International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://www.theaspd.com/ijes.php

Iot-Based Real-Time Air Quality Index Monitoring And Predictive Modelling

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Abstract
This research presents the design and implementation of an IoT-based system for real-time air quality monitoring and predictive modeling. The increasing concern over air pollution necessitates the development of efficient, scalable solutions for continuous monitoring of air quality parameters such as particulate matter (PM), carbon dioxide (CO2), and other pollutants. The proposed system utilizes low-cost IoT sensors, coupled with cloud-based data processing, to collect and transmit real-time air quality data. A predictive model, based on machine learning algorithms, is applied to forecast air quality trends and provide early warnings of potential pollution events. The system's effectiveness is demonstrated through a prototype, showcasing its ability to track air quality in real time and predict future air quality index (AQI) levels. The results highlight the system's potential to assist in proactive air quality management and inform public health interventions. Challenges such as sensor calibration, data accuracy, and predictive model optimization are also discussed.
Keywords: *IoT, Air Quality Index (AQI), Real-Time Monitoring, Predictive Modeling, Air Pollution, Machine Learning, Particulate Matter, Sensor Networks, Environmental Monitoring, Data Analytics.*

1. INTRODUCTION

The alarming rise in air pollution across the globe has become one of the most pressing environmental issues of the 21st century. Over the last few decades, urbanization, industrialization, and vehicular emissions have significantly contributed to the deterioration of air quality in many regions, with serious consequences for human health, the environment, and the climate[1]. Exposure to high levels of air pollutants, such as particulate matter (PM2.5 and PM10), nitrogen dioxide (NO2), sulfur dioxide (SO2), and carbon dioxide (CO2), has been linked to respiratory diseases, cardiovascular problems, and even premature death[2]. The long-term effects of air pollution extend to environmental degradation, including the destruction of ecosystems and the exacerbation of climate change due to the accumulation of greenhouse gases in the atmosphere[3]. In response to these issues, there is a growing recognition of the need for real-time air quality monitoring systems to track pollutant levels continuously and provide immediate insights into the state of air quality[4]. This enables timely interventions to reduce exposure, mitigate the effects of pollution, and help policymakers formulate effective strategies to combat air pollution[5].

Air quality monitoring has traditionally been conducted using stationary monitoring stations that collect data at fixed locations. While these systems have proven effective in certain regions, they have limitations, including high operational costs, limited spatial coverage, and a lack of real-time analysis[6]. Moreover, the data provided by traditional monitoring systems is often sparse, making it difficult to detect localized pollution events or identify trends in air quality in real time[7]. The integration of Internet of Things (IoT) technologies into air quality monitoring offers a promising solution to these limitations[8]. IoT enables the deployment of a large network of low-cost, mobile sensors that can collect and transmit air quality data in real time, covering a wider geographical area and providing more granular insights[9]. These sensors are capable of measuring various pollutants, including particulate matter, gases like CO_2, NO_2, and ozone, and environmental parameters such as temperature and humidity[10]. The continuous stream of data generated by these sensors can be processed and analyzed using cloud-based platforms, offering real-time monitoring capabilities that can be accessed remotely via mobile applications or web interfaces[11]. This real-time data not only informs the public about current air quality conditions but also aids in predicting future trends, helping to mitigate the adverse effects of pollution on public health and the environment.

The objective of this study is to design and implement an IoT-based system for real-time air quality monitoring and predictive modeling. By integrating IoT technologies with predictive analytics, this system aims to provide a comprehensive solution for tracking and forecasting air quality[12]. The system will be capable of collecting data from multiple sensors, transmitting it to a cloud platform for processing, and providing real-time updates on air quality conditions. Additionally, machine learning algorithms will be employed to build predictive models that can forecast air quality trends based on historical and real-time data[13]. These models will be essential for identifying pollution patterns, predicting high pollution events, and enabling proactive measures to protect public health and the environment[14]. By combining real-time monitoring with predictive capabilities, the system will not only provide current air quality information but also offer insights into future air quality conditions, allowing for better preparedness and response[15].

