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Research Article

Implementing raspberry Pi for tracking black carbon with machine learning in climate monitoring

M.Chandrakala[1*] and M.V. Lakshmaiah[2]
Research Scholar, Department of Electronics and Communication, Sri Krishnadevaraya University, Anantapur, Andhra Pradesh, India – 515003[1]
Professor, Department of Physics and Electronics, Sri Krishnadevaraya University, Anantapur, Andhra Pradesh, India – 515003[2]

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Abstract
Nowadays, air pollution represents one of the most serious public health and environmental challenges globally. It adversely affects human well-being, weather patterns, and environmental conditions. This pollution arises from various sources, including hazardous emissions from industries, vehicle exhaust, and the increasing presence of harmful substances and particulates in the atmosphere, leading to air contamination. Pollutants such as carbon monoxide (CO) and carbon dioxide (CO_2) contribute to negative impacts on environmental factors like temperature, humidity, and air pressure. Additionally, black carbon particles, emitted through various combustion processes, significantly harm both the environment and human health. Consequently, there is a pressing need to measure and evaluate air quality effectively, facilitating prompt decision-making. In this research, a system was developed that offers a user-friendly interface, providing insights for individuals, communities, and organizations. This empowers them to take informed actions towards reducing air pollution levels. Our system employs a combination of the PM7003 sensor, Raspberry Pi, additional sensors, Internet of Things (IoT) connectivity, cloud computing, and machine learning. It is specifically designed to detect fine particulate matter (PM), including PM2.5, PM1, and PM10 particles, in the air. The system is also equipped with sensors to monitor environmental parameters such as humidity, air pressure, temperature, CO, CO_2, and black carbon particles. This robust system enables timely and wise decision-making to mitigate air pollution. Variations in air quality graphs clearly demonstrate the influence of pollutant concentrations on climate change. Our results, comparable to real-world scenarios, were validated against air quality standards and guidelines. Four favourable outcomes were identified from our work. By employing machine learning algorithms, our system can predict air pollution levels with high accuracy, providing reliable forecasts based on historical data and meteorological factors.

Keywords
Air pollution, Black carbon particles, Raspberry Pi, Air quality, Sensors, IoT, Machine learning and PM7003 sensor.

1.Introduction
One of the most vital elements that constitute our biosphere is air. As all modernization attempts (i.e., extensive industrialization) are impacting the quality of the air (i.e. air pollution [1]), the constituents of air like N_2, carbon monoxide (CO), carbon dioxide (CO_2), Sulfur dioxide (SO_2), etc. are altering owing to the injection of considerable number of outside pollutants into the air. Consequently, the overall air quality changes daily. These alterations in the air composition causes an impact on the ecology (i.e., impairs the wellness of human beings and impacts the health of other flora and fauna as well).

For reducing this impact, air quality tracking systems are being developed. These systems are primarily utilized to gain an understanding of how the air quality and composition of contaminants [2] alter over any period.

1.1Background
With the fast expansion of economic activity in our nation, the establishment and operation of chemical manufacturing facilities [3] are becoming more common, which tends to increase the possibility of pollution-related accidents, particularly accidents caused due to air pollution [4].

Air quality is a critical atmospheric constituent which influences both the welfare of the environment and

*Author for correspondence

human being. In several nations throughout the globe, standardized indices like the air quality index (AQI) are employed to quantify the level of pollution in the atmosphere.

The pollution in the air (i.e., influenced by geographical and meteorological factors) will be greatly intense for a shorter duration whenever it occurs, however, it causes serious damage or potentially serious damage to both the environment and human beings. It is inferred that air pollution constitutes one of the globe's most serious health and environmental issues at present. It can harm the well-being of human beings, weather, and ecology. Over time, several strategies (for instance, [5, 6]) have been developed for measuring pollutants in the air. Particulate matter (PM), nitrogen dioxide (NO_2), and SO_2 in the atmosphere have grown into a major issue because they affect the well-being of human beings in a variety of ways, including the development of chronic obstructive pulmonary ailment. As a result, it is critical to install a practically possible monitoring system to reduce the impacts/ severities caused due to air pollution.

Additional parameters, like black carbon, have been considered as AQI elements besides the majorly considered AQIs [7]. This is because black carbon is significantly associated with the harmful consequences of aerosol particles than commonly observed PM, particularly its (black carbon) relation to cardiac impacts [8]. Nevertheless, this is yet to be put into practice nationally since not every reference station in metropolitan areas performs continual black carbon evaluations. Furthermore, black carbon tracking is not mandated by environmental legislations laid out by several countries, which is the prime reason for not being able to implement the full-fledged monitoring system tracking black carbon. Assessment sites that have already established facilities to trace black carbon may not be able to carry out extensive assessments due to two reasons, namely, (i) corruption of information or (ii) breakdowns in equipment. As a result, air quality frameworks are required for redressing issues by carrying out the information gap restoration and forecasting of quality in the air.

Over the years, a typical air automated tracking systems with the aid of lab-based investigation have started to integrate highly sophisticated device techs, rendering it to be huge, an unsteady process, and a substantial expenditure. Big-scale deployment becomes unrealistic due to its substantial expenses and big size. This system is limited to use at critical surveillance sites of a few important firms, rendering the information from it to be unsuitable for forecasting general pollution levels (especially in case of air pollution as realized in [9]).

Consequently, the researchers have started to integrate the tech of internet of things (IoT) with environmental surveillance to solve the challenges of standard surveillance systems and identification approaches alongside the lowering of examination costs [10, 11]. Over the years, with the substitution of monitoring devices with the sensor infrastructure (of related tech) as a replacement to the conventional observation-based investigation, it is possible to set out affordable sensors dynamically throughout the entire region for all-round monitoring and offering information assistance for the forecast.

As a result, IoT is now being widely deployed in all major sectors [12–14], and it also serves an important part in any air quality tracking framework that is operated by using precisely measuring sensors. These kinds of tracking schemes tend to disclose the quality of air, usually in units like parts per million (PPM). These kinds of systems could visually display the result via a web page to ensure the proper tracing of the quality that is being maintained in the air in a much simpler way. The tracking task becomes even simpler by integrating the tracking systems with additional devices like smartphone or a personal computer (PC).

1.2Challenges

From the perspective of monitoring of air quality, there have been some common and uncommon challenges realized from time to time. The major challenges of those reported in the earlier literatures have been discussed according to [15]:

- Many of the investigation works like [16–18] claim that sensors bought for reduced cost could generate data that cannot be dependent upon. Whenever the data collected by the sensors are not dependable (i.e., unreliable), it is certain that the decisions taken based on that data will be also become not dependable. Finally, this adversely affects the performance of the entire air quality monitoring systems.
- The challenges exist in the selecting the proper method for measurement by sensor. If we select inappropriate method for measurement, then the values measured will be subjected to uncertainties.
- Novel techniques introduced by many of the air quality monitoring systems tend to bring newer issues pertaining to its trust levels.

- In general air quality monitoring systems built based on IoT tend to be much different than its conventional versions in the follower way: though the advanced systems are robust, dependable, and could be deployed places containing over-population, these systems still incur most cost.
- A few challenges could be realized when the stations of the systems are built spending reduced cost and are applied to air quality surveillance in a larger scale.

Now moving onto the challenge realized to black carbon tracing systems. Climate-warming qualities and negative health impacts possessed by black carbon has made it to gain a lot of interest. Long-term data in metropolitan surroundings, however, are limited, probably because black carbon surveillance is not mandated by regulations governing the environment.

To evaluate the severity of air pollution throughout the world, AQI has been established to streamline the handling of complicated combination and the interaction of numerous air contaminants. The AQI may be viewed as a tool for providing easy and visible data (i.e., about pollution prevailing in the atmosphere) to everyone. Since various parts of the country possess distinct AQIs depending upon various regional air-quality norms, the majority of the firms take the mass concentration of the PM (including PM2.5- fine particles and PM10- thoracic particles) into consideration along with constituents like Ozone (O_3), NO_2, CO, and SO_2 for knowing the rate of contaminants present in the atmospheric air. PM2.5- Fine PM is a particle composition that is one of the main sources of pollution in the environment, which is linked to dangerous health consequences of different degrees of contact.

PM2.5 is also found to be the prime cause for the death arising due to lung cancer disease. (Note: PM2.5 tends to cause both acute and chronic lung cancer diseases). Because PM2.5 is made up of a variety of different compounds, effective reduction of the same is only possible by knowing the health impacts of those different compounds. Furthermore, particles emitted by fuel burning are especially known to cause death.

Another element that tends to adversely influence our environment (thus influencing our climate) is black carbon. In the past few decades, much emphasis has been placed on the growth of procedures for rectifying mistakes in black carbon evaluations and coefficients of absorption of aerosol using filter approaches [19–21]. Black carbon (one of the elements of PM2.5) is believed to be linked with both climatic influences and health consequences for human beings. Furthermore, this kind of black carbon is linked to trucks and buses, which frequently are diesel-powered.

