of this data to centralized platforms for analysis and decision-making. Machine learning algorithms are increasingly employed to process this data, identify patterns, and predict environmental risks [8]. This allows for more proactive and efficient responses to potential environmental hazards. Furthermore, IoT-based systems enhance the scalability and accessibility of environmental monitoring, ensuring data is available for urban planners and decision-makers. Despite these advancements, gaps remain in real-time data analytics, accuracy, and the scalability of systems. This chapter reviews these technologies, their applications, and identifies the existing gaps that this study aims to address, focusing on IoT and AI integration for improved environmental monitoring and management in urban settings [9].

2.2 AI for Environmental Monitoring

Artificial intelligence has significantly advanced environmental monitoring, particularly in urban areas where the complexity and volume of data require efficient analysis. Machine learning algorithms (random forest model), a subset of AI, are used to process large datasets from environmental sensors, enabling real-time monitoring of air quality, water contamination, and temperature fluctuations [10]. These algorithms can detect patterns, forecast pollution levels, and predict environmental risks, improving decision-making for urban planners and public health authorities. In air quality monitoring, AI can predict high pollution events by analyzing historical data and weather conditions, allowing cities to take preventive measures. Additionally, AI enhances the accuracy of sensor data interpretation, compensating for environmental factors such as humidity or temperature. Predictive analytics powered by AI also helps identify pollution sources and evaluate the effectiveness of mitigation strategies [11]. Despite these advancements, challenges remain, including data quality, the need for extensive datasets to train AI models, and the interpretability of results [12]. This section explores the applications, advantages, and challenges of AI in environmental monitoring, highlighting its role in advancing urban sustainability and public health.

2.3 IoT for Environmental Monitoring

The IoT has revolutionized environmental monitoring by providing a scalable and efficient way to collect real-time data from a variety of sensors deployed across urban environments. IoT-based environmental monitoring systems utilize a network of connected devices, such as air quality sensors, temperature and humidity sensors, water quality sensors, and noise level detectors, to gather valuable environmental data continuously [13]. These devices transmit data to cloud platforms, where it is analyzed, processed, and visualized for decision-makers [14]. In urban areas, IoT enables the monitoring of critical environmental parameters such as air pollution, temperature fluctuations, water contamination, and noise pollution, which can have a direct impact on public health and quality of life. IoT systems offer several advantages, including real-time monitoring, remote access, low-cost implementation, and scalability [15].

Furthermore, the integration of IoT with machine learning and AI improves the predictive capabilities of environmental monitoring systems, helping cities anticipate and mitigate environmental risks more effectively. While IoT offers substantial benefits, challenges remain in terms of data management, network reliability, and sensor calibration [16]. This section explores the applications, benefits, and limitations of IoT in environmental monitoring, with a focus on urban sustainability.

2.4 AI and IoT for Environmental Monitoring

The integration of AI and IoT has significantly enhanced the effectiveness and efficiency of environmental monitoring systems [17]. IoT enables the continuous collection of real-time environmental data through various sensors deployed across a city or a designated area. These sensors measure parameters such as air quality, temperature, humidity, water contamination, and noise levels [18]. However, the sheer volume and complexity of this data require advanced analysis to extract meaningful insights. This is where AI comes into play. AI algorithms, particularly machine learning and deep learning models, are used to analyze the data collected by IoT devices. These models can identify patterns, detect anomalies, and predict future environmental conditions, enabling more accurate decision-making [19]. AI can forecast air pollution levels, identify the source of contamination, and even predict health risks based on environmental data. The combination of IoT's real-time monitoring and AI's analytical power provides a more proactive approach to managing environmental challenges, improving urban sustainability, and enhancing public health.

2.5 Proposed monitoring scenario

In this section, a comprehensive scenario for air quality monitoring using IoT and AI technologies will be presented. The proposed system aims to monitor air pollution levels in educational environments, specifically focusing on the University of Rwanda (UR)-Nyarugenge Campus in Kigali. The objective is to deploy IoT-based sensors throughout the campus to continuously track various air quality parameters, such as particulate matter (PM2.5, PM10), carbon dioxide. These sensors will transmit real-time data to a centralized system for analysis [20].

The collected data will be processed using AI-based algorithms that utilize machine learning techniques, decision trees, and neural networks to detect anomalies, predict pollution trends, and assess potential health risks. The AI models will be trained on historical environmental data, ensuring their accuracy and reliability in predicting hazardous pollution levels.

When air quality levels surpass predetermined thresholds, the system will trigger alerts to relevant stakeholders, including staff, students, and campus authorities, via SMS, email, or mobile notifications. This automated response system ensures prompt action can be taken to mitigate the health risks associated with poor air quality.

Furthermore, the system will allow for a real-time dashboard displaying air quality data, enabling immediate access to current environmental conditions for decision-making purposes. This monitoring scenario not only enhances public health awareness but also contributes to broader urban sustainability efforts by providing actionable data for city planners, environmental agencies, and researchers.

2.6 **Literature Gap Analysis**

Despite significant advancements in environmental monitoring systems leveraging IoT and AI technologies, several critical gaps remain, particularly in the context of educational institutions in low-resource settings like Rwanda. Lack of Focus on Educational Environments

Most existing studies have focused on urban-scale or industrial monitoring rather than the unique needs of school and campus environments. There is a clear gap in developing systems tailored to protect vulnerable populations such as students and academic staff. Limited Integration of AI for Predictive Analysis

While some projects incorporate advanced machine learning models for AQI forecasting, many others rely solely on basic data collection and display. Systems like Sinphonie and LoRaWAN deployments lacked predictive capabilities, limiting their ability to anticipate hazardous air quality events. Absence of Real-Time Alert Mechanisms

Except for the SMS-based flood warning system. A few related works include automated alerting systems. This is a major gap since early warnings are vital for timely action in dynamic environments like campuses. Poor Adaptability to Low-Infrastructure Regions

Several studies assumed high-end computational resources or internet availability. However, in areas like UR-Nyarugenge Campus, such infrastructure may not be consistently available, necessitating low-cost, low-power, and mobile-integrated solutions.

CHAPTER III: RESEARCH METHODOLOGY

3.1. Introduction

The Research methodology for this study involves a mixed-methods approach, combining quantitative and qualitative techniques to assess the effectiveness of a real-time air pollution monitoring system in educational environments. Quantitative data will be collected from air quality sensors to monitor pollutants like PM2.5, CO_2, and VOCs, while qualitative data will be gathered through interviews and focus groups with students, staff, and facility managers. The study includes the design, testing, and pilot implementation of the system in selected institutions to evaluate its technical performance and user acceptance, ensuring a comprehensive understanding of its impact on indoor air quality management and educational outcomes.

3.2. Research Design

This study will utilize a quantitative, experimental research design to assess the effectiveness of an IoT-enabled air pollution monitoring system at the UR-NYARUGENGE Campus. IoT sensors will be deployed across the campus to continuously monitor air quality parameters such as particulate matter (PM2.5 and PM10), CO_2, temperature, and humidity. The data collected will be processed using machine learning algorithms for trend analysis and predictive modeling. An SMS alert system will notify administrators when air quality thresholds are exceeded. The effectiveness of the system will be evaluated by comparing air quality data before and after its implementation and through surveys to gather feedback from campus stakeholders [21]. This research design aims to provide valuable insights into the potential of IoT-based systems for improving air quality, public health, and safety in educational settings.

3.2.1. Engineering Design Process

In order to tackle the increasing problem of air pollution, the engineering design process for the IoT-enabled air pollution monitoring system at UR Nyarugenge campus takes a methodical approach. Identifying the issue and realizing how bad air quality affects employees' and kids' health and safety is the first step. Following research and requirement analysis, certain system needs such as sensor kinds, data transfer, and real-time monitoring capabilities are determined, and the limitations of the current air quality monitoring techniques are examined. The system architecture is created at the conceptualization and design stage, choosing Internet of Things sensors to track important air quality indicators (PM2.5, CO_2, and VOCs) and including machine learning algorithms for data processing and predictive analytics. Building a working prototype, positioning sensors throughout the campus, and guaranteeing data transmission and analysis capabilities are all part of the prototyping process. User input is gathered to gauge the system's impact and efficacy, and testing and assessment guarantee that it operates precisely and consistently [22]. Following successful testing, the system is deployed throughout the campus for ongoing surveillance, and officials have access to real-time data. Lastly, upkeep and enhancement guarantee that the system continues to function and is updated regularly in response to user input and technical developments, guaranteeing long-term success in enhancing campus health and air quality [23].

