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An Intelligent and Secure Air Quality Monitoring System Using Neural Network Algorithm and Blockchain

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ABSTRACT
Indoor air pollution is more dangerous for residents. So, it is necessary to monitor the quality of indoor air and take some preventive steps to reduce the possible dangers to the health of the inhabitants. The cost and maintenance factors of air quality (AQI) systems lead the researchers to model, design, and implement low-cost indoor AQI monitoring systems. In this research, we proposed an indoor AQI monitoring system with a data-driven model to predict the AQI through the Neural Network Algorithm and Block-chain. The Internet of Things (IoT) connects and processes data, and low-cost sensors collect the data from the environment. The Indoor Air Quality system consists of temperature, humidity, Carbon Di Oxide, Particulate Matter, Carbon Mono Oxide, and LPG. The data are collected from five different sensors, and the NN decision-making model is used to predict the AQI to prevent harmful situations. The suggested IoT-based smart block-chain technology plays a vital role by imparting scalability, privacy, and reliability. This study will work effectively with ease of use, cost-effectiveness, and maintenance of the entire system.

KEYWORDS
Air quality monitoring; Decision and prediction; IoT; NNA

1. INTRODUCTION

The air pollution and quality of air research get the attention of academia and industry due to a massive increase in deaths in low- and middle-income countries [1]. Seven million deaths have been recorded due to air pollution. The major causes of these premature deaths are the severe impact of air quality (AQI) on our respiratory and blood circulation systems. Due to this alarming situation of death toll, many countries have started monitoring AQI and taken steps to control and minimize pollution by improving the AQI. There are many different techniques to monitor and control AQI such as remote air sensing and static AQI monitoring stations. The smart systems monitor and control AQI has many dimensions like mobile-based AQI monitoring [2–4], smart home systems are supported by Inter of Things (IoT) [5,6] and block-chain technology [7], indoor AQI control systems [8,9]. In this study, our major aim is to design an indoor AQI monitoring and control system using IoT sensors and block-chain. Furthermore, the secure data will be accessed from homes remotely. The motivation is to increase the effectiveness of AQI with a low-cost monitoring system with ease of maintenance and usage.

The basic level of air pollution has five standards: PM, CO_2, SO_2, O_3, and NO_2 [10]. The IQA is imperative for those people who invest most of their energy working in limited spots. Major contributors to air pollution are cooking, housekeeping activities, toxic sprays maintenance activities, and cleaning activities. Home cleaning and maintenance activities emit harmful particles also add pollution to the environment. Indoor AQI is one of the main reasons for premature deaths in urban life [11]. There are many AQI monitoring and management systems using IoT, in which the sensors are used to collect the data from different locations and IoT devices are used to provide processing and decision-making support [12–14]

The Internet is a digital fabric waving into everyone's lives in one way or another. The Internet is just not connecting people, connecting things too, so it's commonly referred to as the IoT [15]. Things are connected to other things with the adaptability to sense and communicate; it's more like human beings' interaction with other humans using basic empirical senses. IoT block-chain provides a common language for devices to communicate with each

Figure 1: Sources of indoor air pollution

other securely. Sensors and actuators are the backbones of IoT [16,17].

IoT framework includes sensors and secure networks by using block-chain to gather data. They are related to IoT when signals are exchanged. Every sensor is different, so each IoT application requires distinctive sensors. Advanced sensors are basic and direct to interface with a microcontroller-exploitation Serial Peripheral Interface (SPI) bus [16]. Expansion of industrialization and urbanization, nature has been polluted at an exasperating speed. Pollution of land, water, and air, including groundwater and the ocean, is a type of environmental pollution [18,19]. Causes of pollution include numerous elements with discharging strong, fluid and vaporous substances to nature during industrial activities. Air pollution causes health problems as the toxins scatter through the air [20–22].

Figure 1 represents the main contributors to air pollutions for indoor pollution. The major source of this type of saturation is kitchen appliances, home appliances, and activities such as cleaning, cooking, pest control toxic ingredients. The second source is ventilation appliances like air conditioning and heating systems. Lead, carbon dioxide, carbon mono oxide are also produced during cooking and house maintenance activities. Bacteria, viruses, mold spores, dust mites, and other (dust components) agents travel through humidity that causes pollution.