Consequently, several studies like [22, 23] conducted research in this context since black carbon adversely influence the climate and the well-being of human beings. These studies found that there was an association between short-term health impacts [24]. Most of these kinds of studies came to know that the association between short-term health impact and black carbon was considerably stronger than those association held by the particles like PM2.5 and PM10 (PM having diameters less than 2.5 m and 10 m, respectively) [7]. Black carbon is also one of the significant factors [25] contributing to the phenomenon of global warming (i.e., causing climate change), although its impacts are primarily short-termed. Black carbon is causing the climatic change because of its ability to absorb light [26]. The negative consequences on climate and the well-being of human beings are anticipated to be reduced as the quality of air gets improved [27].

1.3Objectives

The major objectives of our research concerned with the climate monitoring of black carbon detection using Raspberry Pi with machine learning are presented in the below bulletins:

- To use and integrate various sensors like BMP180, DHT11, DHT11, MQ2, MQ135, and PM7003 sensors.
- To make use of the advanced reduced instruction set computer (RISC) machine (ARM)-based minicomputer-based raspberry Pi as the central processing unit (CPU).
- To integrate the sensors in the transmitting end so that the results are obtained using liquid crystal display (LCD) and cloud server in the receiving end.
- To monitor the air quality by continuously monitoring the parameters like pressure, humidity/ temperature, CO, CO_2, PM 1, PM2.5, and PM 10 using the sensors like BMP180, DHT11, MQ2, MQ135, and PM7003, respectively.
- To draw out the measured parameters and plot the graph in a data-wise manner for aiding the climate monitoring and its subsequent maintenance by detecting the black carbon (It includes PM 1, PM2.5, and PM 10).

In the research outlined in this paper, an ARM-based mini-computer (Raspberry Pi), sensors, Internet of Things (IoT) connectivity, and machine learning are combined to develop a cutting-edge climate monitoring system. The primary objective of this system is to monitor and improve climatic conditions for a healthier and more sustainable future. This is achieved by detecting particulate matter (PM) and black carbon, thereby addressing air pollution. The successful management of air quality, crucial for maintaining favorable climate conditions, is enhanced through the application of machine learning, enabling earlier detection and better forecasting of climatic changes.

The remainder of the paper is structured as follows: Section 2 offers a review of recent literature related to atmospheric air, encompassing its management, monitoring, and prediction, and includes a comparative table summarizing the works discussed. Section 3 details our methodology, covering the principle of operation, components used, analog-to-digital conversion, integration of machine learning, data presentation on an LCD, system configurations, advantages, the role in health contexts, and applications. Section 4 presents all the results obtained. Section 5 discusses these results, ranging from graph-based comparisons to the identification of limitations. Finally, Section 6 concludes the paper, providing remarks on the research and outlining potential future work.

2.Literature review

In this section, recent literature, including publications from the year 2023, focusing on atmospheric air and its associated management, monitoring, and prediction methodologies is reviewed. This is followed by a comparative table showcasing the differences and similarities among all the surveyed works, accompanied by an overview of these works.

With the support of utilizing the capabilities of the Raspberry Pi single-board computer and GraphLab, a machine learning framework was deployed for tracking and analysing indoor air quality [28]. The hardware platform for data gathering and processing was the Raspberry Pi, while the tools and algorithms for data analysis and visualization were provided by GraphLab. The Raspberry Pi was frequently connected to a variety of sensors, including ones for temperature, humidity, CO_2, PM, and volatile organic compounds (VOCs). The dominant indoor environmental factors used in this work were continuously measured by these sensors. This sensor data was gathered by the Raspberry Pi and sent to the GraphLab framework for additional analysis. GraphLab made it possible to use machine learning methods on the obtained data.

The purpose of the suggested system [29] was to create a comprehensive air quality monitoring system by utilizing the capabilities of the Raspberry Pi across the IoT platform. The solution contained the installation of several air quality sensors that were linked to the Raspberry Pi. These sensors collected data on several variables, including airborne pollutants like PM, CO, O_3, and others. The Raspberry Pi acted as the centre node, gathering data from these sensors, and sending it to the internet or a local server for processing and analysis.

In [30] combining the capabilities of the raspberry pi and web socket technologies was provided. The Raspberry Pi, which acted as the main hub for data collecting and processing in this system, was connected to air quality sensors. PM, CO, O_3, and other air pollutants were measured by the sensors along with other factors. The sensor data was collected and locally processed by the Raspberry Pi. For monitoring air quality in a variety of situations such as homes, businesses, schools, or industrial settings, the air quality monitoring system utilizing raspberry pi and web socket was a useful and effective option. It provided real-time data streaming, a user-friendly interface, and smooth connectivity between the Raspberry Pi and the web server or client application, ensuring prompt access to crucial air quality data.

To track and assess interior air pollution levels in real-time, this suggested work [31] combined the capabilities of Raspberry Pi and IoT technologies. In this system, the Raspberry Pi served as the main hub for data gathering and processing and was connected to a variety of air pollution sensors. PM, CO, VOCs, and other contaminants prevalent in the interior environment are measured by these sensors. The sensor data was gathered by the Raspberry Pi and sent to a local server or cloud platform for additional processing. By offering in-depth data analysis, real-time monitoring, and actionable insights, the suggested system utilizing Raspberry Pi helped to create healthier indoor environments. It was advantageous for a variety of environments, such as homes, businesses, schools, or healthcare institutions, where occupant’s health and productivity depend on maintaining acceptable indoor air quality.

A novel IoT implementation approach was offered by [32] as a new way to construct a framework for monitoring the quality of air. A low-power wide area network was used in this system to send the air quality data that portable sensors promptly capture. The IoT cloud processed and performed analysis on all air quality data. The entire system for monitoring the quality of the air, including the hardware and software, was created, and effectively implemented in urban settings. Results from the experiments demonstrated the dependability of the suggested system in air quality sensing and partially revealed the patterns of air quality changes.

An IoT-dependent framework for monitoring the air quality of smart cities was suggested and created by [33]. Smart devices were used to access real-time air quality data, which was then evaluated to determine how it affects city people. The smart devices measured airborne hazardous PM concentrations such as PM2.5 and PM10, CO, temperature, smoke, humidity, liquified petroleum gas (LPG), and other dangerous gases. Through an Android application, the obtained data was accessible to everyone worldwide.

The concerns of communication topology architecture, evaluation of quality of service (QoS) levels against accuracy, throughput estimation, and optimization of power usage were all addressed in [34]. To detect air quality parameters like PM10, PM2.5, CO, temperature, and humidity, the suggested IoT-dependent design for monitoring the quality of air was implemented at indoor and outdoor sites. Both indoor and outdoor testing sites were used to evaluate the proposed system at various quality-of-service levels. The studies were successful in reliably delivering the messages according to the methodology used, and this accuracy was also noted.
To estimate the emissions of ship black carbon, [35] developed four different machine learning techniques such as support vector machine (SVM), XG boosting (XGB), artificial neural networks (ANNs), and lasso regression. The prediction models were created using information collected from marine engines that were identical to them operating under different steady-state settings. According to the findings, lasso regression was less accurate at predicting outcomes than SVM, XGB, and ANN, and the respective model-adjusted R2 values were 0.9810, 0.9885, 0.9885, and 0.6088. XGB and SVM outperformed ANN in terms of model stability and training costs, even though ANN exhibited the best prediction performance. The results demonstrated the viability of machine learning in predicting the emissions of ship black carbon and may serve as a guide for lowering the emissions of ship black carbon and developing emission limits.

With the use of machine learning prediction algorithms, [36] proposed a methods-based strategy to forecast black carbon liberation during the functioning of furnaces in industries. To train machine learning models, the work employed a real data set containing historical operations. Through assessment with actual data, the most appropriate strategy that best matched the features of the data set and restrictions for the implementation was discovered in real production scenarios. The evaluation's findings show that using a predictive model, it was feasible to forecast the unwanted black carbon liberation well in advance.

Five models were used by [37] for the computation of the atmospheric black carbon mass-absorption sampling, including three theories of light scattering, an empirical design based on measurements of particle mass concentrations, and a machine learning design created in their earlier work. The designs were assessed using the factors of accuracy and simplicity. The Mie theory for externally mixed particles tends to under-predict atmospheric black carbon mass-absorption sampling, whereas the empirical model for internally mixed particles that was taken into consideration tends to over-predict atmospheric black carbon mass-absorption sampling. When black carbon was densely coated (for example, after aging effect and combining with other substances in the atmosphere), the present SVM design performed badly according to an analysis of the effect of coating material on black carbon cores.