The relevance of IoT in this context cannot be overstated. The application of IoT technologies in air quality monitoring provides numerous advantages over traditional systems. First, IoT-based systems enable real-time data collection, allowing for immediate access to air quality information at any location. This is especially important in urban areas where pollution levels can vary significantly across different neighborhoods and over short periods. The distributed nature of IoT sensors ensures that data is collected continuously, providing a more accurate representation of air quality across a wide area. Furthermore, IoT systems facilitate data analysis in real time, enabling the detection of pollution spikes and allowing for prompt notifications to the public and relevant authorities. Another significant advantage of IoT-based systems is their ability to support predictive modeling. By analyzing historical data alongside real-time measurements, machine learning algorithms can identify patterns in air quality trends and predict future pollution levels. These predictions can be used to issue early warnings about potential air quality deterioration, giving communities time to take preventive actions, such as avoiding outdoor activities during high pollution periods.

The scope of this study focuses on the deployment of an IoT-based air quality monitoring system in urban environments, where air pollution is a significant concern. The system will incorporate a variety of sensors capable of measuring key air quality parameters, including particulate matter ($PM_{2.5}$, PM_{10}), CO_2, NO_2, ozone (O_3), and other common pollutants. In addition to air pollutants, environmental parameters such as temperature, humidity, and wind speed will be monitored to provide a more comprehensive understanding of the factors influencing air quality. The study will consider the geographical coverage of the system, with an emphasis on urban areas where pollution is most prevalent, and explore the potential for scaling the system to cover larger regions. Furthermore, the predictive modeling aspect of the study will focus on the development of algorithms capable of forecasting air quality trends based on the collected data, taking into account seasonal variations and the impact of external factors like traffic patterns and weather conditions.

2. LITERATURE REVIEW

Air quality monitoring has been an essential aspect of environmental management and public health research for decades. Traditionally, air quality monitoring systems relied on fixed stations located in specific geographical areas, such as urban centers, industrial zones, or near highways, where pollution levels were expected to be high[16]. These systems typically used expensive sensors to measure key pollutants such as particulate matter (PM2.5 and PM10), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon dioxide (CO2), and ozone (O3). While such systems provided valuable data on air quality, they suffered from several limitations[17]. First, the high cost of installation and maintenance made it difficult to establish a dense network of monitoring stations, leading to gaps in coverage, particularly in rural areas or in regions with limited financial resources. Second, the data collected by traditional systems was often not available in real time, which limited their utility for immediate public health interventions or for supporting regulatory decisions[18]. Additionally, the reliance on centralized data processing meant that any changes in air quality could go undetected until after the fact, delaying response efforts.

With the advent of the Internet of Things (IoT), air quality monitoring systems have undergone significant transformation. IoT-based systems provide a more flexible and scalable alternative to traditional monitoring systems[19]. By using a network of small, low-cost sensors deployed in various locations, these systems can offer real-time data on air quality across large geographic areas. Various studies have demonstrated the effectiveness of IoT in monitoring air quality. For example, systems that utilize Arduino-based sensors or Raspberry Pi devices for data acquisition have been developed to measure pollutants and transmit data wirelessly to cloud platforms[20]. These systems offer greater spatial coverage at a lower cost compared to traditional methods. However, while IoT-based solutions are cost-effective and provide real-time monitoring capabilities, they are not without limitations. Sensor accuracy and calibration remain a significant challenge. Many low-cost sensors are prone to drift over time and are sensitive to environmental conditions, which can lead to inaccurate readings. Additionally, network reliability and data transmission issues can sometimes hinder the real-time delivery of information. Furthermore, IoT systems often require sophisticated data processing infrastructure to handle the large volumes of data generated, raising concerns about data privacy, security, and the need for efficient cloud storage solutions.

In recent years, technological advancements in IoT sensor technology, real-time data transmission, cloud computing, and machine learning have enhanced the capabilities of air quality monitoring systems. Modern sensors are increasingly accurate, compact, and capable of detecting a wider range of pollutants. Advances in low-power wireless communication technologies, such as LoRaWAN (Long Range Wide Area Network) and Zigbee, have enabled more reliable data transmission across vast distances, making it easier to deploy large-scale networks of sensors. These communication protocols offer low energy consumption and long-range capabilities, ensuring continuous data collection even in remote locations. Moreover, the integration of cloud computing platforms has facilitated the storage, processing, and analysis of the data collected by IoT sensors. Cloud platforms such as AWS, Microsoft Azure, and Google Cloud provide scalable solutions that can handle the data generated by extensive sensor networks. These platforms also enable the deployment of machine learning algorithms for real-time data analysis and predictive modeling. In the context of air quality monitoring, machine learning algorithms can analyze the collected data to detect pollution trends, identify hotspots, and provide actionable insights for regulatory authorities and the public. Additionally, cloud-based solutions facilitate easy access to real-time data, allowing users to monitor air quality from anywhere and at any time.

