Real-time Air Quality Monitoring in Smart Cities using IoT-enabled Advanced Optical Sensors

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***Abstract*—Air quality control has drawn a lot of attention from both theoretical research and practical application due to the air pollution problem's increasing severity. As urbanization accelerates, the need for effective air quality monitoring in smart cities becomes increasingly critical. Traditional methods of air quality monitoring often involve stationary monitoring stations, providing limited coverage and outdated data. This study proposes an Internet of Things (IoT) centred framework equipped with inexpensive devices to monitor pollutants vital to human health, in line with World Health Organization recommendations, in response to the pressing issue of air pollution and its increased importance. The hardware development entails building a device that can track significant contamination percentages. Ammonia, carbon monoxide, nitrogen dioxide, PM2.5 and PM10 particulate matter, ozone, and nitrogen dioxide. The gadget is driven by the ESP-WROOM-32 microcontroller, which has Bluetooth and Wi-Fi capabilities for easy data connection to a cloud server. It uses PMSA003, MICS-6814, and MQ-131 sensors. The gadget activates indicators when a pollutant concentration exceeds the allowable limit, enhancing its software to enable immediate response and intervention. This work leverages the robust cloud architecture of Amazon Web Server (AWS) to integrate it into the system and improve accessibility and data control. This combination no longer just ensures data preservation but also enables real-time tracking and analysis, which adds to a comprehensive and preventive strategy for reducing air pollution and preserving public health. With an RMSE score of 3.7656, the Real-Time Alerts with AWS Integration model—which was built in Python—has the lowest value.**

Keywords*—Internet of Things (IoT); air quality control; low-cost sensors; ESP-WROOM-32 microcontroller; Amazon Web Server (AWS)

I. INTRODUCTION

Air quality refers to the way filthy the air human’s breath. On a typical day, that take over 20,000 breath. Have we considered the toxins, pollen, and dirt we may be breathing? Whenever the air quality is poor, contaminants in the atmosphere can cause eye irritation, irritated the lungs, and respiratory system injury. Fresh air is a basic prerequisite for a healthy atmosphere in which all reside and study [1]. An Air Quality Analysis is an evaluation conducted to determine the benchmark quality of the air and is often necessary for any kind of development which has the ability to damage the present situation or if the surroundings having the capacity to impact sensitivity construction [2]. Air quality may be checked both indoors and outside. An air quality evaluation measures the quantity and quality of air inside the confines of a building or structure. Indoor air quality sampling varied, but typically involves collecting and analyzing air samples with swab/sticky pads. An outdoors atmosphere evaluation can range from a basic screenings to a more extensive study that includes dispersal modelling [3]. The sort of air quality evaluation needed is determined by a variety of criteria, which involve the development's scale, intended place of residence, and existing information of pollutants present around the construction area[4]. A thorough air quality evaluation ought to determine air pollution exposed using the "Air Quality Impact Significance Criteria - New Exposure" and demonstrate any preventative actions related with the development's layout, location, and operations to decrease air pollution [5]. An Air Quality Analysis may be required in support of an inquiry for clearance for works that may have a significant influence on regional traffic moves, transportation structure, or are located near established busy roadways. An appropriate Air Quality evaluation for planned should comprise an inspection of the environmental conditions about the development through surveillance or modeling, an evaluation of the air quality through the construction phase, as well as a monitoring of the air purity through the period of operation. Tracking air quality monitors contaminants such as gases and particulates. Measuring such contaminants enables the enhancement of the atmosphere via construction planning, management, and mitigation methods. Enhancing air quality is critical in decreasing negative health consequences and offering an improved standard of life [6].

According to the World Health Organization (WHO), pollution in the air causes 4.2 million premature deaths annually in urban and rural regions worldwide. According to the US Environmental Protection Agency, particulates with a measurement of less than ten µm is unique of the biggest pressures to community health due to its easy passage through respiratory systems, producing significant health damage. According to Valdivia in and Pacsi, Metropolitan Lima (LIM) is sensitive to high levels of PM_{10} due to its rapid manufacturing and economic expansion, as well as its big human population, which accounts for 29% of the country's total population.To mitigate the impairment wrought by PM_{10} to public health, the WHO developed level thresholds ideal for achieving a minimum adverse effect on health5. In different nations, multiple regulations have been passed to regulatePM_{10} concentrations and air quality in overall, such as those developed in Peru by the Ministry of the Environment as well as in the United States by the Environmental Protection Agency (EPA). In recent decades, several predictions methodologies have been modified and modified to better understand way pollution function in the natural environment at the level of molecules, including predicting diffusion and dispersal trends according to molecule dimension and class [7]. Nevertheless, predictions based on findings tend to have a low accuracy . The EPA describes inside air quality (IAQ) as the purity of airborne in buildings grounds or sealed rooms that can have a substantial influence on the well-being of tenants, ease, and performance rates [8], It has been established that human activity, manufacturing processes, and rising traffic on roadways are the main culprits causing the decline of the natural world [9]. In addition to various outside factors, low thermal ease levels owing to excessive moisture and temperature in confined buildings, insufficient ventilation administration, dangerous construction supplies, and every day human behavior all have an impact on IAQ [10]. The increasing levels of dangerous pollutants [11].