Came up with a novel technique for constructing air quality surveillance framework with the deployment of state-of-the-art IoT tech [38]. In this work, a low powered wide area networking was deployed to transmit the data as it soon as it gets gathered by the sensory devices. These sensors devices were intended to gather every info pertaining to the quality of air by proper integration of IoT tech. They integrated both software tools and equipment for enabling their air quality surveillance framework to gather data across towns spread throughout the country. The outcomes obtained by their experimental investigations revealed that their approach was able to precisely monitor the quality of atmospheric air, Finally, this work draw out a few trends that were causing the alteration in the quality of air.

This work [39] had the primary goal of analysing the interior surrounding surveillance systems for the purpose of raising the standard of living of human beings. This work developed a novel technique that was relying on the newer metrics considering both the pollutant composition along with its exposure period. Additionally, the dependability of this interior surrounding surveillance system was imposed by utilizing correct managerial methodologies, permitting anyone to check out uncertainties of measurement while taking managerial decisions. This kind of approach was able to provide considerable control upon the possibly dangerous situations and aid in determining a favourable trade-off lying between health and the energy effectiveness goals.

Considering the importance of data quality in the performance of any environment tracing frameworks, [15] carried out an investigation of the quality of data concerning pollutants tracked by the air quality aware system. This system followed a structured mapping approach and made use of existing instructions for evaluating the quality of data. In this investigation, they recognized the major quality traits of data concerning pollutants along with its respective improvisation techniques. With the successful investigation of over seventy manuscripts, they identified that precision and accuracy were the most generally chosen data quality traits by numerous earlier works reported in th same genre. Though precision and accuracy were the most chosen data quality traits, different works tend to utilize different calibration approaches for calibrating those traits.
Despite the slight associations between the air quality variables and mobility of human beings in the working site, [40] developed a novel air quality surveillance system by establishing interdependence existing between these 2 kinds of time sequence data (i.e.) interdependence of air quality upon the movement of human beings in the interior conditions. They considered working site as one of the major interior conditions in their work. They variables that they took were PM 2.5, PM 10, and CO_2. Particularly, a sensor link was drafted across the interior conditions for continual observation of air quality variables. Parallely, an additional sensing element identified the movement of concerned individuals across the study region. At last, the authors exhibited an interdependence between the interior air quality variables and interior movement trends.

An air quality evaluation and forecasting framework was developed by [41] with the special focus being given only to the city- Surat between 2020 and 2023 by deploying framework called as auto-regressive integrated moving average (ARIMA). They obtained and compared the levels of SO_2 and NO_2 for knowing about air contamination taking place in the city of Surat. Their outcomes obtained experimentally revealed that their devised framework called as ARIMA surpassed the performance of other conventional frameworks. As per their discovering, the quantity of NO_2 was raising despite the decrease of SO_2 quantity, thereby affecting the air quality.
Now, we present a tabulation showing the comparison of all the surveyed works in the below *Table 1*.

Table 1 Comparison of surveyed works

S. No.	Citations	Methods/contributions	Results	Advantages	Limitations
1.	[28]	Faster and simpler Raspberry Pi-based interior air monitoring framework.	They plotted and investigated the fluctuations of dust, CO_2, and CO particles.	Their framework was able to be cost-effective and smaller in its dimensions by being able to give rise to raised level of modularity.	This framework was only limited to the indoor air quality measurements and does not hold good for outdoor air quality measurements.
2.	[29]	Raspberry Pi-based air quality monitoring framework was built specifically to investigate the air quality at Delhi.	They obtained and compared the measured and anticipated readings of parameters (both during evening and day times) like Pressure, Temperature, CO_2, CO, Relative Humidity, and PM 2.5	With the deployment easily available microcontroller like Raspberry Pi, they were able to build cost-effective and highly accurate air quality framework.	They only considered PM 2.5 and left other harmful particle like PM10 and while building their air quality framework.

S. No.	Citations	Methods/contributions	Results	Advantages	Limitations
			for correlating the air quality at Delhi.		
3.	[30]	Air quality tracing system was incorporated using web socket and Raspberry Pi for knowing the whereabouts of both interior and exterior quality of air.	The rate of contamination was examined by realizing the levels of pollutants like smoke, methane, CO_2, and CO.	Their web socket and microcontroller (Raspberry Pi)-based system hold good for both interior and exterior air quality measurements.	Their system was constructed to trace stationary objects and thus cannot be applicable for movable objects. Furthermore, there were concerns realized concerning many aspects like storage administration, data, and security being a simple air quality tracing system.
4.	[31]	The rate of air pollution within the interiors were monitored using Python and Raspberry Pi for cautioning through alarm.	By using their interior air monitoring framework, they obtained the pollution-critical values and investigated all those values using the ThingSpeak-based graphs.	In addition to the air pollution monitoring, this framework also facilitated a much flexible alarm mechanism that could be triggered based on any pre-defined threshold pollutant levels.	This framework was only limited to the indoor air pollutant measurements and does not hold good for outdoor air pollutant measurements.
5.	[32]	IoT server-based air quality monitoring framework was built using an advanced Machine-to- Machine (M2M) communicating approach known as low power wide area tech.	They deduced a comprehensive comparative study to trace the air quality using significant performance measures like individual air quality index (IAQI), carrier-to-interference (C/I), and AQI by considering critical pollutants, namely, CO, PM 2.5, PM 10, O_3, NO_2, SO_2, and O_3.	As this work made use of low power wide area tech, it was able to trace the quality of air across wider area.	Despite air quality monitoring framework being more robust covering wider area using low power wide area tech, there was no provision of alarm to alert the people.
6.	[33]	A wide area covering IoT-based air pollutant tracing system was put into practice for the welfare of people living in a city so that they can be aware of the pollution.	They obtained and compared the measurements of several pollution-critical parameters like PM 2.5, PM 10, CO, LPG, humidity, and smoke using ThingSpeak.	As this system used ThingSpeak and android platform for plotting and interpreting the measured values, it ensured the air pollutant to be traced by all people in a city due to its user-friendly interface.	This framework was not applicable to indoor air pollution tracing. Furthermore, they were other major air pollutants that were not considered in this tracing system.
7.	[34]	An improved IoT-based air quality tracing system was designed by adopting optimal power usage and evaluation of QoS.	They deduced many air quality observations concerning the contaminants like CO, PM 2.5, and PM 10 by considering both situations like interiors and exteriors.	This IoT-based system hold good for both interior and exterior air quality measurements.	Despite being an improved air quality tracing system with 2 major adaptations, it still did not consider significant pollutants like CO_2 and black carbon.
8.	[35]	A ship-specific black	Through their	Having considered	This air tracing

S. No.	Citations	Methods/contributions	Results	Advantages	Limitations
		carbon trace prediction framework was constructed with 4 types of machine learning approaches, namely, SVM, XGB, ANNs, and lasso regression.	investigation on the black carbon levels, the prospects of machine learning in the marine emissions were revealed.	black carbon, their marine emission prediction framework was more robust.	framework was only limited to marine applications.
9.	[36]	An industry-specific black carbon trace prediction methodology was put frothed by using machine learning techniques like Logistic regression, SVM, ensemble approach, and k-nearest neighbours (k-NN).	Through their obtained results, this work proved that the early prediction of unwanted quantity of black carbon emissions through the industrial furnaces was possible.	Commercial industries being one of the primary sources of air pollution, deploying black carbon trace prediction methodologies would serve as a best solution to cut down air pollution in longer run.	This prediction methodology was limited only to furnaces used by numerous factories.
10.	[37]	Five different kinds of frameworks were used as the major contributor for the computation of atmospheric black carbon (through sampling of mass-absorption of it).	They compared and correlated all the five different frameworks in means of performance metrics like time, accuracy, etc. against computation of the atmospheric black carbon mass-absorption sampling	Their entire context of research was concerned with the accuracy and simplify unlike other conventional stereotypical methods.	This methodology of computing the atmospheric black carbon mass-absorption sampling could not be efficient when it encountered thick-coated black carbons.
11.	[38]	An air quality monitoring scheme was introduced using an advanced approach known as low power wide area tech by relying on IoT prospects for serving numerous cities of our nation.	This work revealed several interesting patterns through their obtained results for prominent contaminants like SO_2, CO, PM, etc.	This work was able to trace the quality of air across wider area having using the tech of low power wide area. Furthermore, this work facilitated the monitoring through two mediums like android platform-based device and web application.	Though this work had considered the prominent contaminants, still it has failed to consider critical pollutants like black carbon and CO_2.
12.	[39]	An enhanced air quality surveillance methodology was developed by considering a novel metrics like pollutant composition along with the time of exposure.	They deduced several patterns by analyzing several pollutants like PM, CO, CO_2, and total volatile organic compounds (TVOC).	This work considered the uncertainties in the measurement of parameters so that right decisions were made by their air quality surveillance methodology.	Though this methodology had considered the uncertainties while air quality surveillance, it has not been built to be fail-safe.
13.	[15]	Air quality aware system was studied by relying mainly on the major quality traits of data concerning pollutants along with its respective improvisation techniques.	This work revealed that precision and accuracy were the mostly chosen by the researchers of the related filed by their in-depth investigation of many related works.	This work was able to accomplish an insightful map between the data quality concerning pollutants along with its respective improvisation techniques to provide the future directions for the researchers of the same field.	This investigation was limited only to data quality, and did not consider any other factor related to an air quality aware system.
14.	[40]	A novel air quality surveillance system was	They revealed the considerable	This kind of surveillance system	This surveillance system was not