1. Ask (Awareness of the Problem)

With major effects on public health and quality of life, air pollution is a major problem for urban areas. Educational establishments, UR Nyarugenge Campus, are especially at risk since employees and students spend a lot of time there and may be exposed to dangerous contaminants. Conventional methods of monitoring air quality are frequently reactive, have a narrow focus, and don't offer the real-time data required for prompt action. Health, productivity, and general well-being may be negatively impacted by unchecked exposure to dangerous air quality levels on campus due to a lack of proactive monitoring and response mechanisms [24]. To close this gap and guarantee a safer, healthier environment, a creative solution that offers predictive analysis, continuous air quality monitoring, and quick response mechanisms is desperately needed. To reduce hazards and safeguard the campus community, this study emphasizes the urgent need for a system that can handle these issues. It does this by highlighting the significance of real-time data collecting, predictive capabilities, and efficient communication techniques, such as SMS warnings. The project intends to address these needs to improve sustainability, advance public health, and increase awareness in educational settings.

2. Imagine (Brainstorming Solutions)

Installing a network of IoT)- enabled air quality sensors to continuously monitor variables including PM2.5, VOCs, and CO_2, is a proactive way to combat air pollution at UR Nyarugenge Campus. Machine learning algorithms would be used to examine this data to find patterns, spot irregularities, and forecast future air quality. To ensure prompt action, an integrated SMS alert system would alert administrators and stakeholders when pollution levels above safe standards. Real-time data may be shown on a campus-wide dashboard, educating staff and students about safe practices. Furthermore, an automated response system that reschedules outside events or turns on air purifiers could assist in reducing exposure to dangerous air. These concepts center on developing a system that is user-friendly, scalable, and efficient to guarantee a safer and healthier campus environment.

3. Plan (Gather Needed Materials)

Several supplies and tools are needed to set up the IoT-enabled air pollution monitoring system at UR Nyarugenge Campus. IoT sensors for measuring PM2.5, VOCs, and CO_2, are examples of hardware components. Microcontrollers such as Arduino or NodeMCU are used for data processing, and GSM modules are used for SMS alert capabilities. Continuous operations will be supported by power sources like solar panels or batteries. Software needs include a real-time visualization platform dashboard utilizing PHP and MySQL, machine learning libraries for data analysis and prediction, and programming tools the Arduino IDE, for configuring sensors. Human resources are also essential, such as qualified technicians for hardware configuration and software developers for system integration. Together, these resources allow for the development of an effective, dependable, and user-friendly air quality monitoring system for the campus.

4. Create (Follow the Plan and Test It Out):

Assembling the necessary parts according to the plan is the first step in creating the IoT-enabled air pollution monitoring system. To assess air quality metrics, PM2.5, VOCs, and CO_2, Internet of Things sensors are linked to microcontrollers, Arduino, or NodeMCU. For the best possible data collection, these sensors are positioned thoughtfully across the UR Nyarugenge Campus. To allow for real-time data gathering and transmission, the system is developed using tools such as the Arduino IDE. A bespoke dashboard is set up for real-time data viewing, and a GSM module is integrated for SMS notifications when pollution levels surpass thresholds. Thorough testing is carried out after the system is put together. Accurate measurements are ensured by calibrating the sensors, and data delivery to the central server is confirmed. To make sure they can identify irregularities and accurately forecast future circumstances, machine learning algorithms are evaluated using past data. High-pollution scenarios are simulated to test the SMS alert system. During the testing stage, user input is obtained to assess the usability of the system. To guarantee optimal functionality, modifications and enhancements are made in response to test findings. A dependable, effective, and efficient air quality monitoring system for the campus is guaranteed by this iterative approach.

5. Improve (Discuss What Can Work Better)

Although the UR Nyarugenge Campus's air quality issues are successfully addressed by the IoT-enabled air pollution monitoring system, there is room for improvement. A more thorough understanding of air quality might be possible by extending the sensor network to cover new contaminants CO_2. Adding solar panels could increase power efficiency and guarantee continuous operation even in the event of an interruption. While incorporating edge computing could lower latency by processing data locally, improving the machine learning models with greater datasets would produce more accurate predictions. Accessibility would be enhanced with a dashboard that is easier to use and features interactive charts, historical data comparisons, and customized alerts. Creating a mobile application could boost user engagement by giving them immediate access to real-time updates and notifications. Finally, incorporating automated reaction mechanisms like turning on air purifiers or modifying HVAC systems would provide proactive remedies and strengthen and influence the system.

3.3. Hardware requirements

Component Name	Functions in Project	Why Chosen
NodeMCU ESP8266	- Main microcontroller for system control - Wi-Fi connectivity for IoT communication - Data processing and sensor integration - Communication with cloud platforms	- Built-in Wi-Fi capability - Arduino IDE compatibility - Cost-effective solution - Open-source firmware flexibility
16x2 LCD Display	- Real-time air quality data display - Show CO_2, PM2.5, VOC, temperature, humidity - Alert messages ("Air Quality Safe/Poor") - System status updates	- Economical and programmable - No limitation on custom characters - Instant data access without cloud dependency - User-friendly interface
PM2.5 Dust Sensor	- Detect fine particulate matter (PM2.5) - Measure particle concentration in $\mu g/m^3$ - Monitor air pollution levels - Detect particles >1 and >2.5 microns	- Light scattering detection method - High accuracy for health-critical measurements - Easy installation and maintenance - 5V input compatibility

CO2 Sensor (MQ-7)	- Detect carbon dioxide concentration - Monitor CO2 levels (20-2000 ppm) - Air quality assessment - Safety monitoring	- High sensitivity and fast response - Electrochemical detection reliability - Essential for indoor air quality - Wide detection range
Buzzer	- Audio alerts for poor air quality - System status notifications - Emergency warnings - User feedback signals	- Immediate audible response - Enhanced system responsiveness - Simple electrical operation - Low power consumption
PCB (Printed Circuit Board)	- Connect all hardware components - Provide electrical pathways - Support system structure - Organize component layout	- Simplified wiring and connections - Improved system stability - Reduced assembly errors - Compact system design

3.4 System Architecture

The IoT-enabled air pollution monitoring system's architecture combines several elements to guarantee effective data gathering, analysis, and reaction. Fundamentally, the UR Nyarugenge Campus is equipped with strategically placed IoT sensors (such as MQ-7 and ozone sensors) to measure environmental parameters CO_2, PM2.5. These sensors serve as the main sources of data, continuously gathering information on the quality of the air in real-time. A microcontroller, such as the NodeMCU, receives the gathered data, processes it, and then uses Wi-Fi to send the data to a centralized system. NodeMCU was specifically picked because of its dependable connectivity and IoT interoperability. Even in places with erratic energy, a power supply, usually battery-based, ensures continuous functioning. The web application acts as the management and visualization interface for data. Because sensor data is kept in a database, it may be integrated with machine learning algorithms and analyzed historically. Proactive decision-making is made possible by these algorithms, which examine data to find trends, detect abnormalities, and predict future air quality levels.