Indoor surroundings are also connected to the worsening wellness of building inhabitants, particularly older adults, newborns, people with impairments, and domestic women, who spending the majority of their lives inside [12] .As a result, it is critical to grasp all elements of inside airborne pollution (IAP) and its influence on the general population, as well as discover suitable IAQ management techniques in sealed buildings. According to a study of over 30,000 organizations in the United States, indoor air quality control is the country's top priority since it is inflicting significant harm to the well-being and health of individuals [13]. On the other hand, long-lasting medical impacts include pneumonia, pulmonary TB, hostile gestation results, asthma, chronic bronchitis, cancer, and coronary artery disease that individuals may experience after frequent & extended exposure [14] A wide range of contaminants harm the well-being of structure inhabitants in homes, workplaces, cafés, medical facilities, and retail malls. Because of the increased traffic activities, manufacturing operations, and facilities ambient air pollution values are rising sharply, that eventually explains for the declining IAQ values. [15].

The researchers have previously released thorough systematic studies that emphasize existing improvements in the area of IAQ monitoring and examination, as well as emphasizing the significance, difficulties, and future years sights of this significant area of studies, in order to offer knowledge about the associated research [16]. Aside from this, various papers were released on the creation of forecasting algorithms using neural networks, artificial intelligence, and advanced learning methodologies to provide building residents with an early warning of dangerous pollutant concentrations. In addition, the authors released a systematic review to emphasize the contributions already established scholars in the subject, as well as the gaps in knowledge [17]. The researchers gathered present data from 4 separate countryside and urban sites on six significant IAQ parameters, namely, $\mathrm{PM_{10}}$, $\mathrm{PM_{25}}$, $\mathrm{CO_2}$, CO, $\mathrm{NO_2}$, as well as two critical thermal convenience factors, humidity and temperature. Finally, the model was modified utilizing the pattern searching technique to advance the correctness of predictions, allowing the suggested system to be applied in real-time settings to prevent the negative implications of low IAQ levels [18]. The suggested model is dubbed continuous because it employs an evolving set of input characteristics based on the selected response variable for predictions.

Key contributions are as follows:

- The urgent problem of air pollution is addressed by proposing an Internet of Things system with inexpensive sensors for real-time monitoring of important air contaminants.
- Ensures a focused and effective strategy by focusing on contaminants that are critical to human health and adhering to World Health Organization recommendations.
- Provides a comprehensive understanding of air quality by developing a hardware approach capable of calculating the amounts of important pollutants including PM2.5, PM10, ozone, carbon monoxide, nitrogen dioxide, and ammonia.
- Enables smooth data transfer to a cloud server for effective monitoring and analysis by utilizing the Wi-Fi and Bluetooth capabilities of the ESP-WROOM-32 microcontroller.
- Establishes a mechanism whereby the apparatus activates indicators when the concentration of pollutants exceeds allowable limits, improving its software for prompt reaction and interference, and supporting proactive air quality management.
- Enhances the overall efficacy of air pollution prevention efforts by integrating Amazon Web Server (AWS) into the system and utilizing its reliable cloud architecture for simplified data management, storage, and real-time tracking and analysis.

The following is how the investigation progresses: In Section II. Related studies perform a thorough analysis of earlier research, focusing on prediction issues and the wide range of optimization techniques used in such settings. In Section III, a thorough investigation of issue statements is conducted. Section IV elaborates on the suggested method or plan of action to deal with these difficulties. The entire topic of performance evaluation metrics and criteria is covered in Section V. Subsequently. Section VI serves as the essay's conclusion by summarizing the main findings and learning.

II. Related Works

Air pollution is a key contributor to global warming, and efforts to address it are gaining traction. Urban areas use computer technology (IT) and communications technologies to reduce emission levels and noise pollution. The goal is to reduce health-related hazards and improve understanding about the impacts of pollutants in the air exposures. The present research explores the major concerns of a current pollution tracking scheme, such as sensors, connection procedures, collecting data and transfer over routes of communication, and information security and uniformity. Safety is a significant emphasis of the suggested IoT system.The system's additional parts are also focused on security. This document includes a bill for supplies and protocol specifications required for the planning, creation, and execution of an IoT system, in addition to security issues. The paper's evidence of concept (PoC) addresses IoT security issues regarding communiqué pathways among linked device gateway and the cloud-based systems to which information is sent. The security measures adhere to recognized principles, guidelines, and regulations, leading to a consistent and healthy system., the software can read and analyze the collected data, creating pollutant maps using modelling techniques. The maps are utilized to undertake real-time treatments, such as redirecting transportation in a chief metropolis, to reduce concentrations of airborne contaminants using information gathered for a year in a row. When paired with traffic control equipment (cameras and traffic signals), this technology may minimize vehicle emissions by constantly proposing other courses or even demanding reroute if pollution levels are exceeded. Still, the study must concentrate on case studies for implementing the PoC with improvements to various medium cities in collaboration with local governments in order to observe the traffic affect models and how they interact into additional advanced city systems, since current projects like AirVisual are limited [19].