S. No.	Citations	Methods/contributions	Results	Advantages	Limitations
		developed by establishing interdependence of air quality upon the movement of human beings in the interior conditions (especially in the working site-considering interior conditions).	interdependence of air quality upon the movement of human beings in several interior conditions by considering pollutants like PM 2.5, PM 10, and CO_2.	could be beneficial in crowded sites like shopping malls, where the movement of human beings is exponential.	applicable to exterior air quality tracing and it was limited only to interior conditions. Furthermore, they were other major air pollutants that were not considered in this surveillance system.
15.	[41]	An air quality evaluation and forecasting framework was developed by focusing only in the city- Surat with the deployment of ARIMA.	They obtained and compared the levels of SO_2 and NO_2 for knowing about air contamination taking place in the city- Surat.	The rates of data variations during the course of the entire work were very less, which directly influences the accuracy of forecasting.	This air quality evaluation and forecasting framework was only limited to the city- Surat. Furthermore,

After reviewing major literatures including those published in this year 2023 that were concerned about the atmospheric air and its related management, monitoring, and prediction methodologies, it is much evident that the black carbon has been one of the significant contributors of the air pollution. Despite being significant when it comes to air quality monitoring (also for climate monitoring), it is still not analyzed by much work and has not been investigated thoroughly. As a result, identifying the traces of black carbon has become a necessity whenever we need to investigate the traces of PM.

3.Methods

In this work, we suggest a technique to address this problem using a Raspberry Pi board and a few sensors. MQ2, MQ135, DHT11, and PM7003 can measure air temperature, humidity, gas concentration, and the existence of PM (also including black carbon). The BMP180 sensor is responsible for measuring the air pressure. These sensor measurements are continuously transferred to the cloud platform. Using this technology, we make it feasible to continuously monitor the meteorological conditions. Data will be shown on the LCD. We require an analog-to-digital converter (ADC) to send data from the gas sensors to the Raspberry Pi because the sensors generate analog values. If the sensors are correctly placed at right spot and if the measurements made by the sensors are ensured to be free from errors (excluding the known uncertainties), then the public health and environment impacting adverse consequences like poor air quality, temperature consequences, nutritional consequences, infectious ailments, etc. (according to [42]) could be prevented and maintained. As seen in the above block diagram shown in *Figure 1*, we are using the Raspberry Pi as the processing unit. All the remaining constituents like the MQ-2 sensor, DHT11 sensor, LCD, BMP180 sensor, MQ-135 gas sensor module, and PM7003 are integrated into the processing unit - Raspberry Pi. In addition to LCD, we also facilitate the displaying via the web application deployed in an appropriate manner using the Python Language. The constituents like the MQ-2 sensor, DHT11 sensor, BMP180 sensor, MQ-135 gas sensor module, and PM7003 are connected (physically integrated) to the transmitting end of the Raspberry Pi, whereas, the LCD and Python-based web application are connected to the receiving end of the Raspberry Pi.

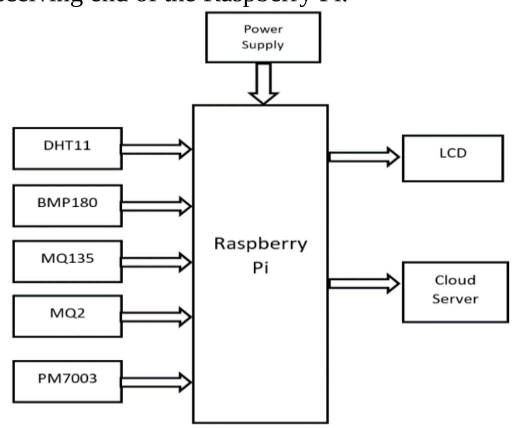

Figure 1 Block diagram of our climate monitoring system using machine learning and raspberry Pi

3.1Principle of operation

Machine learning in embedded systems is the integration of machine learning algorithms and techniques into small, resource-constrained devices like microcontrollers, IoT devices, or embedded systems. This makes it possible for these devices to carry out intelligent functions, make predictions, and modify their behaviour in response to inputs without the need for constant online access. These devices can handle and analyse data in real time by integrating machine learning capabilities locally, making them more responsive and effective. Robotics, autonomous vehicles, smart home gadgets, industrial automation, and healthcare are just a few examples of the many fields where machine learning in embedded systems finds applications. To achieve effective and precise performance within the boundaries/ limitations of the device, machine learning models must be deployed on embedded systems, which requires careful consideration of CPU resources, power consumption, memory constraints, and model optimisation strategies.

Web applications in embedded systems offer remote device and system monitoring and control using a web-based interface. The integration of machine learning algorithms empowers the system to analyse the collected data, detect patterns, and identify potential air pollution sources or trends. With its user-friendly interface and actionable insights, this advanced climate monitoring system using Raspberry Pi serves as a valuable tool for individuals, communities, and organizations in safeguarding and improving the weather around us for a healthier and sustainable future.

Now, let us discuss the transfer process of measurements done by sensors. The process of continuously transferring sensor measurements to a cloud platform involves a series of steps, including sensor data acquisition, data formatting, communication protocols, and storage or processing in the cloud.

- Gas sensors, environmental sensors (e.g., temperature, humidity), and other relevant sensors measure environmental parameters.
- Analog signals from sensors are converted to digital signals by an ADC, making them suitable for digital processing.
- Hypertext transfer protocol (HTTP) is widely used for web communication, and hypertext transfer protocol secure (HTTPS) ensures secure data transfer over the internet.

Then, we will move to the security aspect of the sensor data that is being transferred. When transmitting sensitive environmental data to the cloud, it is important to use robust security measures for protecting the confidentiality, integrity, and availability of the data.

- Use strong encryption protocols (such as transport layer security (TLS) /secure sockets layer (SSL)) to secure the communication channel between the sensors/devices and the cloud server. This ensures the encryption of the data transmitted over the network so that it cannot be easily intercepted by unauthorized parties.
- Implement access controls to restrict access to sensitive environmental data. Define and enforce roles and permissions for users and devices, allowing only authorized individuals or systems to access specific data sets or perform certain actions.
- If communication with the cloud is facilitated through application programming interfaces (APIs), ensure that these interfaces are secure. Implement proper authentication and authorization mechanisms for API access to prevent unauthorized access to data.

3.2Components used

The components utilized for the proposed IoT-dependent system for climate monitoring using machine learning and Raspberry Pi have been discussed in detail along with the typical diagrammatic representations of all the components used.

A.Raspberry Pi

Popular single-board computers like the Raspberry Pi provide a variety of project and application options. It was created by the Raspberry Pi Foundation and is renowned for its accessibility, adaptability, and affordability. The Raspberry Pi board has a processor, memory, input/output pins, and several ports that let it communicate with other devices and interact with the physical environment. Both novice and seasoned developers can use it because it is compatible with Linux-based operating systems like Raspbian and supports Python. The Raspberry Pi has a wide range of uses thanks to its small size and low power consumption, including media centres, education, robotics, home automation, the IoT, and prototyping. It has developed into a well-liked platform for tinkering, learning, and developing original solutions, enabling people and groups to delve into the worlds of computing and electronics.

B.MQ2 Sensor

The MQ-2 sensor is a gas sensor module widely used for detecting various combustible gases and smoke in the air. It is commonly employed in applications such as gas leakage detection, fire detection systems, and indoor air quality monitoring. The MQ-2 sensor operates based on the principle of gas conductivity, where the presence of certain gases alters the electrical resistance of the sensor.

It can detect gases like methane, propane, butane, alcohol, smoke, and more. The module typically consists of a sensing element, a heater to increase sensitivity and a built-in analogue output that can be interfaced with microcontrollers or another circuitry.

However, it is important to note that while the MQ-2 sensor can detect gas presence, it does not provide precise gas concentration measurements. For accurate gas concentration measurements or specific gas detection, more specialized sensors may be required.

C.DHT11 sensor

The DHT11 sensor is diversely deployed as well as the economical sensor that is capable of measuring both humidity and temperature in numerous uses. The DHT11 sensor is designed to provide accurate and reliable measurements while being easy to integrate into electronic projects. The sensor utilizes a resistive humidity sensing component and a thermistor for temperature measurement. When connected to a microcontroller or Arduino, the DHT11 provides a digital output signal, making it simple to interface with another circuitry.

It has a temperature quantification span of zero to 50 °C giving rise to an accuracy of ±2 °C, and a humidity measurement range of twenty percent to ninety percent giving rise to an accuracy of ±5 five percent. It is commonly used in home automation systems, weather stations, environmental monitoring, and other projects that require monitoring and controlling temperature and humidity levels.