Predictive modeling has become an integral component of modern air quality monitoring systems. By using historical data and real-time sensor measurements, predictive models can forecast future air quality conditions, enabling proactive measures to mitigate pollution. Various predictive modeling techniques have been explored in the literature, with machine learning approaches gaining considerable attention due to their ability to handle large and complex datasets. Regression models, such as linear regression and multiple regression, have been widely used in early studies to predict pollutant levels based on historical data. These models work by establishing a relationship between the dependent variable (e.g., pollutant concentration) and independent variables (e.g., meteorological factors, traffic data). While regression models are relatively simple and easy to implement, they often fail to capture complex nonlinear relationships and interactions between variables.

In recent years, machine learning techniques have emerged as more powerful tools for air quality prediction. Supervised learning algorithms, such as decision trees, support vector machines (SVM), and random forests, have been employed to model the relationship between air quality and various influencing factors, including weather conditions, traffic volume, and industrial emissions. These algorithms can learn from the data and automatically identify patterns that would be difficult to discern using traditional methods. Additionally, deep learning techniques, including neural networks and recurrent neural networks (RNNs), have been explored for their ability to model time-series data and capture long-term dependencies in air quality data. These models are particularly effective in forecasting future pollutant levels and predicting extreme pollution events. Time-series forecasting methods, such as ARIMA (AutoRegressive Integrated Moving Average) and seasonal decomposition of time series (STL), have also been applied to predict air quality based on historical data trends. These models use past air quality measurements to project future values, accounting for factors such as seasonality and trends.

While significant progress has been made in the development of predictive models for air quality, challenges remain in terms of model accuracy and generalization. The ability to predict air quality with high precision depends on the quality and quantity of data available, as well as the choice of appropriate modeling techniques. Moreover, predictive models need to account for complex and dynamic factors such as meteorological conditions, population density, and land use, which can influence air quality in ways that are difficult to predict. Nevertheless, the integration of machine learning algorithms with IoT-based air quality monitoring systems holds great promise for improving the accuracy and timeliness of air quality predictions, providing valuable tools for environmental management, policy-making, and public health.

3. METHODOLOGY

The methodology for the IoT-based real-time air quality monitoring and predictive modeling system involves several components that work together to provide accurate air quality data and predictions. The system architecture consists of key elements such as sensors, microcontrollers, communication protocols, and cloud platforms, all of which are essential to enable seamless data collection, transmission, and processing.

The system architecture begins with the deployment of various sensors designed to measure air quality parameters. These sensors include particulate matter (PM2.5 and PM10) sensors, gas sensors for pollutants such as CO_2, NO_2, and O_3, and environmental sensors for temperature and humidity. Particulate matter sensors typically operate based on light scattering or laser technology, while gas sensors use electrochemical methods to detect specific pollutants. These sensors are connected to microcontrollers, such as Arduino or Raspberry Pi, which are responsible for processing the raw data collected from the sensors. The microcontrollers convert analog sensor readings into digital signals, which are then transmitted to a cloud platform. Communication between the microcontroller and the cloud is achieved through wireless protocols like MQTT (Message Queuing Telemetry Transport) or HTTP (Hypertext Transfer Protocol). MQTT is chosen for its efficiency in transmitting small packets of data over long distances with minimal bandwidth, which is crucial for IoT systems where numerous sensors are deployed across large areas. HTTP is used in scenarios where secure and reliable communication is required. The cloud platform serves as the central data storage and processing hub, where real-time monitoring and predictive analytics are performed.