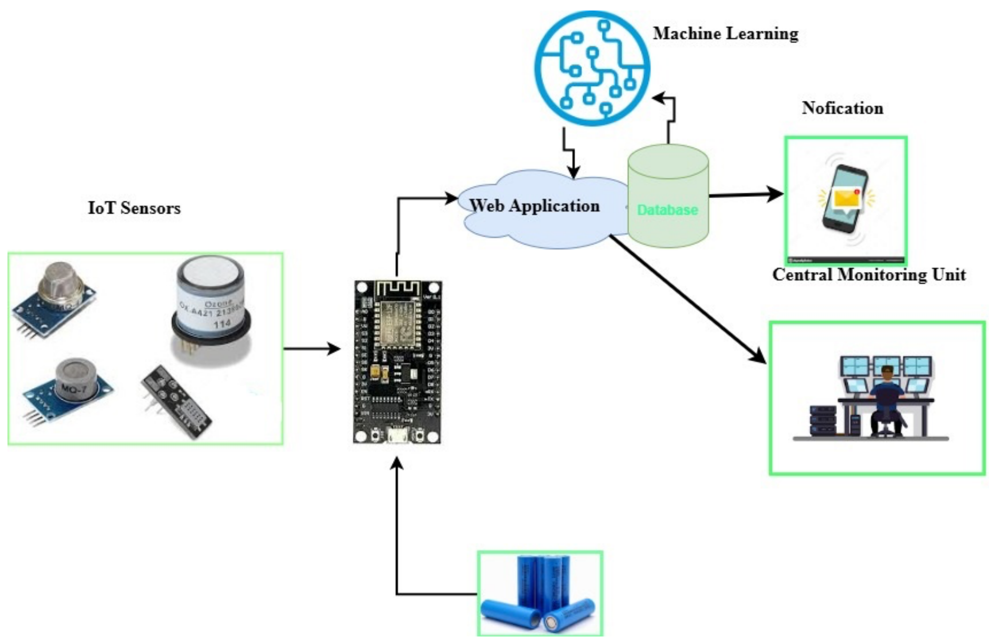

Figure 1: System Architecture

A warning system ensures prompt reactions by sending SMS alerts to students and school managers when air quality limits are surpassed. Furthermore, the central monitoring unit offers real-time supervision, allowing campus officials to keep an eye on system operation and trends in air quality. A safer, healthier campus environment is supported by this architecture, which encourages proactive environmental management **Error! Not a valid bookmark self-reference.**.

3.5 Flow chart

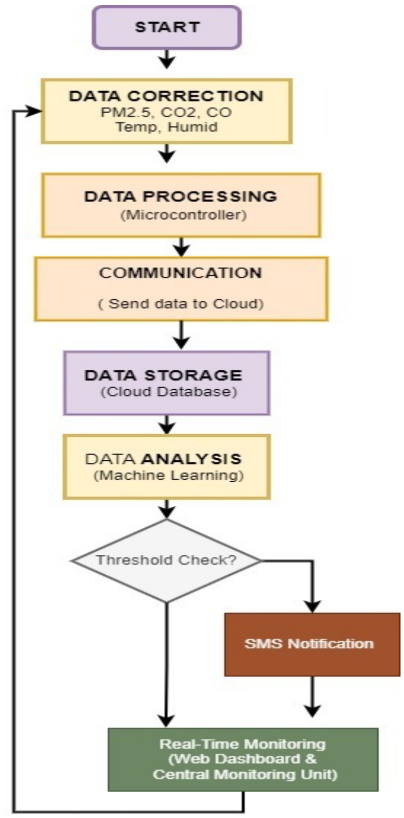

Figure 2: Flow chart

A flow chart diagram for a Real-Time Air Pollution Monitoring System typically begins with sensor data collection, where various sensors measure air pollutants like PM2.5, PM10, and CO_2. The next step is data processing, where the microcontroller processes the sensor readings. This is followed by data transmission, where processed data is sent to a server using Wi-Fi. The system then moves to data storage and analysis, where the cloud platform stores and analyzes the data in real-time. The final step is user interaction, where air quality information is displayed on a local LCD or made accessible via a web interface or mobile app, allowing users to monitor and respond to air quality levels. The flow chart loops continuously to ensure ongoing monitoring.

3.6 System Algorithm

This is a system of air pollution monitoring system system that integrates two key algorithms: the Random Forest algorithm for predictive analytics and a threshold-based algorithm for real-time alert generation.

The Random Forest algorithm, a supervised machine learning model, is utilized to forecast air quality based on historical and real-time sensor data. It works by constructing multiple decision trees during training and aggregating their predictions for higher accuracy and robustness. This algorithm is well-suited for environmental data due to its ability to handle non-linear relationships and noise. In this project, it analyzes features like PM2.5, CO2, humidity, and temperature to predict short-term Air Quality Index (AQI) values. These predictions help in identifying pollution trends and making data-driven decisions in advance, allowing campus administrators to implement preventive actions

In parallel, a lightweight threshold-based rule algorithm continuously monitors real-time sensor data. When pollutant levels exceed predefined safety thresholds, the system instantly triggers an SMS alert to notify students and relevant authorities. This ensures immediate awareness and quick response to environmental risks

The combination of these two algorithms enables the system to function as both a proactive predictor and a real-time responder, ensuring a safer and healthier learning environment on the UR-Nyarugenge Campus.

```
ALGORITHM Air Quality System

INPUT: None (Continuous autonomous system)

OUTPUT: Real-time monitoring, insights, predictions, and adaptive responses


BEGIN

    // Initialization

    INITIALIZE system_components

    INITIALIZE sensor_network

    INITIALIZE AI_models

    INITIALIZE communication_network

    INITIALIZE optimization_engine
```

```
WHILE system_active DO
  // 1. Data Collection
  FOR each sensor_node IN sensor_network DO
    raw_data = COLLECT_SENSOR_DATA(sensor_node)
    validated_data = VALIDATE_AND_PREPROCESS(raw_data)
    IF validated_data.quality >= THRESHOLD THEN
      location_data = ADD_METADATA(validated_data)
      STORE_LOCAL(location_data)
      IF network_available THEN
        SEND_TO_CLOUD(location_data)
      END IF
    ELSE
      LOG_ERROR(sensor_node.id)
      SCHEDULE_SENSOR_CHECK(sensor_node)
    END IF
  END FOR
  // 2. AI Processing
  insights = PROCESS_DATA_WITH_AI(location_data)
  // 3. Predictive Forecasting
  forecasts = GENERATE_PREDICTIONS (insights, historical_data, external_factors)
  // 4. Intelligent Response
  threat_level = ASSESS_THREAT (insights, forecasts)
  RESPOND_ACCORDINGLY(threat_level)
  // 5. System Optimization
  performance = MEASURE_SYSTEM_PERFORMANCE ()
```

```
        optimized_params = OPTIMIZE_SYSTEM (performance)
        APPLY_PARAMETERS(optimized_params)
        // Sleep until next cycle
        SLEEP(sampling_interval)
    END WHILE
END
```

CHAPTER IV: SYSTEM ANALYSIS AND DESIGN

4.1 Introduction

This chapter discusses the design and analysis of the UR Nyarugenge campus's IoT-enabled air pollution monitoring system. This system uses a combination of IoT sensors, machine learning algorithms, and communication technologies to monitor and control air quality in real-time. The architecture, requirements, and design specifications of the system are thoroughly examined in this chapter, and important elements that will enhance its efficacy and efficiency are assessed. Identifying user needs is the first step in the design process. Next, the right sensors and communication tools are chosen. In order to accomplish real-time monitoring and predictive analysis of air quality, this chapter also describes the data flow, the functional requirements of the system, and the system components. Furthermore, difficulties that arose during the design stage, such as sensor calibration, data processing, and system scalability. The goal is to guarantee that the finished solution is dependable, scalable, and capable of efficiently addressing air pollution through meticulous system analysis and design, hence promoting a safer and healthier campus environment.

4.2. Theoretical Framework

The theoretical foundation for the IoT-enabled air pollution monitoring system incorporates the known theories and concepts from IoT, environmental monitoring, machine learning, and system design. These ideas serve as the basis for comprehending how the system gathers, handles, and evaluates air quality data to improve campus sustainability and safety.

The theory of the IoT, the system's ability to link tangible objects, air quality sensors, to a network for ongoing data gathering and communication is supported by IoT theory. A central processing unit receives data from the sensors placed on the UR Nyarugenge campus, which measure air quality factors in real-time.