However, it is important to note that while the DHT11 is a cost-effective option, it may not offer the same level of accuracy and precision as more advanced sensors.

D.LCD

A LCD is a commonly used display technology in embedded systems that provides visual feedback and information. When considering the front view of an LCD, it typically consists of a rectangular screen that displays text, graphics, or other visual content. The front view often includes a grid of pixels arranged in rows and columns, with each pixel capable of displaying different colours or shades. The front view may also feature buttons or touch-sensitive areas for user input, allowing interaction with the embedded system. In contrast, the back view of an LCD typically involves the electronic components that drive the display. This includes a backlight which illuminates the screen for improved visibility. The backlight is usually provided through a series of light-emitting diodes (LEDs) positioned behind the display panel. The back view also encompasses the control circuitry responsible for receiving data and commands from the microcontroller or system, decoding and processing the signals, and driving the appropriate pixels to display the desired content on the front view.

E.BMP180

The BMP180 is a precision barometric pressure and temperature sensor that provides accurate measurements of ambient temperature and atmospheric pressure. BMP180 sensory device is generally used in uses like climate forecasting, indoor navigation, and height measurement systems. It incorporates a micro-electro-mechanical systems (MEMS) pressure sensor and an integrated temperature sensor.

It communicates with microcontrollers or other digital circuits through an I2C interface. This sensory device could measure pressure, giving rise to a resolution of up to 0.01 hectoPascals (hPa) and temperature giving rise to a resolution of 0.1 °C. It has a wide operating range for both pressure and temperature measurements, making it suitable for a range of indoor and outdoor applications. The BMP180 is a reliable and versatile sensor that offers higher accuracy and precision compared to simpler pressure sensors like the BMP085.

F.MQ135 gas sensor module

The MQ-135 is a gas sensor module widely used for detecting and measuring various air pollutants such as ammonia, smoke, benzene, CO_2, and more harmful gases. The MQ-135 sensor is commonly employed in air quality monitoring systems, gas leakage detectors, and indoor air quality assessments. The sensor operates on the principle of the resistance change of its tin dioxide-sensitive layer when exposed to different gases. The MQ-135 can measure the concentration of the target gas by monitoring the resistance fluctuation. The MQ-135 is a low-cost sensor, thus its accuracy could not be as high as that of more sophisticated gas sensors. Consequently, only qualitative measures are frequently made using it, rather than the quantitative ones. To ensure accurate and dependable findings, it is advised to do calibration and routine sensor inspections.

G.PM7003 sensor

The PMS7003 is a digital and versatile particle concentration sensor designed to measure the number of suspended particles in the air, providing real-time and accurate concentration data. It employs laser scattering technology, which involves illuminating particles in the air with a laser and collecting the scattered light at a specific angle to generate a curve of scattered light intensity over time. This principle ensures precise measurement of particle concentration. The sensor exhibits high performance with a minimal resolution particle size of 0.3 µm, enabling the detection of even small particles. It also boasts a zero-error alarm rate, ensuring reliable and accurate data output. The PMS7003 offers real-time response and continuous data acquisition capabilities, making it suitable for applications requiring immediate and ongoing monitoring. The numbers (PM1, PM2.5, and PM10) associated with PM (also denoting the black carbon), such as represent different size ranges of these particles. The PM size categories like PM1, PM2.5, and PM10 are significant because the size of the particles determines their behaviour in the atmosphere and their potential health impacts when inhaled. PM2.5 particles, being smaller, can penetrate deep into the respiratory system and have been linked to various health problems, including respiratory and cardiovascular issues. PM10 particles are larger and primarily impact the upper respiratory system. Monitoring and controlling the levels of these PM sizes are crucial for assessing air quality and protecting public health.

3.3Analog to digital conversion

The ADC plays a crucial role in converting analog signals from gas sensors into digital signals so that they can be processed by the Raspberry Pi. Gas sensors often output analog voltage signals proportional to the concentration of the detected gas. To interface these sensors with digital systems like the Raspberry Pi, an ADC is used to convert the continuous analog signal into a discrete digital format so that they can be read and processed by the digital input pins of the Raspberry Pi. With regards to any sensors being used, the analog to digital conversion of its measured values is necessary. For instance, we will discuss the steps involved in the conversion of values measured by the gas sensors in the following pointers:

- Gas sensors, such as MQ series sensors (e.g., MQ-2, MQ-135), typically produce analog voltage signals as their output. The voltage level varies based on the concentration of the detected gas.
- The digital signal, now in a format that the Raspberry Pi can understand, is sent to the Raspberry Pi's general-purpose input/output (GPIO) pins. From there, the Raspberry Pi's software can process the digital data, apply calibration factors if necessary, and interpret the concentration of the detected gas.
- The choice of ADC depends on the specific requirements of the gas sensors and the Raspberry Pi interface. Some gas sensors may have built-in ADCs, simplifying the interface. Alternatively, an external ADC may be used. The MCP3008 is a popular choice for interfacing analog sensors with the Raspberry Pi. It's a 10-bit ADC with eight channels.

3.4Integration of machine learning

Choose a machine learning algorithm suitable for the required task. Common algorithms include:

- Linear Regression
- Decision Trees
- Random Forests
- SVM
- Neural Networks (for more complex tasks)

Gather a dataset that represents the input features and corresponding target values for the machine learning task. This dataset should be diverse and representative of the real-world scenarios the model will encounter. Integrate the machine learning model into the Raspberry Pi application code, ensuring compatibility with the programming language and libraries available on the device.

3.5Presentation of data with LCD

In this section, we will describe the way in which LCD is being used for presenting all the observed data in the following pointers:

- Connecting an LCD to a Raspberry Pi involves several steps, including hardware connections and software configurations. The specific details can vary depending on the type of LCD.
- Once the display is connected and configured, you can use programming languages like Python to control the LCD and present real-time data
- The refresh rate depends on the type of display and the specific application. High-definition multimedia interface (HDMI) displays typically operate at standard refresh rates (e.g., 60 Hertz (Hz)), while smaller thin film transistor (TFT) displays may have their refresh rates.

3.6System-specific configurations/ considerations used

In this section, we are discussing the configurations that have been used for the major sensors in our IoT-based climate monitoring system.

A.DHT11

- Humidity measuring range: 20%~90% RH (0~50 degree (temperature compensation).
- Temperature measuring range: 0~+50degree.
- Humidity measurement accuracy: ±5.0%RH.
- Temperature measurement accuracy: ±2.0degree.
- Low power consumption.
- Relative humidity and temperature measurement

- All calibration, digital output
- Excellent long-term stability

B.MQ2

- Operating Voltage: +5Volt (V)
- Preheat Duration:20 second (S)
- Analog Output Voltage:0 to 5 V
- Dimension:36x20x21 mm

C.MQ135

- Power:2.5V ~ 5.0V
- Detecting Range: 10ppm-300ppm NH3, 10ppm-1000ppm Benzene,10ppm-300ppm Alcohol
- Relative humidity:<95%RH
- Dimension: 40.0 milli metre (mm) × 21.0mm

D.BMP180

- Pressure Range: 300 hPa to 1100 hPa (0.3 bar to 1.1 bar)
- Pressure Resolution: 0.01 hPa (or 1 Pa)
- Temperature Range: -40°C to +85°C
- Temperature Resolution: 0.1°C
- Pressure Accuracy: ±1 hPa (or ±100 Pascals (Pa))
- Temperature Accuracy: ±1.0°C
- Communication Protocol: inter-integrated circuit (I2C)
- I2C Address: 0x77 (or 0xEE, depending on the state of the end of conversion (EOC) bit)
- VDD Supply Voltage: 1.8 V to 3.6 V (typical 3.3 V)
- E.PMS7003
- PM1.0, PM2.5, and PM10 concentration readings (micrograms per cubic meter - µg/m³)
- The PMS7003 provides real-time measurements and updates at a specific sampling rate, often in the range of 1 Hz.
- Universal Asynchronous Receiver-Transmitter (UART) serial communication is commonly used for interfacing with microcontrollers or other devices.
- The operating voltage is typically in the range of 4.7 V to 5.3 V.

F.Raspberry Pi 4 Model B

- Voltage: 5V
- Current: Up to 3A (15Watt (W))
- Voltage: Varies (e.g., 3.3V or 5V)
- Current: Varies (e.g., milli-Ampere (mA) range)

G.Power Supply

- Main Power Supply: 5V, 4A (20W)
- Sensor Power Supply: 3.3V, 1A (3.3W)
- Backup Power:
- UPS: 12V, 7Ah (84 Watt Hour (Wh))
- Voltage Regulation:
- Voltage Regulator for Sensors: 5V to 3.3V regulator.