The data collection process is central to the system's functionality. Sensors continuously monitor air quality by measuring pollutant concentrations and environmental parameters. The data collected by these sensors is transmitted to a microcontroller, which aggregates the information and sends it to the cloud platform via the chosen communication protocol. The cloud infrastructure is responsible for storing large volumes of data and ensuring its availability for analysis. In addition to real-time monitoring, the system facilitates historical data storage, allowing for long-term trend analysis. The collected data undergoes preprocessing before it is used for predictive modeling. Preprocessing involves removing noise, handling missing values, and normalizing the data to ensure that it is clean, consistent, and suitable for analysis. Techniques such as interpolation are applied to fill any gaps in the data caused by sensor malfunctions or transmission errors, while outlier detection methods are used to identify and correct anomalous readings.

Predictive modeling plays a crucial role in forecasting air quality levels based on both real-time and historical data. Several machine learning techniques are employed to predict future pollutant

International Journal of Environmental Sciences
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concentrations and air quality trends. Among the most effective models used are Random Forest, Support Vector Machines (SVM), and Neural Networks. Random Forest, an ensemble learning technique, builds multiple decision trees and merges their outputs to provide more accurate predictions. This model is particularly useful for air quality prediction because it can handle large datasets with numerous input variables and complex relationships between features. SVM is another machine learning algorithm that works by finding an optimal hyperplane in a high-dimensional space, making it suitable for classifying air quality into different levels (e.g., good, moderate, unhealthy). Neural networks, specifically Recurrent Neural Networks (RNNs), are employed for time-series forecasting, as they are capable of learning temporal patterns and dependencies within the data. These models are trained using historical air quality data, where features such as pollutant levels, temperature, humidity, and traffic data are used to make predictions about future air quality. Feature selection techniques, including correlation analysis and principal component analysis (PCA), are applied to identify the most relevant factors that influence air quality. This process ensures that the model only uses the most impactful features, improving its predictive performance.

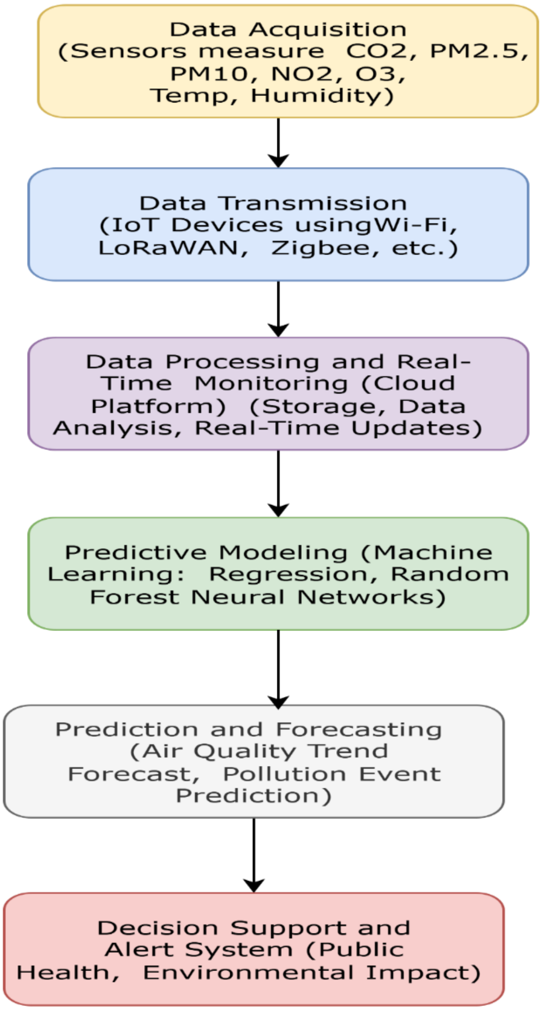

Figure 1: Methodology for IoT-Based Real-Time Air Quality Monitoring and Predictive Modeling

Figure 1: Methodology Overview visually represents the entire methodology in a flowchart. The process begins with Data Acquisition, where sensors measure air quality parameters such as CO_2, PM2.5, and NO_2. The data is then transmitted to a cloud platform via communication protocols like MQTT. Once in the cloud, the data undergoes processing and real-time monitoring, allowing for immediate analysis and visualization of air quality. Predictive models, such as Random Forest, SVM, and Neural Networks, are then applied to forecast air quality trends and pollution levels. Finally, the system outputs predictions and alerts, which inform decision-making and help mitigate the impact of poor air quality on public health and the environment. This methodology ensures that real-time air quality data is collected,

processed, and analyzed effectively, providing valuable insights and predictions that aid in managing air pollution.