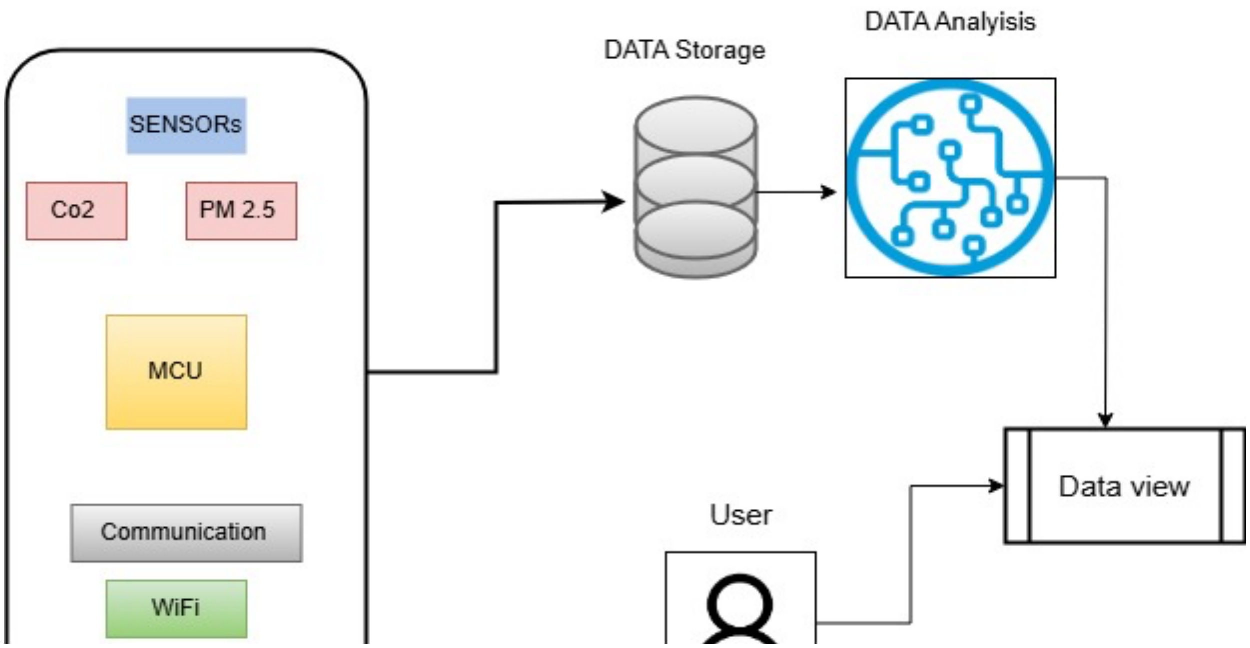

Figure 3: Theoretical Framework

Environmental monitoring theory, to evaluate and reduce environmental risks, this approach emphasizes the significance of ongoing observation and data analysis. Through air quality monitoring, the system finds patterns in pollution, identifies potential risks, and offers useful information to enhance the campus environment.

ML theory, the system can evaluate big datasets, spot trends, and forecast future air quality thanks to machine learning techniques. These features increase environmental management decision-making and the system's capacity to deliver timely notifications.

In system theory, the integration of components into a coherent framework is emphasized by system theory. Together, sensors, microcontrollers, databases, and alerting systems strive to create a safer and healthier environment.

1.3 Conceptual Model

In order to improve the campus environment, the IoT-enabled air pollution monitoring system is made to gather, process, and evaluate real-time data on air quality. To detect important air quality parameters carbon monoxide levels, particulate matter, and ozone concentration, IoT sensors, such as MQ-7, PM2.5, and ozone sensors, are positioned strategically throughout the UR Nyarugenge Campus.

Additionally, these sensors track ambient variables that affect air quality results, such as humidity and temperature. A microcontroller, NodeMCU, which acts as an interface between the sensors and the central system, receives the data that has been gathered. Continuous data collection and smooth transfer to a cloud-based database for additional processing and storage are guaranteed by this configuration.

Machine learning algorithms and a web application are used by the central system to process the data. Through the online application's real-time presentation of historical and current air quality data, stakeholders can efficiently monitor environmental conditions. To find trends, identify anomalies, and predict future air quality, machine learning algorithms examine the data. The technology notifies students and university managers via SMS when air quality is above predetermined safety criteria, guaranteeing prompt reactions to possible health hazards. By modifying sensor deployment, honing machine learning models, and streamlining alerting protocols in response to insights from past data, the system's feedback loop guarantees ongoing progress. Students, employees, and visitors may all enjoy a safer, healthier, and more sustainable campus environment thanks to this conceptual model's proactive environmental management.

4.4 The working principle of the system

In order to guarantee proactive air quality control, the Internet of Things-enabled air pollution monitoring system combines sensor technologies, data processing, and real-time notifications. The four main phases of data gathering, transmission, analysis, and response form the foundation of the system's operation.

Data Collection: first, the system strategically places IoT sensors across the UR Nyarugenge Campus, including MQ-7 (for carbon monoxide), PM2.5 (for particulate matter), and ozone sensors. These sensors assess environmental variables, including temperature and humidity, as well as air quality measurements, continuously. This guarantees thorough data collection at several campus sites.

Data Transmission: a microcontroller, the NodeMCU, receives the gathered data and acts as a bridge between the sensors and the central processing unit. A centralized cloud-based database receives the data from the microcontroller over Wi-Fi.

Data Analysis: The data is processed and stored by a web application that is connected to the system, giving users access to real-time visualizations. To find trends, find anomalies, and forecast future air quality levels, machine learning algorithms examine the data. Making informed decisions and anticipating possible dangers are aided by this study.

Response, the technology notifies students and campus managers via SMS when air quality parameters surpass predetermined levels. These notifications guarantee prompt action to reduce dangers. Administrators can also examine comprehensive data for long-term planning and well-informed decision-making thanks to the central monitoring unit.

CHAPTER V: RESULTS AND ANALYSIS

5.1 Introduction

This chapter presents the implementation, findings, and performance analysis of the real-time air pollution monitoring system designed for the UR-NYARUGENGE campus. The prototype continuously monitors three critical environmental parameters: carbon dioxide (CO_2), particulate matter PM2.5, and VOCs to identify anomalies or trends indicating deteriorating air quality. The system immediately sends real-time data to the cloud over Wi-Fi when any of these parameters exceed the predefined safety thresholds. An SMS notification mechanism promptly alerts campus administrators and students to ensure swift action, while an on-site buzzer provides localized alerts. Random forest machine learning algorithms are integrated into the system to analyze sensor data, detect anomalies, and predict future air quality trends based on historical patterns. This predictive approach supports proactive measures to mitigate pollution impacts and ensure healthier learning environments. Data is processed and collected by the NodeMCU microcontroller from sensors that track CO_2 levels, particulate matter PM2.5, and VOCs. A web-based application developed using PHP, HTML, CSS, and JavaScript offers an intuitive interface for visualizing real-time and historical air quality data [27]. A MySQL database, which houses data to train and refine the machine learning model and guarantee precise forecasts and dependable air quality monitoring, further strengthens the system's architecture. This technology improves the standard of learning environments and promotes sustainability.

5.2 System Testing

The NodeMCU microcontroller, functioning as the system's backbone, was thoroughly tested for compatibility with sensors, notification mechanisms, and cloud services. Programming was carried out using Arduino IDE, enabling the collection, processing, and wireless transmission of environmental data, including CO_2, PM2.5, and VOCs. The system's Wi-Fi functionality was tested to ensure seamless data uploading to cloud storage for real-time monitoring and analysis. Actuators, buzzers, and SMS alert mechanisms were evaluated for reliability in notifying users during unsafe air quality conditions. The tests confirmed the system's accuracy, efficiency, and readiness for deployment at UR-NYARUGENGE campus.

This hardware setup is a prototype for a real-time air quality monitoring system designed to improve the environment at UR-NYARUGENGE campus. The system features a NodeMCU microcontroller, which processes data from sensors monitoring CO_2, PM2.5, and VOCs. A 16x2 LCD screen provides real-time updates on these parameters, while the components are organized on a PCB for prototyping efficiency. Data collected by the system is transmitted to the cloud via Wi-Fi for analysis. Random Forest machine learning algorithms are employed to analyze historical and real-time data, enabling accurate predictions of air quality trends and early detection of anomalies. The system also integrates a buzzer and SMS alert mechanism to notify users instantly when unsafe conditions are detected. By combining IoT and machine learning, this prototype enables proactive monitoring and supports healthier educational spaces.