(Note: For LCD, Supply Voltage: 5V and Board Dimensions (LxWxH) mm.: 80 x 36 x 10 is being considered)

3.7Advantages

The probable advantages that could be derived out of our state-of-the-art climate monitoring system using machine learning and Raspberry Pi are pointed out below:

- The deployment process is simpler.
- The update process across the mobile phones takes place straightforwardly.
- It is also suitable for monitoring of even the remote sites.
- The most precise monitoring of Pollution becomes possible.

3.8Role of our system with examples towards healthier environment

In this section, we will discuss the role of climate surveillance system in promoting proactive measures for a healthier environment supported with a few scenarios (according to [42]) leaving a positive impact. The adverse environmental impacts like poor air quality, temperature consequences, nutritional consequences, and infectious ailments are known to cause deterioration in the health of all human beings. Therefore, these health deteriorations could be avoided/ reduced with the prospects served by the advanced climate or air monitoring systems at hand. For instance, let us consider three scenarios, which are as follows:

- All the vector borne ailments like malaria and dengue fever that are primarily caused due to the sudden change of climatic conditions can be prevented or avoided partially if those unforeseen changes can be controlled and maintained.
- Population moving from one place to another place due to the sea level increase can be prevented or avoided partially if the unforeseen rise of temperature can be controlled and maintained.
- All kinds of breathing ailments experienced by human beings that are caused due to the air pollution can be prevented or avoided partially if the unforeseen rise of the air pollutants can be controlled and maintained.

3.9Applications

The probable applications that could be served using our state-of-the-art IoT-dependent monitoring system for climate using machine learning and Raspberry Pi have been indicated below:

- Tracing of air quality prevailing indoors becomes possible.
- Tracing of numerous Industrial variables becomes possible.
- Permitting any relevant info accessible to each user.
- Choosing of sites for reference tracing depots.
- Better management and improvement of weather becomes possible.

4.Results

The results are purely based on the gathered data from the sensors and integrated tools. So, for avoiding the lapses in the overall performance, we will be carrying out the below two processes as follows:

Data validation: Implement robust data validation mechanisms in your software to identify outliers or implausible sensor readings. This can include range checks, threshold comparisons, or statistical methods to detect anomalies.

Error logging: Set up a comprehensive error logging system to record instances of unusual or erroneous sensor readings. Logging can aid in diagnosing issues and improving the overall system. The photographs of the sensors and LCD screen in the proposed system are shown in this results section. The real-time air quality displayed on an LCD screen is shown in the below *Figure 2.* The screenshot of the Raspberry Pi-connected system monitor screen is expressed in the below *Figure 3.*

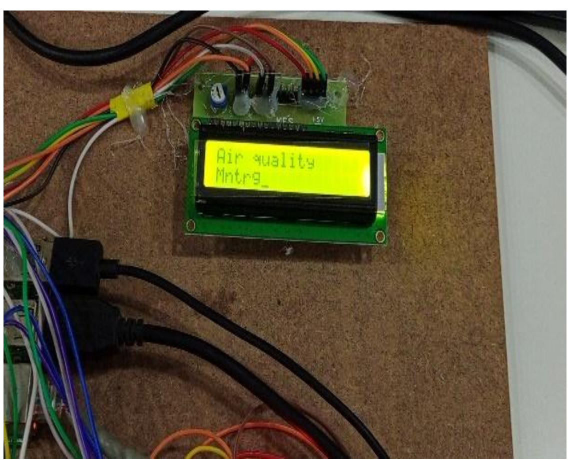

Figure 2 Photograph of the LCD screen in the proposed system

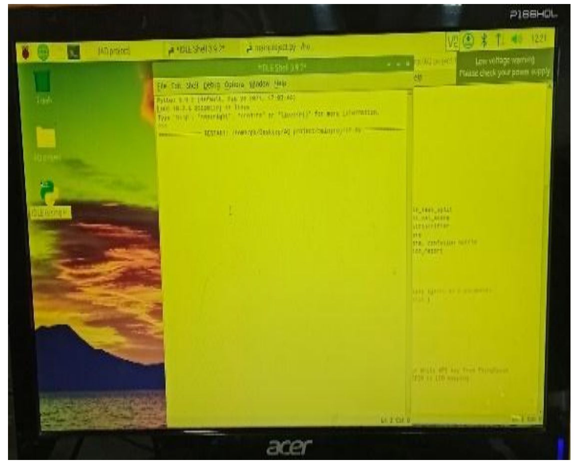

Figure 3 Photograph of the monitor screen connected to the Raspberry Pi

DHT11 sensor is implemented here to measure the real time temperature values. It is capable of measuring temperature in the range of 0°C to 50°C (32°F to 122°F) with an accuracy of ±2°C, and relative humidity in the range of 20% to 80% with an accuracy of ±5%. The LCD showing real-time temperature and humidity values as sensed by the DHT11 sensor is denoted in the below *Figure 4.*

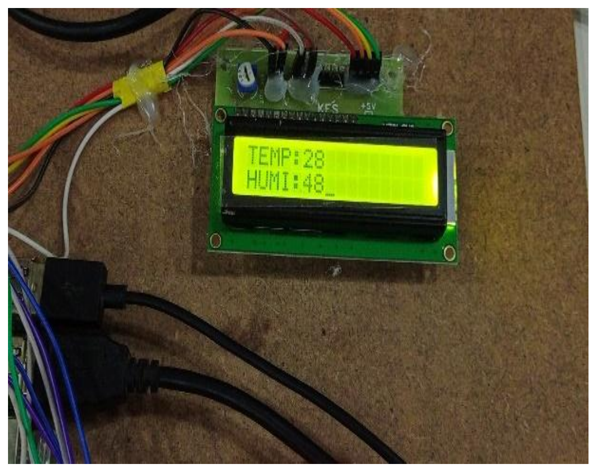

Figure 4 Photograph of the LCD showing the real-time temperature and humidity readings

MQ2 and MQ135 sensors are implemented here to measure the "CO and CO_2" values. MQ-2 and MQ-135 sensors are designed to detect various gases in the air. CO and CO_2 values sensed by these sensors are displayed on an LCD screen as represented in the below *Figure 5.*

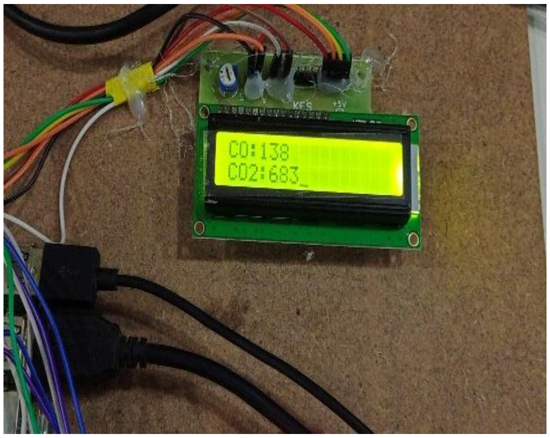

Figure 5 Photograph of the LCD screen showing the CO and CO_2 values

BMP180 sensor is implemented here to measure the real time atmospheric pressure values. It provides digital output for accurate pressure readings. As a status indicator, “PRE” is displayed on the LCD as in below *Figure 6*. This feature utilizes machine learning algorithms to forecast potential air pollution levels, providing proactive measures for a healthier environment. The displayed “PRE” serves as a visual cue for users to take preventive actions and ensure better air quality.

Figure 6 Photograph of the LCD showing the atmosphericpressure value

PMS7003 provides real-time measurements and updates at a specific sampling rate. Various fine PM such as PM2.5, PM1, and PM10 particles in the air are measured using the PMS7003 sensor and displayed and the LCD screen as signified in below *Figure 7*.

Figure 7 Photograph of the LCD showing the PM2.5, PM1, and PM10 particles values

The screenshot of the various values sensed through the above-mentioned sensors are displayed through the Raspberry Pi connected to the monitor screen as indicated in below *Figure 8.*

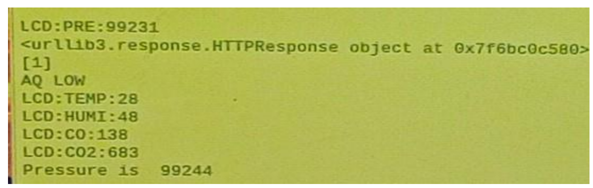

Figure 8 Photograph of the values being displayed on the monitor screen connected to the Raspberry Pi

5.Discussion

In this work, we are measuring and monitoring the parameters like pressure, humidity/ temperature, CO, CO_2, PM 1, PM2.5, and PM 10 monitor with the deployment of the sensors like BMP180, DHT11, MQ2, MQ135, and PM7003, respectively.

5.1Overview of setup

The project integrates various sensors, IoT connectivity, and machine learning for comprehensive air quality monitoring. The photograph of the complete setup is depicted in below *Figure 9*. With Raspberry Pi as the core component, it enables real-time data collection and analysis. The system empowers users with actionable insights to address air pollution issues effectively. The temperature values taken for five weeks at an interval of one week each are considered. These values are plotted in the form of a graph as shown in below *Figure 10*. The temperature decreases initially, then starts to increase gradually. Then the temperature remains constant after which temperature drops.