The quantity of IoT-based applications for smart cities is growing rapidly, as is the volume of data generated by those applications. To guarantee long-term growth, administrations and city stakeholders take proactive steps to manage this data and forecast effects in the future. Techniques based on deep learning have been applied to a variety of large-scale information forecasting challenges. This motivates us to apply methods based on deep learning for predicting IoT data. As a result, this research proposes a unique deep learning algorithm for analyzing IoT smart city data. A new model that utilizes Long Short-Term Memory (LSTM) networks for predicting upcoming air quality levels in a smart city. The suggested model's assessment findings are positive, indicating the method may also be utilized to solve other innovative city prediction challenges. However, one major limitation of this work is the low generalization of the suggested LSTM-based model, as its efficacy may be highly influenced by specific features of the analyzed smart city data. Furthermore, the research might fail to address possible privacy and security concerns related to managing and analyzing confidential IoT data in a smart city environment [20].

Sometimes emissions have grown owing to a variety of factors, including growing populations, greater car usage, manufacturing, and urbanization, among others that have had a substantial impact on human health. To pay attention to the circumstance. The research involves an air pollution surveillance system that is an Internet of Things via sensors dependent structure. You monitor the overall condition of the air via a web server on the World Wide Web and produce warnings while the quality of the air goes beyond an established limit, and these suggests if enough dangerous gas have been detected in the atmosphere such as benzene, smoke, NH_3, CO_2, and alcohol. The expansion of commerce and rapid human population urbanization have a negative influence on global air quality. Long-term exposure to air pollution causes chronic heart and lung ailments, which endangers people's well-being. Every day, thousands of companies and billions of automobiles emit massive amounts of pollutants in the atmosphere. As a result, monitoring pollutants in the air has become vital. The investigation presents the creation of an Internet of Things-driven air quality surveillance system and analyzes the effectiveness of the air pollution tracking system. But the disadvantage of this research is that the efficiency of the IoT-based air quality tracking systems may be affected by the exactness and dependability of the sensors utilized, potentially leading to mistakes in contaminants estimations [21].

Exhaling and breathing filthy air has major health repercussions. Regular surveillance and record-keeping can help to reduce the impact of air pollution. In addition, early forecast of pollution levels can assist government agencies in taking proactive environmental protection actions. In this study, researchers suggested employing the ml methods and IoT for tracking pollutants in the air in smart cities in the future. The Pearson coefficient reveals a strong link between contaminants and meteorological factors. In contrast to typical sensor networks, this study employs a cloud-and IoT architecture that collects information obtained from airborne pollutants sensors and weather conditions sensors. Thus delivers twofold dependability and lower expenses greatly. The amount of sulphur dioxide (SO2) and particulate matter (PM2.5) was predicted using an artificial neural network. The encouraging outcomes show that ANN is a trustworthy choice for pollution surveillance and forecasting systems. The models They developed attained Root Mean Squared Error values of 0.0128 and 0.0001 for SO2 and PM2.5, respectively. However, one disadvantage of this research is its dependence on Pearson correlation to create a significant connection among contaminants and meteorological indicators can simplify the complicated relationships in the atmosphere's dynamics, which could contribute to less precise forecasts [22].

Pollution of the atmosphere has grown into a dangerous issue in many nations throughout the world in recent decades as a result of human activity, manufacturing, and urbanization. PM2.5, a kind of air pollution with a circumference of fewer than 2.5μm, poses a significant health risk. PM2.5 levels vary according to a number of variables, such as meteorological and the quantity of other contaminants in metropolitan areas. In the present study, constructed a deep learning system that predicted the hourly prediction of PM2.5 concentrations in Beijing, China, using CNN-LSTM with a spatial-temporal features by merging historical pollution information, meteorological data, and PM2.5 concentration in neighboring sites. Researchers investigated the differences in performance amongst deep learning models .Results from experiments show that the "hybrid CNN-LSTM multivariate" technique allows for greater precision predictions and outperforms all of the classic models described. Yet, the approach was initially deployed in the metropolitan area of Beijing, China, according to the lack of daily freely available data [23].

As air pollution worsens, the condition of the air prediction has emerged as a critical tool for managing and preventing it. Over the past few years, several approaches for predicting the air's cleanliness have been presented, including determinate, statistical in nature, and neural network approaches. Still, these approaches have drawbacks. The deterministic approach approaches need costly calculations and particular expertise for parameters recognition, but statistics techniques' forecast ability is limited owing to the linear assumptions and the issue of multicollinearity. In contrast, many deep learning approaches are unable to detect periodic trends or acquire information about the long-term associations of air pollutant concentration. Furthermore, there are few systems that can produce accurate predictions for environmental forecasts at higher time resolutions, including every day, every week, and occasionally each month .The approach is to use the bi-directional LSTM model to learn from PM2.5's dependence over time, as well as learn via transfer to transfer information obtained at lower time resolution to higher periodic resolutions. The previously suggested methodological paradigm is tested with a case study in Guangdong, China. The framework's efficiency is contrasted with other regularly used machine learning techniques, and the findings reveal that the suggested TL-BLSTM model has less mistakes, particularly at higher temporally resolutions. But it is utilized when the number of samples is restricted or whenever the modeling procedure is too complicated and technologically costly [24].