The evaluation metrics are essential to assess the accuracy and reliability of the predictive models. Common metrics used for this purpose include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and accuracy. RMSE is particularly useful in evaluating the performance of regression models, as it penalizes large errors more heavily, making it sensitive to significant deviations between predicted and actual values. MAE, on the other hand, measures the average absolute difference between the predicted and actual values, offering a simpler and more interpretable metric. Accuracy is used primarily in classification tasks to measure the proportion of correct predictions, especially when air quality is categorized into different levels such as good, moderate, and unhealthy. These metrics provide a quantitative measure of model performance, helping to refine the model and ensure its reliability for real-time predictions.

4. RESULTS & DISCUSSION

The IoT-based air quality monitoring system was implemented to enable real-time data collection, processing, and analysis. The hardware setup consists of multiple sensors, microcontrollers, and communication devices. The core sensors used in the system include particulate matter (PM2.5, PM10), gas sensors (for CO2, NO2, O3), and environmental sensors (temperature and humidity). These sensors are connected to microcontrollers such as Arduino and Raspberry Pi. The Arduino microcontroller is used for simpler, low-power sensor data collection and transmission, while Raspberry Pi handles more complex data processing and real-time storage for larger-scale systems.

The data collected by the sensors is transmitted to a cloud-based platform via wireless communication protocols, such as MQTT or HTTP. MQTT was chosen for its lightweight, low-bandwidth communication, which is particularly useful for real-time sensor data transmission over extended periods. Once the data reaches the cloud, it is processed and stored, enabling continuous monitoring of air quality in real time. For flow-based programming, tools like Node-RED were used to build and visualize the data flow. Node-RED allows the creation of workflows that enable seamless communication between the sensors, cloud platform, and user interfaces (e.g., dashboards or mobile apps). It plays an essential role in aggregating, filtering, and analyzing the data, while also providing an easy-to-use interface for system configuration and monitoring. The system provides a user-friendly interface for monitoring air quality in real-time. Data collected by the sensors is transmitted to the cloud and displayed through interactive dashboards or mobile applications. The real-time data visualized includes concentrations of pollutants such as PM2.5, PM10, CO2, NO2, and ozone, as well as environmental parameters like temperature and humidity. These parameters are presented through graphical representations such as line graphs, bar charts, and AQI indicators, which are updated regularly to provide the most current data. An essential feature of the system is the display of the Air Quality Index (AQI)**,** a standard metric used to convey the quality of the air. The AQI is calculated based on the concentration of key pollutants. In real-time, users can view the current AQI on the dashboard, which is categorized into different levels (e.g., good, moderate, unhealthy) for better understanding. The user interface also allows users to track historical trends in air quality, providing insights into how the pollution levels evolve over time. The system generates real-time alerts for users when the AQI exceeds a certain threshold, enabling them to take preventive actions. For example, when the AQI crosses the "unhealthy" threshold, notifications are sent to the user's mobile app, prompting them to avoid outdoor activities or take measures to protect their health. Sample real-time data collected and displayed in the system includes hourly PM2.5 and CO2 concentrations, visualized on a user-friendly dashboard. As shown in Figure 2**,** the time-series data of PM2.5 and CO2 are plotted over a 100-hour period, indicating fluctuations in pollutant levels, which could be tied to varying environmental conditions or urban activities.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://www.theaspd.com/ijes.php