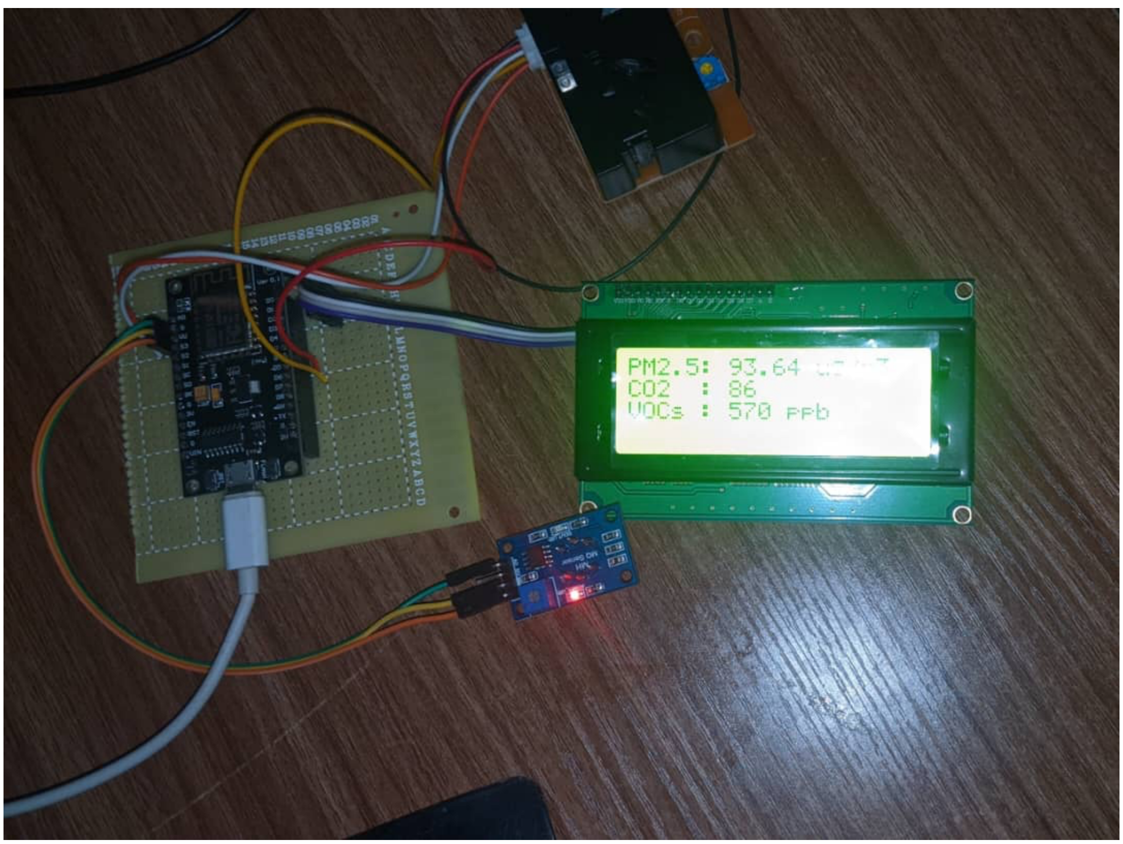

Figure 4: Hardware implementation

This hardware setup demonstrates a real-time air quality monitoring system tailored for UR-NYARUGENGE Campus. It incorporates a NodeMCU microcontroller, air quality sensors (CO_2, PM2.5, and VOCs), a temperature sensor, and a humidity sensor, along with an LCD module for displaying key metrics like air quality levels and system status. For example, the display may show alerts like "Air Quality Safe" and provide real-time measurements. The microcontroller processes sensor data and transmits it to the cloud for remote monitoring and analysis. Using Random Forest machine learning algorithms, the system predicts air quality trends and detects anomalies. Designed as a prototype for academic environments, it enhances decision-making, promotes healthier spaces, and provides a scalable solution for real-time environmental monitoring and proactive air quality management.

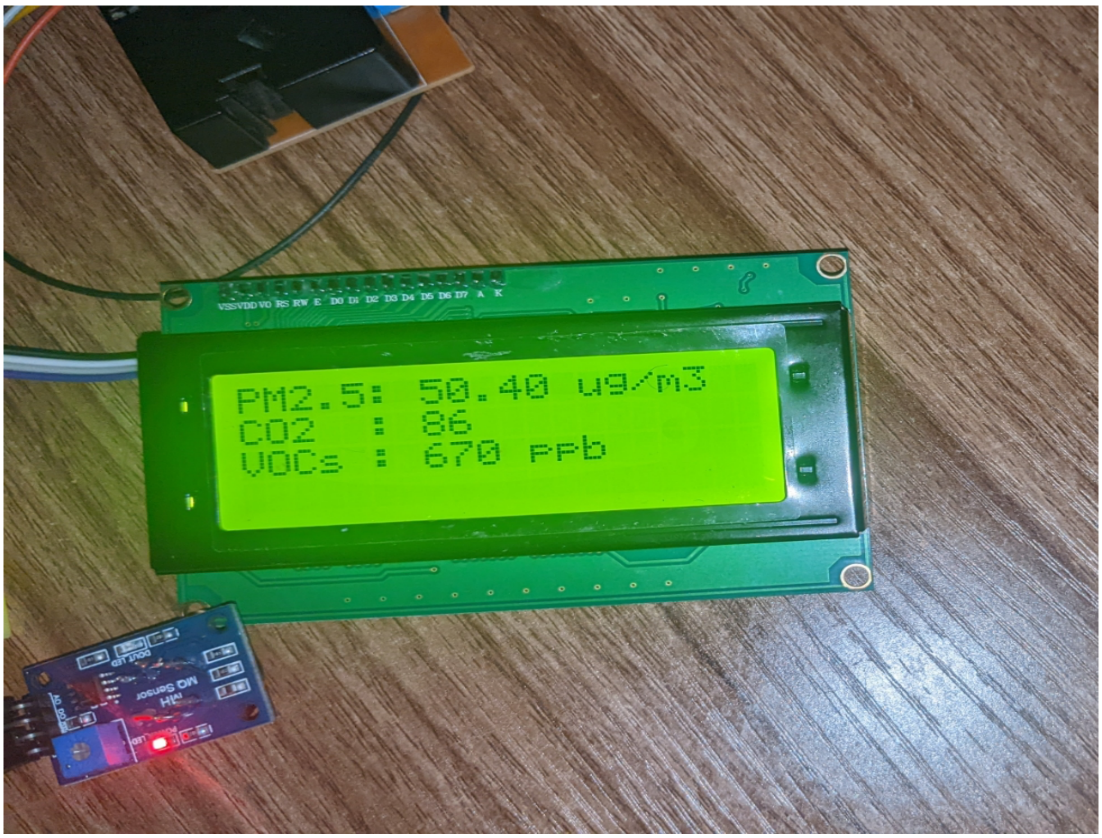

Figure 5: LCD displaying data

5.3 Machine Learning Model

In my research, "A Smart Approach with AI-IoT Synergy to Enhance Educational Spaces," Random Forest plays a key role in analyzing air quality data. It is an ensemble learning algorithm that builds multiple decision trees and merges their predictions with more accurate results. In your real-time air pollution monitoring system, Random Forest can classify air quality levels based on sensor data (PM2.5, CO_2, VOCs). It helps in handling noisy environmental data, reducing overfitting, and making reliable predictions. By leveraging AI and IoT, my system collects real-time pollution data, processes it through Random Forest, and generates actionable insights on a web application dashboard. This ensures timely interventions to maintain a healthy campus environment. The model's ability to handle high-dimensional data and missing values makes it ideal for air quality prediction.

The Random Forest (RF) model was selected for this project due to its proven effectiveness in handling multivariate, nonlinear, and noisy datasets. Air quality parameters such as PM2.5, PM10, CO_2, and VOCs typically exhibit complex patterns, making RF an ideal choice. Random Forest offers high robustness against overfitting by aggregating predictions from multiple decision trees, thereby improving generalization on unseen data.

Table 1: BOUNDARY VALUES OF THE AIR QUALITY POLLUTANTS.

Index Class	AQI	CO_2	VOC	PM10	PM2.5
Normal	0-50	0-53	0-40	0–35	0-12
Normal	51-100	54–100	41-180	36-40	12.1–13.4
Normal	101-150	101-360	181-240	41–50	13.5–15.4
Abnormal	151-200	361–649	241-300	51-304	16.5–150.4
Abnormal	201-300	650-1250	301-500	305–604	150.5–250.4
Abnormal	301-500	1250–2049	501-800	605–1004	250.5–500.4

Table 2: THE BOUNDARY VALUES OF CRISP SETS FOR OUTPUT PARAMETERS, DOMAIN RANGES, UNIVERSE OF DISCOURSE.