The provided paper examines the use of Internet of Things (IoT) and machine learning for air pollution monitoring and prediction. It shows real-time tracking with a focus on security, IoT packages in smart cities and the significance of accurate sensors. Various studies recommend deep gaining knowledge of algorithms, inclusive of LSTM networks, for predicting air quality Challenges include potential sensor inaccuracies and simplified mode. Additionally, a cloud-centric IoT middleware architecture and artificial neural networks are explored for efficient pollution surveillance. These approaches aim to monitor and predict air quality levels in urban environments, facilitating proactive environmental protection measures. However, several limitations are evident across these studies. Firstly, the accuracy and reliability of IoT-based air quality tracking systems heavily rely on the precision of sensors used, which may lead to inaccuracies in pollutant estimations. Additionally, deep learning models may suffer from low generalization, as their efficacy can be highly influenced by specific features of analyzed smart city data, potentially limiting their applicability across different contexts. Furthermore, some studies may oversimplify the complex relationships in atmospheric dynamics, leading to less precise forecasts. Lastly, certain approaches, such as those relying on transfer learning, may face challenges when dealing with limited sample sizes or complex modeling procedures, highlighting the need for further research to address these limitations and enhance the effectiveness of air quality prediction systems.

III. Problem Statement

The growing global problem of air pollution, exacerbated by urbanization, industry, and population expansion, need efficient monitoring and forecasting [24]. The adaptability of deep learning techniques, such as CNN, hybrid models, and LSTM networks, while tackling issues such as sensor errors, privacy issues, and the requirement for complex models in the monitoring and prediction of air pollution. Systems investigate ways to alleviate issues with air pollution by using machine learning and the Internet of Things (IoT). Emphasizing trustworthy and precise sensors is still necessary in research. Additionally, it highlights how urgently the need a comprehensive and reliable forecasting solution to get around the obstacles in the IoT Approach with Real-Time Alerts and AWS Integration for Air Quality Monitoring.

IV. IoT Approach with Real-Time Alerts and AWS Integration for Air Quality Monitoring

The proposed method utilizes the ESP-WROOM-32, a low-cost IoT device equipped with sensors, for real-time environmental tracking. Initial data collection is followed by a pre-processing phase, where the Nearest Neighbour Interpolation Approach is employed for data interpolation and labelling. Subsequently, the ESP-WROOM-32 processes the pre-processed data, ensuring efficient utilization of resources. The system's performance is thoroughly evaluated to validate its effectiveness. Finally, the results are hosted on an Amazon Web Server (AWS), establishing an end-to-end workflow for cost-effective environmental monitoring. The ESP-WROOM-32's low-power capabilities make it well-suited for continuous operation across diverse environmental conditions, enhancing its practicality and reliability for long-term monitoring applications. This integrated approach offers a scalable and affordable solution for real-time environmental tracking, enabling stakeholders to make informed decisions and take proactive measures to address environmental concerns. Fig. 1 shows proposed diagram.

A. *Data Collection*

The dataset encompasses a comprehensive collection of 9357 hourly readings derived from a network of 5 metallic oxide chemical detectors deployed within an Air Quality Chemical Multisensor Device. This device was strategically placed in an openly accessible, heavily polluted area at street level in an Italian city, providing a real-world perspective on airborne chemical concentrations. The data spans a duration of one year, from March 2004 to February 2005, offering a seasonal and temporal understanding of air quality dynamics. However, the dataset acknowledges several challenges that could impact the accuracy of concentration estimates. These challenges include cross-sensitivities among sensors, concept shifts, and sensor changes, as discussed in De Vito et al., Sens. And Act. B. These factors highlight the need for careful data interpretation and analysis to account for potential biases introduced by such challenges. It's noteworthy that any missing values in the dataset are denoted by a value of -200. Addressing these challenges and understanding the intricacies of the dataset is crucial for obtaining reliable insights into air quality dynamics and for developing accurate models for pollution prediction and control [25].

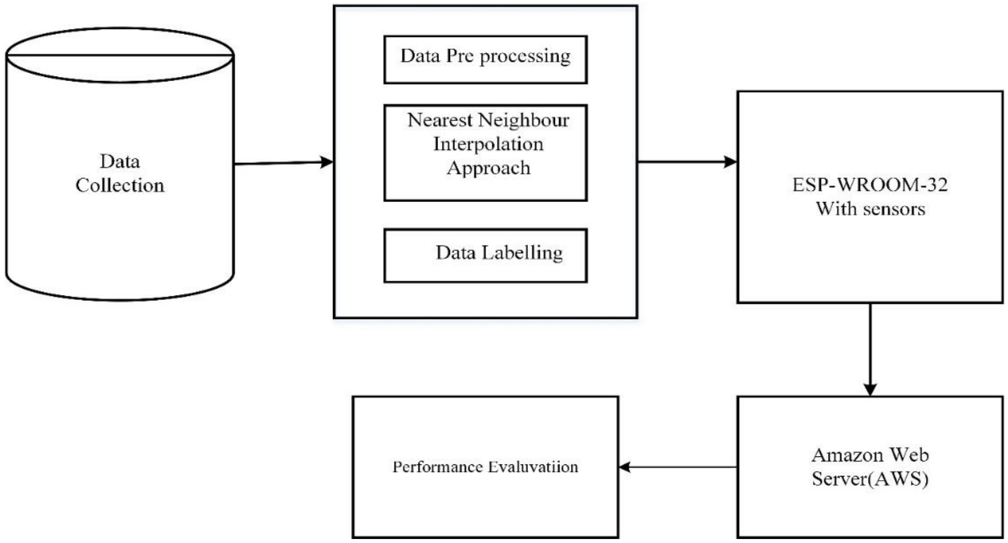

Fig. 1. Proposed diagram.