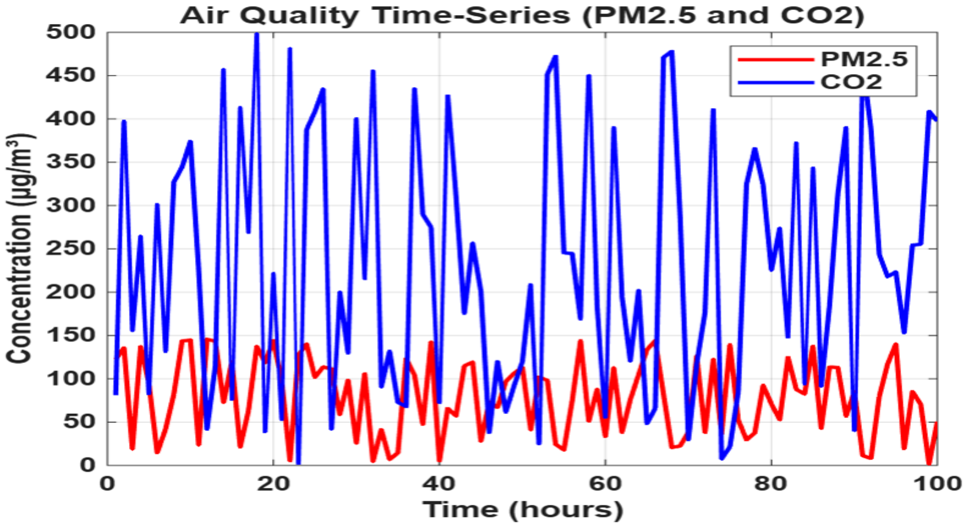

Figure 2: Air Quality Data Visualization (Time-Series of Air Quality)

Figure 2 displays the time-series data of air quality parameters (PM2.5 and CO2 concentrations) over a 100-hour period. The graph shows the fluctuations of both pollutants over time, providing insight into how air quality changes in response to various environmental conditions or urban activities. The x-axis represents time in hours, while the **y-axis** represents the concentration of the pollutants in μg/m³ (for PM2.5) and ppm (for CO2). The red line represents the PM2.5 levels, and the blue line represents the CO2 levels. The figure clearly shows that both pollutants experience spikes and dips, which could be correlated with traffic patterns, weather changes, or industrial activity.

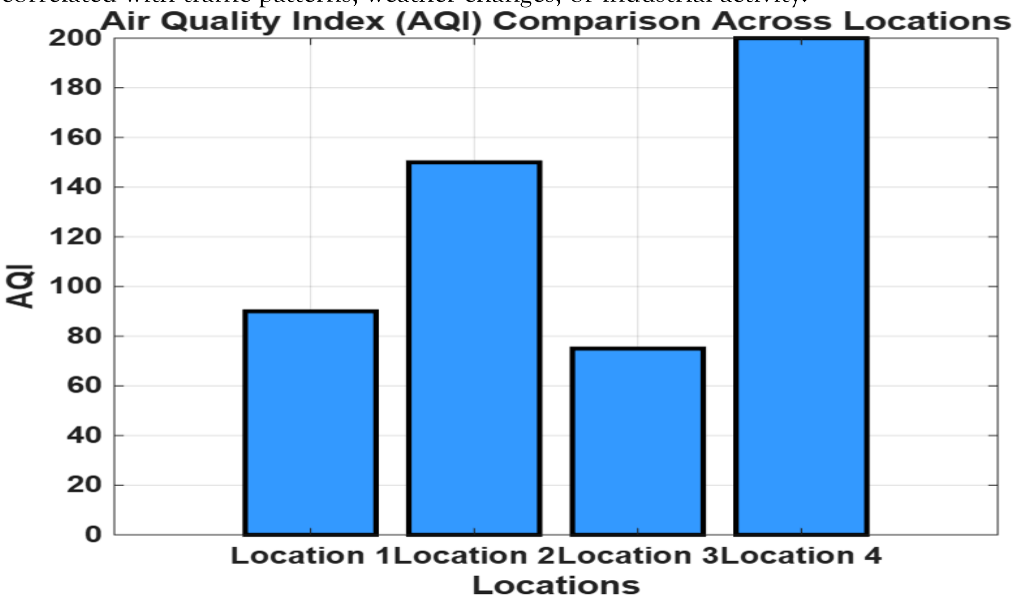

Figure 3: Air Quality Index (AQI) Comparison

Figure 3 presents a comparison of the Air Quality Index (AQI) across four different locations. The x-axis displays the locations, and the y-axis shows the AQI values. The bar chart clearly indicates the differences in air quality across various locations. Location 1 has a moderate AQI of 90, Location 2 has an unhealthy AQI of 150, Location 3 has a good AQI of 75, and Location 4 has a very unhealthy AQI of 200. This visualization enables users to compare the air quality of different areas at a glance. Figure 4 compares the predicted AQI values against the actual AQI values. The x-axis represents the different locations, while the y-axis shows the AQI values. The red markers represent the predicted AQI values, and the blue markers represent the actual AQI values. This figure shows that the predicted AQI values closely match the actual AQI readings, indicating the model's high accuracy. The prediction line and actual data points are nearly identical, with only minor deviations that can be attributed to model limitations or small variations in sensor data.