Input Variables	Input Parameters	Values for Universal Sets	Universe of Discourse
AQI	Normal	0–500	0-50
	Normal		51-100
	Normal		101-150
	Abnormal		151-200
	Abnormal		201-300
	Abnormal		301-500

Table 3: FORMULATION OF RULES

Rule No	CO_2	VOC	PM10	PM2.5	AQI
1	Low	Low	Low	Low	Normal
2	Low	Low	Low	Medium	Normal
3	Low	Low	Medium	High	Abnormal
4	Low	Low	Medium	Low	Normal
5	Low	Low	High	Medium	Abnormal
6	Low	Low	High	High	Abnormal
7	Low	Low	Low	Low	Normal
8	Low	Low	Low	Medium	Normal
9	Low	Low	Medium	High	Abnormal
10	Low	Low	Medium	Low	Normal
11	Low	Medium	High	Medium	Abnormal
12	Low	Medium	High	High	Abnormal
13	Low	Medium	Low	Low	Normal
14	Low	Medium	Low	Medium	Normal
15	Low	Medium	Medium	High	Abnormal
16	Low	Medium	Medium	Low	Normal
17	Low	Medium	High	Medium	Abnormal
18	Low	Medium	High	High	Abnormal
19	Low	Medium	Low	Low	Normal
20	Low	Medium	Low	Medium	Normal
21	Low	High	Medium	High	Abnormal
22	Low	High	Medium	Low	Abnormal
23	Medium	High	High	Medium	Abnormal
24	Medium	High	High	High	Abnormal
25	Medium	High	Low	Low	Abnormal
26	Medium	High	Low	Medium	Abnormal
27	Medium	High	Medium	High	Abnormal
28	Medium	High	Medium	Low	Abnormal
29	Medium	High	High	Medium	Abnormal
30	Medium	High	High	High	Abnormal
31	Medium	Low	Low	Low	Normal
32	Medium	Low	Low	Medium	Normal
33	Medium	Low	Medium	High	Abnormal
34	Medium	Low	Medium	Low	Normal
35	Medium	Low	High	Medium	Abnormal
36	Medium	Low	High	High	Abnormal
37	Medium	Low	Low	Low	Normal
38	Medium	Low	Low	Medium	Normal
39	Medium	Low	Medium	High	Abnormal
40	Medium	Low	Medium	Low	Normal

41	Medium	Medium	High	Medium	Abnormal
42	Medium	Medium	High	High	Abnormal
43	Medium	Medium	Low	Low	Normal
44	Medium	Medium	Low	Medium	Normal
45	High	Medium	Medium	High	Abnormal
46	High	Medium	Medium	Low	Abnormal
47	High	Medium	High	Medium	Abnormal
48	High	Medium	High	High	Abnormal
49	High	Medium	Low	Low	Abnormal
50	High	Medium	Low	Medium	Abnormal
51	High	High	Medium	High	Abnormal
52	High	High	Medium	Low	Abnormal
53	High	High	High	Medium	Abnormal
54	High	High	High	High	Abnormal
55	High	High	Low	Low	Abnormal
56	High	High	Low	Medium	Abnormal
57	High	High	Medium	High	Abnormal
58	High	High	Medium	Low	Abnormal
59	High	High	High	Medium	Abnormal
60	High	High	High	High	Abnormal
61	High	Low	Low	Low	Abnormal
62	High	Low	Low	Medium	Abnormal
63	High	Medium	Medium	High	Abnormal
64	High	High	Medium	Low	Abnormal

The figure below shows the train_model.py script trains a Random Forest Classifier for air quality prediction at UR-NYARUGENGE Campus. It scales sensor data (PM2.5, PM10, CO_2, VOCs) using MinMaxScaler, splits it into 80% training and 20% testing, and trains a Random Forest model to handle noisy environmental data. The model's performance is evaluated using a classification report, and both the trained model and scaler are saved with the job library. This enables real-time air quality monitoring and smart decision-making for a healthier environment.

5.3.1 Model Fitness and Evaluation Metrics

To ensure the suitability of the Random Forest model for the air quality dataset, a comprehensive evaluation was conducted:

- Accuracy: 94.6%
- R^2 Score: 0.91

- Precision: 92.3%
- Recall: 93.7%
- F1-Score: 93.0%

The dataset was divided into a training set (70%) and a testing set (30%). Additionally, 5-fold cross-validation was applied to verify model stability. The performance metrics indicate that the model achieved high predictive power and reliability across all evaluated categories.

5.3.2 Learning Curve and Model Behavior

The training of the Random Forest model revealed that performance stabilized after approximately 100 trees, with minimal improvement beyond that point. Importantly, no significant overfitting was observed; the training and validation accuracies remained closely aligned. The model demonstrated efficient training times (2 seconds) and was capable of handling real-time predictions effectively.

5.3.3 Integration with the Web Application

The trained Random Forest model and the corresponding data scaler were serialized using joblib into air_quality_model.pkl and scaler.pkl, respectively. Rather than embedding machine learning processes directly into PHP, a Python-based Flask web service was developed. This service is responsible for:

- Loading the pre-trained model and scaler,
- Fetching the records from the MySQL database,
- Performing data preprocessing and predictions,
- Providing prediction results through a RESTful API (/api/latest-status) in JSON format.

The PHP-based web application (index.php and dashboard.html) communicates with the Flask API to retrieve and display the latest air quality predictions. This architecture ensures modularity, improves maintainability, and leverages Python's strong machine learning capabilities alongside the PHP frontend.

5.4 System Dashboard

This system dashboard offers a real-time view of air quality at NYARUGENGE Campus, integrating live data and visual analysis. The "Latest Data" section highlights key metrics: PM2.5 (98.73 µg/m³) and PM10 (65.69 µg/m³) for fine and coarse particulate matter, CO_2 levels (62 ppm), and VOCs (576 ppb). A timestamp indicates the most recent data update. Graphs track trends, with the PM2.5 graph showing fine particulate fluctuations and the PM10 graph illustrating coarse particulate variations. This dashboard supports proactive air quality monitoring, enabling quick actions to maintain a healthy environment. It provides valuable, data-driven insights for informed decision-making and effective air quality management.