B. Data Pre-Processing

1) Nearest-neighbor interpolation approach: The unprocessed information from the sensor is captured without any sort of processing. The method of filtering is carried out in the public cloud instead of on the embedded device in order to decrease complication in the system that is embedded. The exceptions and incomplete data are among the maximum characteristic data mistakes in real-time tracing requests a total of three kinds of usual dataset preparatory computation: transforming not-a-number (NAN) data to zero, eliminating NAN data. In the current study, information interpolation is performed using a nearest-neighbour strategy. This strategy is applicable to collections with values that are lacking or outlier situations. Whenever an outlier appears at location z'_i the nearest knowing neighbour's values is utilized as the replacement for the outlier. It will be determined utilizing all of Sensor 2021, 21, 4956 10 of 16 previous data available. The choice of using prior data rather than upcoming information comes since information is collected in immediate time in the form of a series of values is shown in Eq. (1)

$$z'_i = \begin{cases} \frac{z'_{i-1} + z'_{i-2}}{2}, & \text{if } i = 2; \\ \frac{z'_{i-1} + z'_{i-2} + z'_{i-3}}{3}, & \text{if } i = 3; \\ \frac{z'_{i-1} + z'_{i-2} + z'_{i-3} + z'_{i-4}}{4}, & \text{if } i = 4; \\ \frac{z'_{i-1} + z'_{i-2} + z'_{i-3} + z'_{i-4}, z'_{i-5}, \text{otherwise}}{5} \end{cases} \quad (1)$$

2) Data labelling: Data Labelling When inputting details about sensors in the estimate process, an ensemble of records must be characterised as the result in machine learning with supervision. In fact, the air quality index (AQI) is an estimate employed for categorizing the practice of the air in a convinced place. Usually, the AQI is split into numerous limits, each of which has a unique colour and description. It appoints a health care advisor to every range. The threshold level of air quality (see Fig. 2) for a variety of pollutants. The current versions of guidelines and recommendations vary depending on the global organizations. The contaminants the index is computed using the following parameters: CO_2, $PM_{2.5}$ and PM_{10}. The greatest index reflects the AQI at the moment [26].

C. Iot-based Air Quality Monitoring

1) ESP-WROOM-32 with sensors, to enable real-time environmental tracking: The approach suggested in this paper, being a part of a bigger project in progress, comprises the software as well as the hardware layers for actual time environmental tracking via a low-cost IoT device. In the physical coating, a digital circuit design is under construction to create a surface with devices that detect the concentrations of $PM_{2.5}$, PM_{10}, O_3, CO, NO_2 and ammonium (NH_3). Moisture and temperature monitoring were added to the pollution tracking functions to aid in the analysis. The gadget and its application are going to interact over a Bluetooth or WiFi connection. The main elements that are going to be supplied on the gadget's boards which will conduct measurements are as follows. The microcontroller called ESPWROOM-32 (or simply, ESP32), was selected to gather data from the following set of sensors: DHT22, measuring ambient temperature and air humidity; PMSA0003, that successfully evaluates and specifies the levels of PM2.5 and PM10 particles substance; MQ-131, that determines the amount of O3; and MICS-6814, and this measures the levels of CO, NO_2, and NH_3 and is capable of tracking five additional pollutants. A quick overview of the listed elements is provided here.

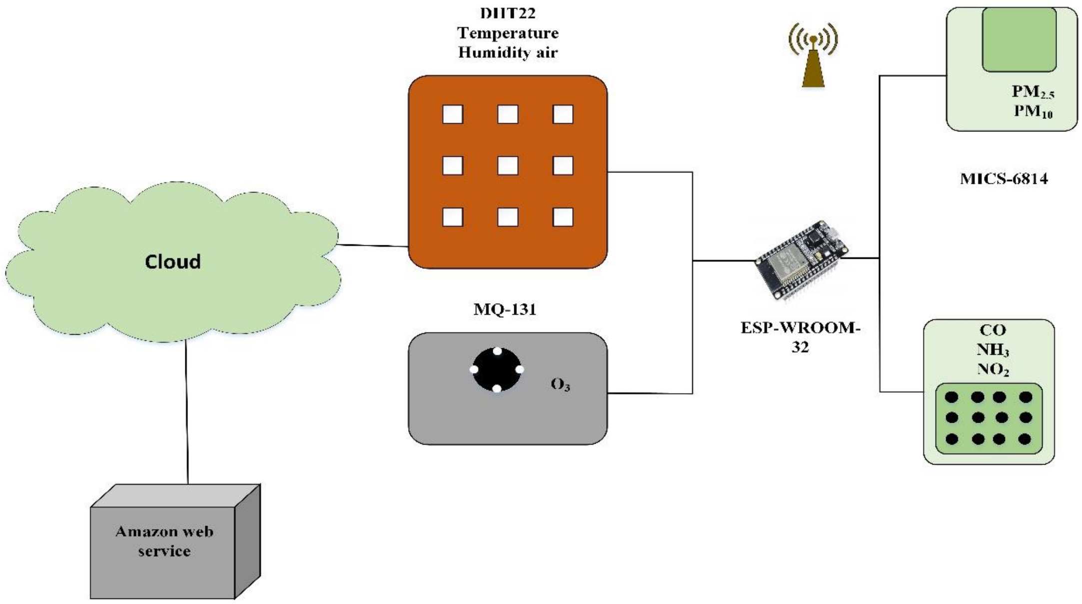

Fig. 2. IoT approach with real-time alerts and AWS integration for air quality monitoring.