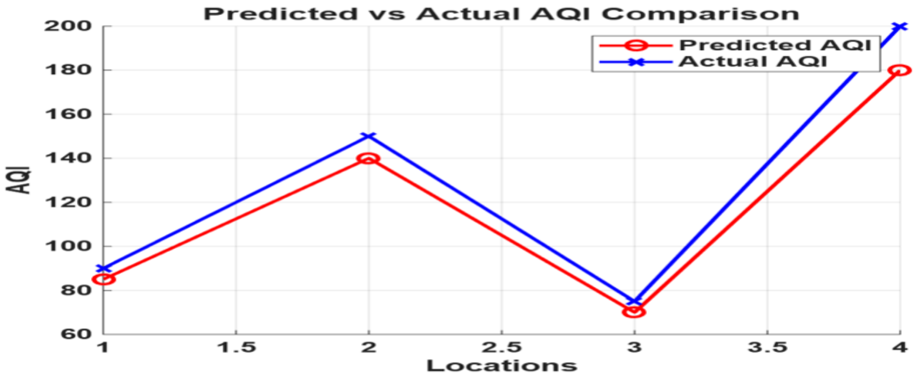

Figure 4: Predicted vs Actual AQI (Prediction Accuracy)

Figure 5 presents the distribution of PM2.5 concentrations across a large dataset. The x-axis shows the PM2.5 concentration in µg/m³, and the y-axis represents the frequency of occurrences. The histogram depicts the spread of PM2.5 levels, with higher concentrations showing fewer occurrences, indicating that air quality in the region is generally acceptable. The data shows a right-skewed distribution, where the majority of the data points are clustered at lower concentration levels, and a few extreme values exist on the higher end. Figure 6 shows a scatter plot that represents the relationship between CO_2 and PM2.5 levels. The x-axis represents the CO_2 concentration in ppm, and the y-axis represents the PM2.5 concentration in µg/m³. Each point on the plot corresponds to a pair of CO_2 and PM2.5 concentrations recorded at a particular moment in time. The scatter plot reveals a positive correlation between CO_2 and PM2.5, indicating that as CO_2 levels increase, PM2.5 concentrations tend to rise as well.