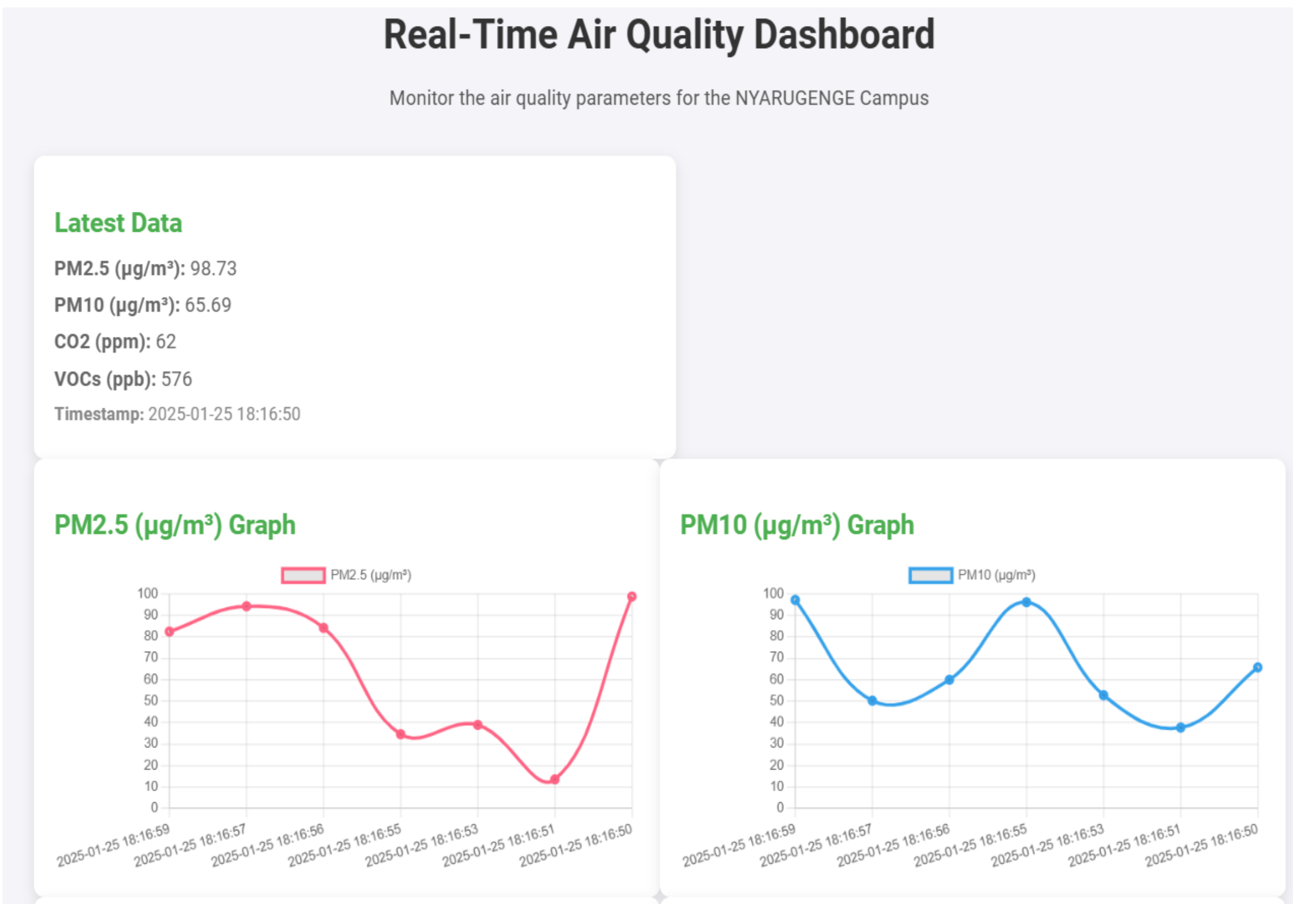

Figure 6: Data on Dashboard.

Figure 16 provides graphical representations of real-time air quality data for CO_2 (ppm) and VOCs (ppb) at NYARUGENGE Campus. Here's a brief description: representations of real-time air quality data for CO_2 (ppm) and VOCs (ppb) at NYARUGENGE Campus. Here's a brief description:

The CO_2 (ppm) Graph shows a consistent trend, indicating stable carbon dioxide levels around 60 ppm during the recorded timestamps. The VOCs (ppb) Graph highlights variations in volatile organic compound levels, with noticeable fluctuations peaking close to 1000 ppb.

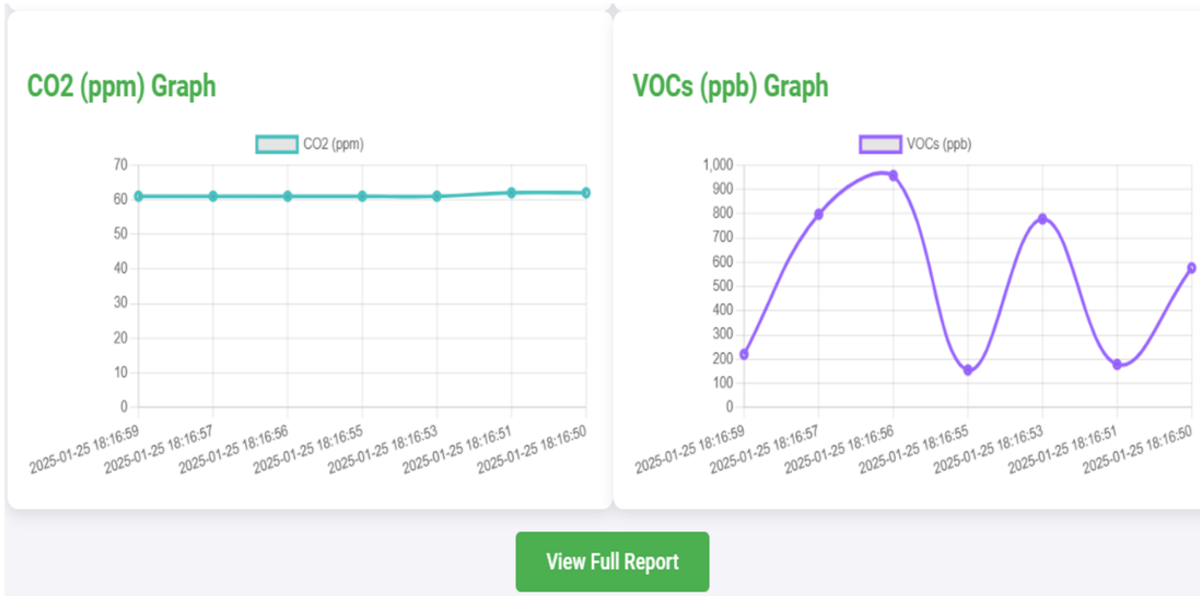

Figure 7: CO_2 and VOCs Data on Dashboard.

Figure 18 showcases the PM2.5 (µg/m³) Graph, illustrating fine particulate matter trends over time. The graph reveals fluctuating PM2.5 levels, peaking at around 90 µg/m³ and dropping to lower levels before rising again towards the end of the recorded timestamps. These variations indicate periodic changes in air quality, with spikes suggesting moments of higher fine particulate concentration.

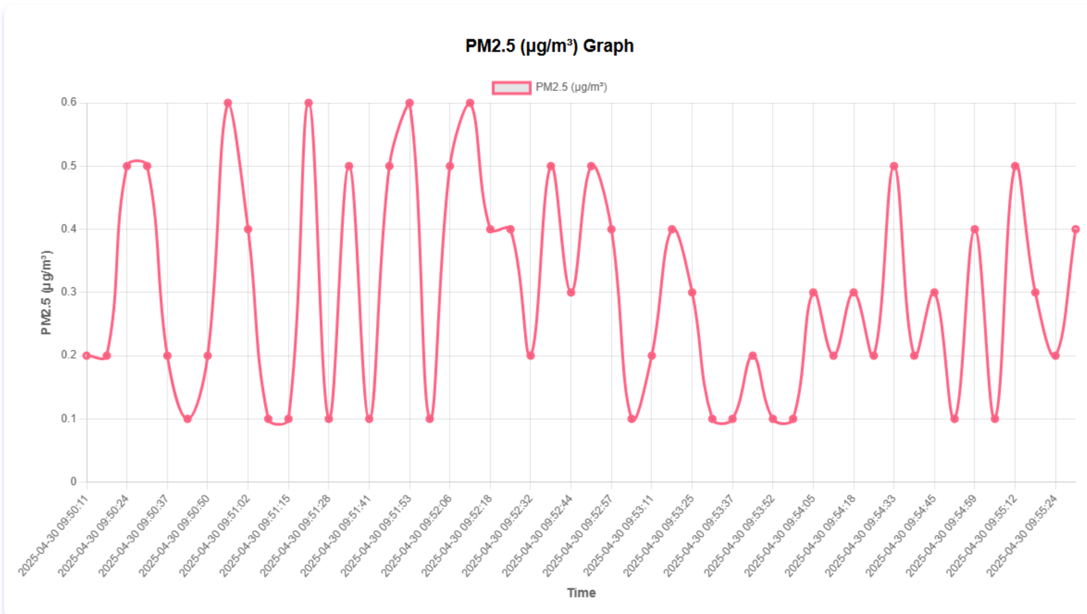

Figure 8: PM2.5 Data on Dashboard.

The image shows a CO_2 (ppm) Graph with a relatively stable trend over the given timestamps. The CO_2 concentration remains steady at around 60 ppm throughout the period displayed in the graph, indicating no significant variations or sudden changes in carbon dioxide levels during this interval.