To avoid potential lack of availability, the watchdog feature is added, which identifies collapses and restarts the microcontroller using three independently timers from the primary system. Sensing measurements region. The PMSA003 is a small digital sensor used for detecting particles dispersed in the air. Particulate matter, often known as dirt, are nanoparticles of varied sizes, & a sensor uses a microprocessor to execute a light scattering-based detection approach to determine the proportions of the atoms and density. The MICS-6814 is a small device that can correctly detect CO, NO2, and NH3 concentrations at the exact same time, using distinct networks for all gas. The device's efficiency is quite promising, and it must be highlighted that it can also detect five additional gases: methane (CH4), propane (C3H8), ethanol (C2H5OH), hydrogen (H2), and isobutane (C4H10). The MQ-131 sensors measure O3 contents with high sensitivity and have a trimpot for calibration in addition to a standard analog output. The DHT22 digital sensors is being chosen for both humidity and temperature surveillance because it offers exact results and is easy to set up [27].

a) Amazon Web Server (AWS): To further streamline data management and accessibility, this work integrates the Amazon Web Server (AWS) into the system, leveraging its robust cloud infrastructure. This amalgamation not only ensures efficient data storage but also facilitates real-time monitoring and analysis, contributing to a comprehensive and proactive approach in combating air pollution and safeguarding public health. Amazon Network Services, a division of Amazon, have offering frameworks for computing services upon request since March 2006. It operates on the "pay as you go" approach. The expenses are decided utilization of amenities AWS's extensive variety of cloud offerings allows for the implementation of a broad spectrum of solutions. In the suggested solution, a server's IoT primary service is utilized for uploading sensors information into the cloud. The procedure of utilizing AWS IoT core services begins with the creation of an AWS account as well as a thing in IoT core that includes the creation of certifications and rules. Information submitted may be viewed by subscribe to the appropriate MQTT protocol account's Testing area of the IoT core. The degree of sophistication is defined by the amount of gadgets that collect data and send it to the Network of Thing via a wireless connection.

V. Results and Discussion

Air quality control system equipped with low-cost gadgets to monitor key pollutants crucial to human health, such as Particulate Matter (PM 2'.5' and PM1'0'), Ozone, Carbon Monoxide, Nitrogen Dioxide, and Ammonia. Utilizing PMSA003, MICS-6814, and MQ-131 sensors powered by the ESP-WROOM-32 microcontroller, the system ensures seamless data transmission to an Amazon Web Server (AWS). In case of pollutant concentrations exceeding permissible levels, the device triggers indicators for instant response and intervention. The integration of AWS not only facilitates robust data storage but also enables real-time monitoring and analysis, contributing to a comprehensive and proactive approach in addressing air pollution and safeguarding public health.

A. Evaluation Metrics

In the experiments employing the subsequent indicators to assess the efficiency of the model for predicting and highlight any possible connection between expected and actual outcomes.

1) Root Mean Square Error (RMSE): Root mean square error computes the square roots of the median value for the squares of the difference among expected or actual information. It is computed as Eq. (2)

$$\mathrm{RMSE_{avg}} = \sum \frac{|\mathrm{Actual\_i} - \mathrm{Predicted\_i}|^2}{n} \quad (2)$$

2) *Mean Absolute Error (MAE):* An indicator of discrepancies among paired observations describing the same phenomena. Examples of contrasting Y against X include expected versus actual results, following time versus initial time, and a single calculating method against another. The MAE is determined as the total of absolute mistakes dividing by the sample's size is given in Eq. (3).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y^{i} - y_{*}^{i}\right| \quad (3)$$

TABLE I. RMSE VALUE COMPARISON

Model	RMSE value
Linear model	17.762865657654
SVR model	6.45565647866557
SARIMAX model	8.8765445567677
Proposed Real-Time Alerts with AWS	3.7656787872687

Table I provided lists four different models and their corresponding values. The RMSE statistic measures the mean variance among the values that the model predicted and what is actually present in the actual data set 1. An algorithm's ability to "fit" an information set improves as its RMSE decreases. The Real-Time Alerts with AWS Connectivity models gets the smallest RMSE value of 3.7656787872687. This suggests because it is the most effective estimate amongst the four options that have specified for the purpose of matching the data set 1.

TABLE II. REGULAR AIR QUALITY IN PPM FOR DIFFERENT LOCATIONS

Location	Average Air Quality (ppm)
Location 1	765.77
Location 2	543.87
Location 3	431.76

Table II lists three different locations and their corresponding Average Air Quality (ppm) values. The Average Air Quality (ppm) as shown in Fig. 3 value is a metric that trials the concentration of airborne pollutants in the atmosphere. Among the three locations, Location 1 has the highest average air quality value of 765.77 ppm, followed by Location 2 with an average air quality value of 543.87 ppm and Location 3 with an average air quality value of 431.76 ppm 1.