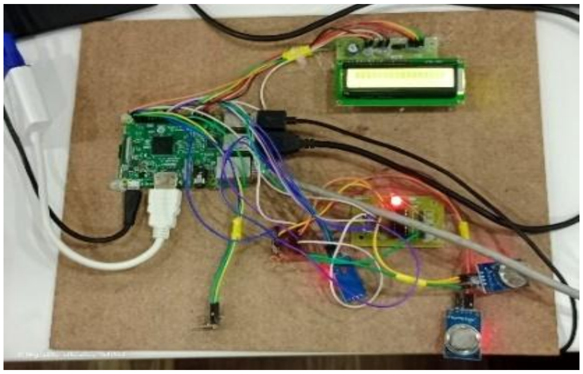

Figure 9 Photograph of the complete setup of the state-of-the-art IoT-dependent air quality monitoring system

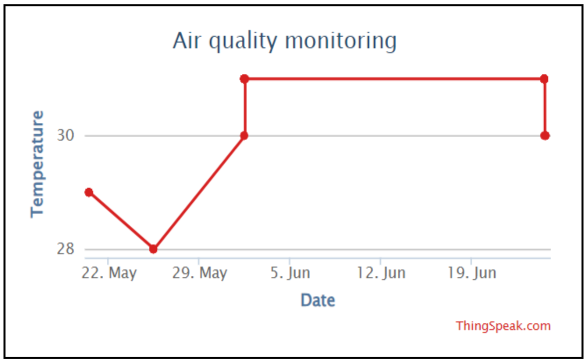

Figure 10 Graphical representation of the temperature readings

5.2Graph-based comparisons

The humidity values taken for five weeks at an interval of one week each are considered. These values are plotted in the form of a graph as shown in below *Figure 11*. The humidity decreases initially, then starts to increase gradually. Then the humidity continues to decrease in the remaining weeks.

The CO values taken for five weeks at an interval of one week each are considered. These values are plotted in the form of a graph as shown in below *Figure 12*. The CO increases initially, then starts to decrease gradually. Then the CO continues to increase in the remaining weeks.

The CO_2 values taken for five weeks at an interval of one week each are considered. These values are plotted in the form of a graph as shown in below *Figure 13*. The CO_2 increases initially, then starts to decrease gradually. Then the CO_2 continues to increase in the remaining weeks.

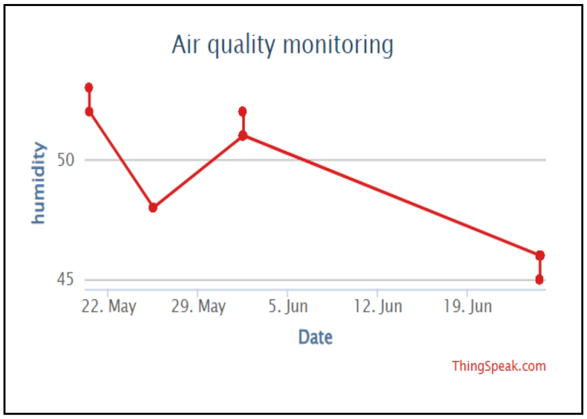

Figure 11 Graphical representation of the humidity readings

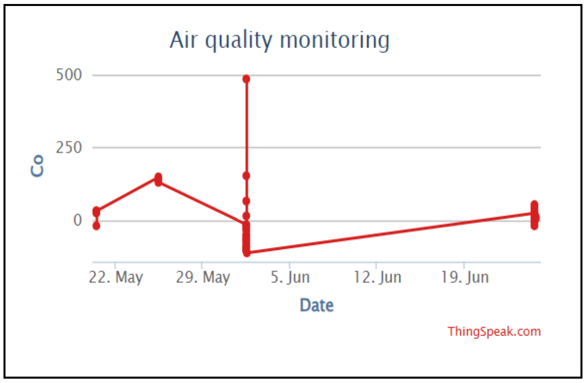

Figure 12 Graphical representation of the CO readings

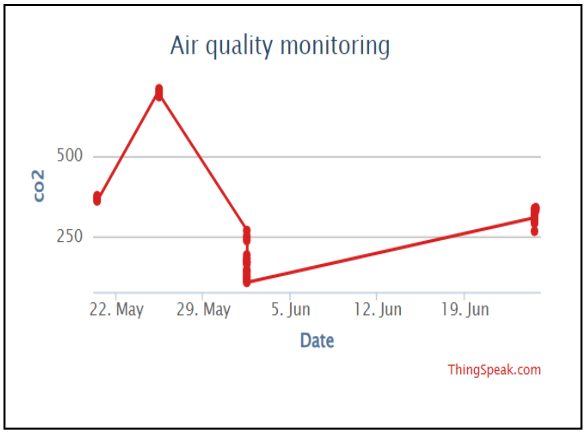

Figure 13 Graphical representation of the CO_2 readings

The pressure values taken for five weeks at an interval of one week each are considered. These values are plotted in the form of a graph as shown in below *Figure 14*. The pressure increases initially, then starts to decrease gradually. Then the pressure increases in the end.

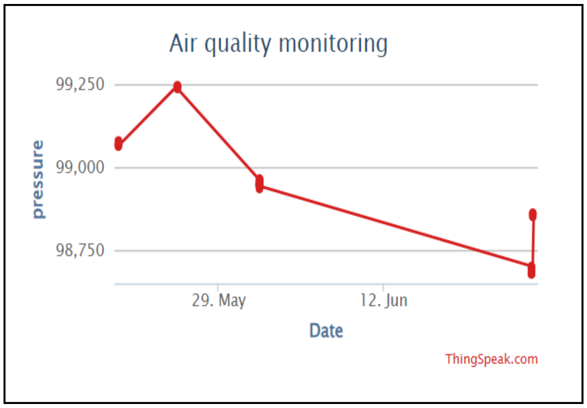

Figure 14 Graphical representation of the pressure readings

The sensor values are uploaded onto the Thingspeak server (IoT). These are the field values uploaded according to the specific sensors and measurements that are used in our air quality monitoring system. Remember to ensure that the data format and types match the requirements of the Thingspeak platform that are using.

The PM1 particle values taken for three hours at an interval of one hour each are considered. These values are plotted in the form of a graph as shown in below *Figure 15*. The PM1 particle tends to go up and down drastically for the first hour. Then it continues to maintain constant value for the remaining two hours.

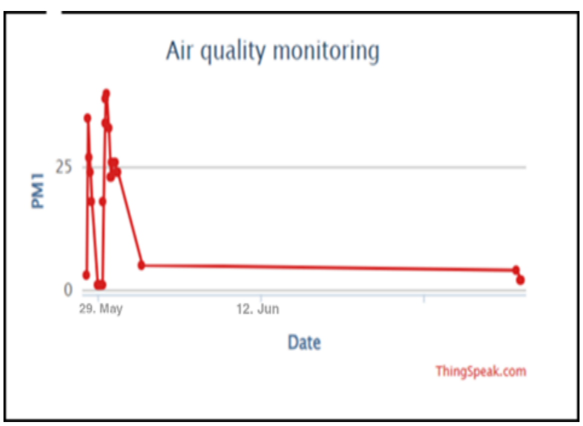

Figure 15 Graphical representation of the PM1 particle readings

The PM2.5 particle values taken for three hours at an interval of one hour each are considered. These values are plotted in the form of a graph as shown in below *Figure 16*. The PM2.5 particle tends to go up and down drastically for the first hour. Then it continues to maintain constant value for the remaining two hours.

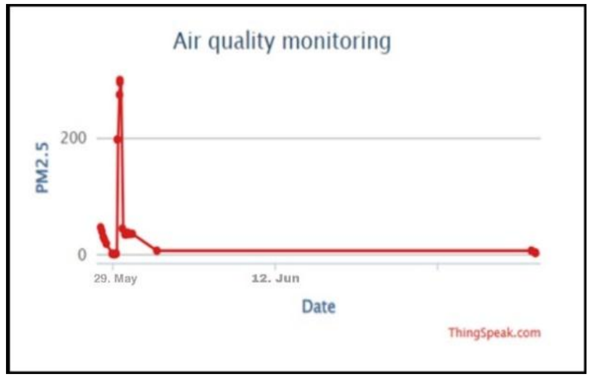

Figure 16 Graphical representation of the PM2.5 particle readings

The PM10 particle values taken for three hours at an interval of one hour each are considered. These values are plotted in the form of a graph as shown in below *Figure 17*. The PM10 particle tends to go up and down drastically for the first hour. Then it continues to maintain constant value for the remaining two hours.