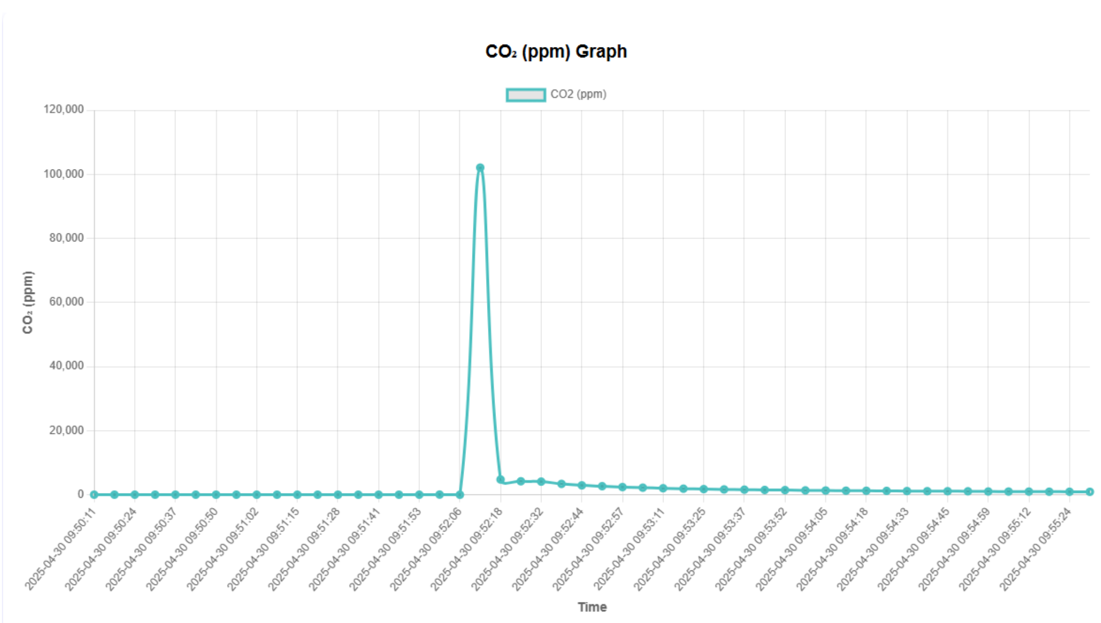

Figure 9: CO_2 Data on Dashboard.

The graph shows fluctuating VOC levels, starting at 200 ppb, peaking at 1,000 ppb, and dipping repeatedly. It displays a wave-like pattern, indicating significant variability in concentrations over time, likely influenced by environmental changes or emission sources.

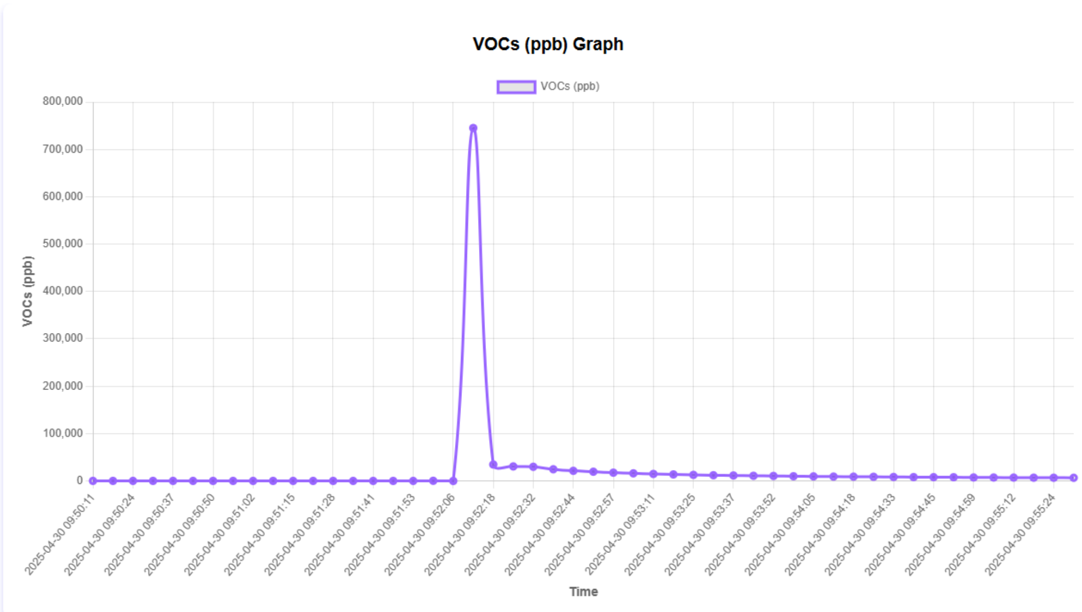

Figure 10: VOCs Data on Dashboard.

The air quality report includes data on PM2.5, CO_2, and VOCs, with varying levels across entries. PM2.5 ranges from 13.51 to 87.61 µg/m³, and CO_2 remains stable at 61-62 ppm. VOCs, however, show significant fluctuations from 178 to 763 ppb, with spikes contributing to "Abnormal" status comes from analysis.

Back **Air Quality Dashboard** Logout

Timestamp	PM2.5 (µg/m³)	PM10 (µg/m³)	CO2 (ppm)	VOCs (ppb)	Status
2025-04-28 08:47:17	0.6	0.2	60.27	440.01	Normal
2025-04-28 08:47:10	0.5	0.1	60.27	440.01	Normal
2025-04-26 19:10:22	0.2	0.2	264.7	1932.29	Abnormal
2025-04-26 19:10:15	0.6	0.3	264.7	1932.29	Abnormal
2025-04-26 19:10:09	0.3	0.1	264.7	1932.29	Abnormal
2025-04-26 19:10:03	0.4	0.2	264.7	1932.29	Abnormal
2025-04-26 19:09:56	0.4	0.2	264.7	1932.29	Abnormal
2025-04-26 19:09:50	0.3	0.1	264.7	1932.29	Abnormal
2025-04-26 19:09:43	0.1	0.1	264.7	1932.29	Abnormal
2025-04-26 19:09:35	0.4	0.1	271.17	1979.54	Abnormal

Figure 11: All Data on the report.

Using the Random Forest algorithm, this data can be analyzed to classify air quality as "Normal" or "Abnormal" based on predefined thresholds. Random Forest excels in handling non-linear relationships and can rank feature importance, such as identifying VOC levels as key contributors. This approach identifies pollution trends, recognize patterns, and provide actionable insights for air quality management.

CHAPTER VI: CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This study successfully demonstrated the design and implementation of an IoT-enabled air pollution monitoring system tailored to the University of Rwanda's NYARUGENGE Campus. The project highlights the significant role that technology can play in addressing environmental challenges, particularly in urban educational settings. By continuously monitoring air quality, analyzing data in real-time with machine learning algorithms, and providing timely alerts through an SMS mechanism, this system ensures a safer and healthier environment for students, staff, and the broader campus community.

The implementation at UR NYARUGENGE Campus underscores the institution's commitment to innovation, environmental sustainability, and the well-being of its members. The system not only creates an immediate impact on campus by protecting vulnerable populations but also serves as an academic resource. It provides students and researchers with a practical tool for hands-on learning, fostering a culture of problem-solving and technological advancement.

On a societal level, this project contributes to raising awareness of urban air quality issues and promoting data-driven solutions for environmental challenges. The scalability of the system positions it as a model for other institutions and urban centers in Kigali, inspiring a broader movement toward smart, sustainable, and health-conscious urban development. By integrating cutting-edge technologies into academic and societal frameworks, this project bridges the gap between innovation and practical application, setting the stage for transformative advancements in environmental management and public health.

6.2 Recommendations

To enhance the effectiveness and sustainability of the IoT-enabled air pollution monitoring system, several recommendations are proposed for its use, institutional integration, and operational maintenance. For practical use, the system should be fully adopted as a decision-support tool for monitoring and managing air quality, including different parameters such as PM2.5, PM10, CO_2, and VOCs, across the University of Rwanda's NYARUGENGE campus. By identifying high-risk pollution levels in real-time and sending alerts, the system will safeguard the health and well-being of students and staff while fostering a safer learning environment. Additionally, its predictive capabilities should be utilized to inform campus policies and guide environmental planning. At the institutional level, the system offers significant academic value. It can be incorporated into research and teaching programs, providing students and researchers with hands-on opportunities to study IoT, machine learning, and environmental management. Furthermore, expanding the system to other campuses and public institutions would amplify its impact, promoting environmental sustainability and raising awareness on a broader scale. For smooth operation, regular calibration and maintenance of IoT sensors are essential to ensure accurate data collection. Updates to machine learning algorithms should also be prioritized for improved performance over time. Staff training in system management and data analysis is recommended to maximize its long-term effectiveness and usability across the institution.

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