Fig. 3 depicts the average air quality of different locations. The Average Air Quality figure illustrates air quality levels across three distinct locations measured in parts per million (ppm). Location 1 exhibits the highest air quality, with a ppm slightly above 700. In contrast, Location 2 records a slightly lower ppm, just above 500. Location 3 demonstrates the lowest air quality among the three, with a ppm slightly below 500. This comparison provides valuable insights into the variation in air quality levels across different geographical areas, aiding in environmental monitoring and decision-making processes.

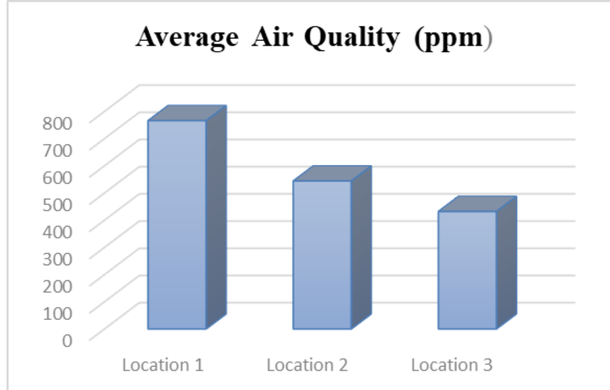

Fig. 3. Average air quality of different locations.

TABLE III. RANGE OF MEASUREMENT CONCENTRATION OF THE SENSOR BY POLLUTANT CERTAINLY

Sensor	Pollutant	Range
PMSA003	PM2.5	10 -1000 ppb 0 –
	PM10	50 – 10000 ppb
MQ-131	O3	500 µg/m³
MICS-6814	CO	1 – 500 ppm
	NO2	0 – 500 µg/m³
	NH3	1 – 1000 ppm

Table III described three sensors each measuring specific air pollutants within specific concentration ranges. The PMSA003 sensor detects particulate matter (PM2.5 and PM10), while the MQ-131 sensor detects ozone (O3). The MICS-6814 sensor measures carbon monoxide (CO) and nitrogen dioxide (NO2) concentrations. These sensors are essential for monitoring air quality, aiding in environmental assessments and public health analyses. Their specifications are crucial for assessing air quality.

Fig. 4 displays the concentration levels of four different gases (CO, CO2, NO2, and SO2) over a period of six days. Each graph is labeled with the gas type and its concentration in shares per million (ppm). The x-axis signifies the days, while the y-axis shows the absorption levels of these gases. Fluctuations in the graphs indicate variations in gas concentrations over time.

Table IV compares three different methods. The Proposed Method stands out for being low-cost, having low power consumption, and high scalability. It also offers real-time tracking with high accuracy. LSTM-OPTISENSE NET, while slightly more expensive and moderate in terms of power consumption and scalability, does provide real-time tracking with medium accuracy. In contrast, Conv-AIRNET is the most expensive, has the highest power consumption, and is the least scalable. Moreover, it lacks real-time tracking but boasts high accuracy.