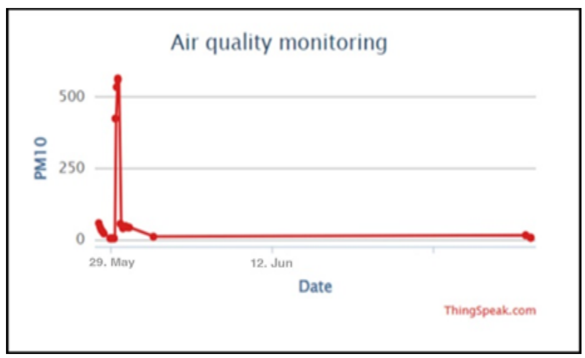

Figure 17 Graphical representation of the PM10 particle readings

Fluctuations or variations in air quality graphs can be attributed to various real-world scenarios or events like increase of PM concentration (prime reason for all kinds of breathing ailments experienced by human beings) that influence the concentration of pollutants in the air. Understanding these fluctuations is crucial for interpreting the data and drawing meaningful conclusions about environmental conditions so that successful climate monitoring becomes possible.

The displayed information on the LCD screen and in graphical representations can be practically utilized by users, both individuals and communities, to make informed decisions and take actions that contribute to better air quality and overall well-being.

- Individuals can adjust their outdoor activities based on the air quality readings. For example, they may choose to limit outdoor exercise or wear masks during periods of high pollution.
- Local authorities can use air quality data to issue public health alerts during episodes of poor air quality. This allows communities to take preventive measures and protect vulnerable populations.

5.3Validation with standards

To assess the air quality and determine whether measured values fall within acceptable limits, it's essential to compare the obtained air quality readings with established air quality standards or guidelines. Different countries and organizations may have their air quality standards. For instance, we have presented the Standard for PM2.5 and PM10 as follows: world health organization (WHO) Air Quality Guidelines recommend annual mean concentrations of 10µg/m³ for PM2.5 and 20µg/m³ for PM10.

5.4Favourable outcomes

- Using Machine learning algorithms, it is possible to give rise to high accuracy in predicting air pollution levels, providing reliable forecasts based on historical data and meteorological factors.
- The real-time monitoring capabilities of the system enable users to receive immediate updates on air quality conditions, facilitating timely decision-making and interventions.
- The “PRE” indicator on the LCD screen aligns well (based on our measurements and observations done) with measured air quality parameters, serving as an effective and user-friendly representation of forecasted pollution levels.
- The information displayed on the LCD screen and in graphical representations has practical utility for individuals and communities, empowering them to take actions that contribute to better air quality.

5.5Limitations

The above-monitored air quality parameters will help one to monitor and thus deliver a few insights for maintaining the climate as applicable. Despite considering the air quality parameters like pressure, humidity/ temperature, CO, CO_2, PM 1, PM2.5, and PM 10, there are still a few more parameters in the air like CH_4, N_2O, HFCs, HCFCs, etc. that were not considered in this current phase of work. Therefore, our climate monitoring system is limited to the considered air quality parameters like pressure, humidity/temperature, CO, CO_2, PM 1, PM2.5, and PM 10.

It is much desirable to make use of Statistical measures and trends (not considered in this phase of work) as these tools are valuable tools for analyzing relationships between different air quality parameters.

- Collect a dataset containing air quality parameters such as PM2.5 levels, AQI, and temperature.
- Calculate the Pearson correlation coefficient to quantify the linear relationship between temperature and each air quality parameter.
- Analyze time series data to identify trends over time. For instance, plot PM2.5 levels and temperature over a period and observe if there are recurring patterns.

The effectiveness of machine learning algorithms in forecasting air pollution levels depends on various factors, including the quality and quantity of data, the choice of algorithms, and the features used for prediction. Evaluating the accuracy of the “PRE” indicator on the LCD screen in correspondence with measured air quality parameters involves assessing the performance of the machine learning model (the same has been merely assumed to be accurate). The same has not been considered in this phase of work. However, we present the related concept.

- Ensure that the training data used for the machine learning model is representative, diverse, and covers a broad range of environmental conditions. High-quality data is crucial for building accurate and robust models.
- Identify the key features (independent variables) that have a significant impact on air pollution levels. Common features include meteorological data (temperature, humidity, wind speed), time of day, and historical pollution levels.

A complete list of abbreviations is summarised in *Appendix I.*

6.Conclusion and future work

In this paper, a climate monitoring system utilizing Raspberry Pi and machine learning for black carbon detection was proposed to improve air quality. IoT technology enhances the process of monitoring various environmental parameters, a key focus of this research being air quality. The deployment of temperature and gas sensors is crucial, as they detect a range of harmful gases that influence the entire monitoring operation. An integrated IoT air pollution system has been developed to address air quality issues, with sensors primarily detecting various hazardous gases present in the environment. The system is equipped with sensors to track humidity, air pressure, and temperature. Moreover, these sensors can be integrated into mobile robots to detect atmospheric pollutants like CO, CO2, and black carbon particles. The system can identify fine particulate matter, such as PM2.5, PM1, and PM10 particles, in the air. Due to their small size, these particles pose significant health risks, as they can penetrate the respiratory system when inhaled. Implementing new protocols can enhance data security across the network. The deployment of such climate monitoring systems allows for a comprehensive understanding of climate patterns by analyzing vast amounts of data. However, there is still a need to incorporate additional features, such as interactive interfaces between citizens and monitoring systems, improved speed and security, and efficient communication protocols suitable for various client and server configurations.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
Not applicable.

Author's contribution statement
M.Chandrakala: Study conception, Design data collection, Investigation on challenges and draft manuscript preparation, Writing-original draft, Analysis and Interpretation of results, Writing-review and editing. **M.V. Lakshmaiah:** Supervision, Writing-reviewing and editing.

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M.Chandrakala completed her postgraduate studies in Electronics and Communication, earning an M.Sc. from Sri Krishnadevaraya University, Andhra Pradesh, India. She then joined as a Junior Research Fellow (JRF) in the UGC-SVU Center for MST Radar Application project, under the guidance of Prof. S. Vijaya Bhaskara Rao at Sri Venkateswara University, Tirupati. Currently, she is pursuing her Ph.D. in Electronics and Communication under the supervision of Prof. M.V. Lakshmaiah at Sri Krishnadevaraya University, Andhra Pradesh. Her research focuses on the variations of black carbon aerosols in South East Peninsular India during the COVID period, utilizing data from Aethalometer instruments.
Email: cnksvu@gmail.com

Prof. M.V. Lakshmaiah serves as the Chairman of the Board of Studies (BOS) and the Head of the Department of Physics with Electronics at Sri Krishnadevaraya University, Anantapur. He has gained international experience as a Postdoctoral Fellow/Visiting Professor in the USA. His academic journey includes completing both his M.Sc and Ph.D. at Sri Krishnadevaraya University. He has also held the position of Dean Director in the Research and

Development department at the same university. Additionally, M.V. Lakshmaiah contributes to the administration of Sri Krishnadevaraya University in the capacities of Secretary and Registrar. With a strong publication record, he has authored over 35 papers in various esteemed national and international journals.
Email: drmvl2009@gmail.com

Appendix I

S. No.	Abbreviation	Description
1	mA	Ampere
2	ADC	Analog-to-Digital Converter
3	APIs	Application Programming Interfaces
4	ANNs	Artificial Neural Networks
5	AQI	Air Quality Index
6	ARIMA	Auto-Regressive Integrated Moving Average
7	ARM	Advanced RISC Machine
8	C/I	Carrier-to-Interference
9	CO	Carbon Monoxide
10	CO_2	Carbon Dioxide
11	CPU	Central Processing Unit
12	EOC	End of Conversion
13	GPIO	General Purpose Input/Output
14	HDMI	High-Definition Multimedia Interface
15	hPa	hectoPascals
16	HTTP	Hypertext Transfer Protocol
17	HTTPS	Hypertext Transfer Protocol Secure
18	Hz	Hertz
19	I2C	Inter-Integrated Circuit
20	IAQI	Individual Air Quality Index
21	IoT	Internet of Things
22	k-NN	k-Nearest Neighbours
23	LCD	Liquid Crystal Display
24	LEDs	Light-Emitting Diodes
25	LPG	Liquified Petroleum Gas
26	M2M	Machine-to- Machine
27	MEMS	Micro-Electro-Mechanical Systems
28	mm	Millimetre
29	NO_2	Nitrogen Dioxide
30	O_3	Ozone
31	Pa	Pascals
32	PC	Personal Computer
33	PM	Particulate Matter
34	PPM	Parts Per Million
35	QoS	Quality of Service
36	RISC	Reduced Instruction Set Computer
37	S	Second
38	SO_2	Sulfur Dioxide
39	SSL	Secure Sockets Layer
40	SVM	Support Vector Machine
41	TFT	Thin Film Transistor
42	TLS	Transport Layer Security
43	TVOC	Total Volatile Organic Compounds
44	UART	Universal Asynchronous Receiver-Transmitter
45	V	Voltage
46	VOCs	Volatile Organic Compounds
47	W	Watt
48	Wh	Watt Hour
49	WHO	World Health Organization
50	XGB	XG Boosting