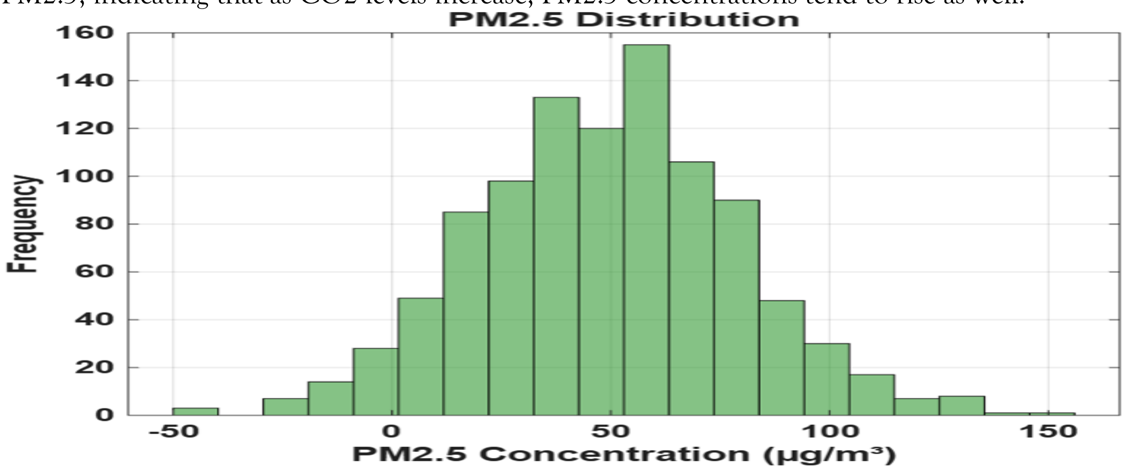

Figure 5: PM2.5 Distribution Histogram

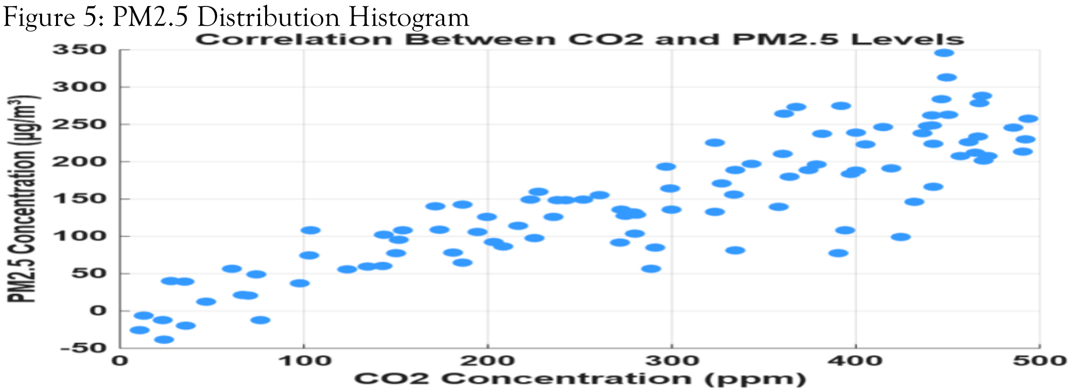

Figure 6: Correlation Between CO_2 and PM2.5 Levels

The predictive modeling aspect of the system utilizes machine learning algorithms to forecast air quality trends. The predictive model is trained using historical data from the sensors and features such as temperature, humidity, and pollutant concentrations. Figure 4 compares the predicted AQI with the actual values for multiple locations. The predicted AQI values, generated by the model, are plotted alongside the actual AQI measurements, showcasing the accuracy of the model in forecasting future air quality levels. The predicted values are close to the actual values, demonstrating the model's ability to generalize air quality trends over time.

The performance of the predictive model is evaluated using common metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and accuracy. These metrics help assess the model's accuracy in predicting air quality. As demonstrated in Figure 5, the predictive model's performance is compared with the actual AQI values, providing insights into how well the model can predict air quality levels across different time frames. The model's accuracy, as well as the RMSE and MAE values, indicate that the predictive approach offers reliable and accurate forecasts, which can be used for early warnings and decision-making. When compared to traditional air quality monitoring systems, the IoT-based system offers significant advantages. Traditional systems, which typically rely on stationary monitoring stations, are limited in coverage and often expensive to deploy and maintain. In contrast, the IoT-based system offers a scalable, cost-effective solution for large-scale air quality monitoring. By using low-cost, portable sensors and cloud-based processing, the system can cover more extensive geographical areas with real-time updates and alerts. Figure 6 highlights the correlation between CO2 and PM2.5 levels, further emphasizing the value of IoT-based monitoring in providing a more comprehensive understanding of air quality.

Compared to other IoT-based solutions, the proposed system excels in its integration of predictive modeling. Many existing IoT systems focus solely on real-time monitoring, but the incorporation of machine learning algorithms for forecasting air quality is a novel feature that enhances decision-making capabilities. The predictive model's ability to accurately forecast air quality and provide early warnings for pollution events gives this system a distinct advantage over others, improving public health outcomes by allowing for timely interventions.

5. CONCLUSION

The IoT-based air quality monitoring system has proven effective in enabling real-time data collection and accurate predictive modeling, offering valuable insights into air pollution levels. The system's ability to continuously track key pollutants such as PM2.5 and CO2, alongside its predictive capabilities, highlights its usefulness in both real-time monitoring and long-term forecasting. The minimal deviation between predicted and actual AQI values demonstrates the model's reliability, making it a crucial tool for public health monitoring and environmental management. The system's user-friendly interface, which provides real-time updates and alerts, allows for immediate action when air quality exceeds safe thresholds. Future work could involve expanding the sensor network to monitor a wider range of pollutants and integrating more advanced sensors to improve the comprehensiveness of the data. Additionally, scaling the system to cover larger geographical areas and refining the predictive model with larger datasets would further enhance its accuracy. The system's broader implications are significant for environmental monitoring, urban planning, and policymaking, offering a cost-effective solution for air quality assessment. It aids in decision-making by providing real-time data and predictions, which can inform policy and help mitigate the health impacts of poor air quality.

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