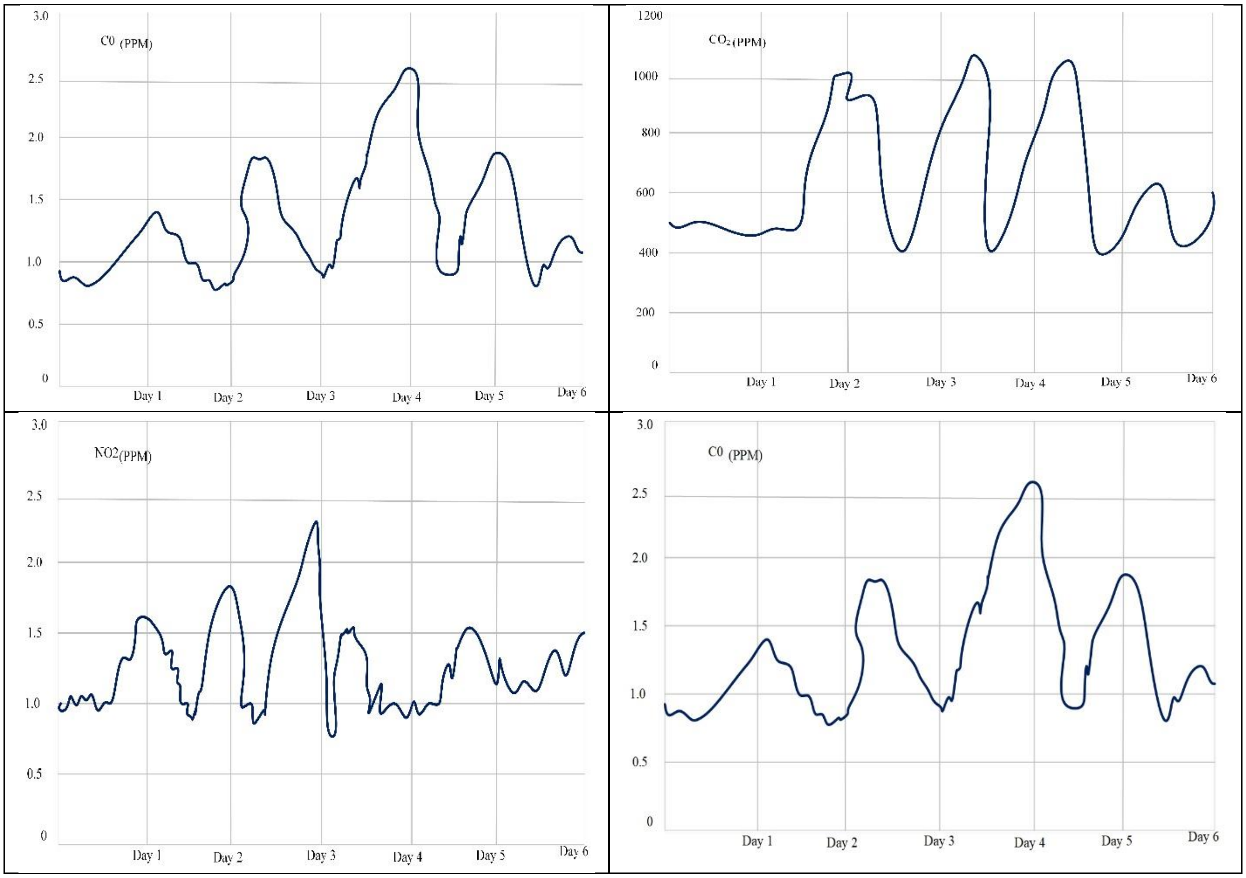

Fig. 4. The attentiveness levels of four different gases.

TABLE IV. COMPARISON OF TRACKING METHODS BASED ON VARIOUS METRICS" OR SIMPLY "TRACKING METHODS COMPARISON TABLE"

	Cost	Power Consumption	Scalability	Real-time Tracking	Accuracy
Proposed Method	Low-cost	Low	High	Yes	High
LSTM-OPTISENSE NET	Moderate-cost	Moderate	Moderate	Yes	Medium
Conv-AIRNET	High-cost	High	Low	No	High

B. Discussions

The proposed Internet of Things (IoT)-based air quality monitoring program emphasizes a proactive and technologically advanced strategy to addressing the growing worldwide challenge of air pollution. Existing methods have limited scalability, accuracy reliant on sensor precision, potential data oversimplification, and dependence on specific features [23]. By incorporating low-cost sensors capable of measuring critical pollutants outlined by the World Health Organization, the system aligns with established health standards. The selection of sensors, including PMSA003, MICS-6814, and MQ-131, ensures a comprehensive assessment of air quality, covering a spectrum of pollutants such as particulate substance, ozone, carbon monoxide, nitrogen dioxide, and ammonia. The utilization of the ESP-WROOM-32 microcontroller, equipped with Wi-Fi and Bluetooth capabilities, enhances the efficiency of data transmission to a cloud server. The system's real-time monitoring capability is a significant advancement, allowing immediate intervention in cases where pollutant concentrations exceed permissible levels. The integration of indicators triggered by such events showcases a commitment to timely response and environmental safety. Moreover, the incorporation of Amazon Web Server (AWS) into the architecture not only ensures secure and scalable data storage but also facilitates real-time tracking and analysis. This comprehensive approach not only aids in pollution prevention but also contributes valuable insights to the broader discourse on environmental management and public health [28]. The study reflects a synergy of theoretical research and practical application, showcasing a robust and cost-effective solution to combat the critical issue of air pollution.

VI. CONCLUSION AND FUTURE WORK

The suggested Internet of Things-based air quality monitoring system is a big step in the right direction toward solving the pressing worldwide issue of air pollution. The ESP-WROOM-32 microcontroller, low-cost sensors, and AWS integration are utilized by the system to provide a workable and expandable real-time monitoring solution for important pollutants. The current study's results corroborate the trend of low-cost methods offering real-time tracking, as seen with the Proposed Method. However, it challenges the assumption that high-cost methods inherently provide better accuracy and scalability, as observed with existing method indicating the need for further exploration into cost-effective solutions without compromising accuracy and real-time tracking The quick reaction system set in motion by pollution exceedances highlights the dedication to public health and environmental safety. Regarding future efforts, the system may be expanded and improved upon continuously. First, the reliability of the gathered data will be improved by improving the precision of pollutant measurements through sensor calibration and validation procedures. Furthermore, investigating more sophisticated machine learning algorithms for data analysis may offer deeper understandings of pollution trends, facilitating the development of better preventative and predictive actions. Furthermore, the system's scalability and adaptability to various environmental conditions should be prioritized, given the possibility of global implementation. The incorporation of this technology into more comprehensive environmental management methods can be facilitated by cooperative efforts with regulatory agencies and urban planners. Furthermore, adding more sensors to track newly developing contaminants and growing the network of monitoring devices can help develop a more thorough understanding of the state of the air at the local, regional, and municipal levels. Essentially, the suggested system lays the groundwork for future research and development in the field of environmental monitoring, paving the way for more intelligent, data-driven approaches to address air pollution and improve community well-being in general.

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