This research study is proposed as a cost-effective, smart, and neural network-based decision-making enabled system, in which secure data are collected through low-cost sensors such as temperature, humidity, carbon dioxide, carbon mono oxide, Particulate Matter, and liquefied petroleum gas. The sensors are connected by the Arduino platform that provides connectivity and enables process and make decision. The proposed system classifies the air into five quality levels: satisfactory, normal, healthy, threatening, and dangerous. The neural network is trained with these air quality classifications through labels and then makes predictions using neural network and warning live secure data collected through systems. The main contributions of the paper are

- The proposed system collects real-time sensors data. Data security is ensured by adopting the block- chain technology.
- The proposed neural network model predicts Air Quality Index using all sensors data.
- The proposed framework will help government organizations/agencies rapidly react to air indexing-related problems by getting real-time data and their emergency level predictions.

The rest of the study is organized as follows. Section 2 presents the related work, Section 3 provides the architecture of the proposed systems, Section 4 presents the implementation details of the proposed system, Section 6 enlists the results and discussion, and Section 7 provides the conclusion and future work.

2. RELATED WORK

In 2021, Amuthadevi *et al.* [23] proposed different AQI monitoring models using various machine learning approaches. They used a dataset consisting of various meteorological factors and applied machine learning techniques to find correlations between different factors. A long–short-term memory algorithm was efficient in analyzing and predicting AQI.

In 2021, H. Zhang *et al.* [24] proposed a cost-effective solution using raspberry pi and different sensors to monitor AQI of an indoor environment. Various environmental factors and pollutants were recorded and analyzed for residential and office areas. Results showed that a residential building had more pollutants than an office building.

D. Zhang *et al.* [25] proposed a system consisting of fixed and mobile IoT sensors in 2020. The system is helpful to get a wide spectrum of AQI from nearby areas.

The Gradient Boost (GB) regressor algorithm was efficient in prediction. This system is beneficial for smart city projects as it has a mobile and fixed sensors network.

In 2019, Kr Cromar [26] describes health issues due to indoor AQI. The major focus is on the increase in air pollution monitoring, using multiple technologies, and communication regarding health issues. It takes advantage of emerging technologies like sensor-based and reliable pollution data and prediction to health issues in global issues.

In 2014, Air Beam, an open-source air sensor system, was released by Habitat Map for personal monitoring for PM2.5. In 2015, U.S. EPA completed a 1-year field evaluation of AQI sensor systems. In 2015–2016, at a pace of almost one new company per week, startups sought to develop an AQI sensor for the consumer market, in 2016, 4-year CITI-SENSE air sensor project engaged citizens. Then a dense city network of hundreds of air sensors was deployed. And the group seeks to close the air sensors gap. In 2017, Citizen Science bills were proposed in the U.S. House of Representatives and the California Assembly Bill. A government was interested in citizen science to provide a pathway for air sensors to affect science and public policy [27].

In 2019, de tazoult *et al.* [28] developed a prototype for monitoring AQI using the block-chain technology. Such a solution could give the secure and reliable problem of data.

Air quality sensors and the write full name (HVAC) control system is vital for people's health. Indoor AQI produced more harmful impacts on residents than outdoor AQI. This is because indoor air can contain two to five times greater contaminants than outdoor air. In an HVAC control system, the research and implementation are substantial. Several groups have completed work on various HVAC-control systems. While these groups' work and research performed well for their application, research involving a greater collection of sensors is negligible [29].

The indoor environment monitoring system was proposed to monitor ozone ingestion. The framework was designed based on the open structure theory. It claimed flexibilities to accommodate the coverage of bigger zones of homes and workplaces. The model for this system was designed on single sensing devices with gateway processing support. The indoor sensing devices may be increased as per the requirement of sensing fields. The gateways and processing devices were also placed inside sensing environments with local area network connectivity [30].

Accomplishing energy maintenance, thermal comfort, and satisfactory indoor AQI is regularly challenging objectives. The dynamic requirement of the system needs the data settings and controlling mechanism for the proposed system. Many different approaches adjusted these dynamic data settings to meet the savings in energy to assess the indoor AQI system. Imprecise information may produce unsatisfactory results and poor decision-making. This phenomenon also leads to inappropriate sensor placing and adjustments. The micro-sensor arrays use semiconductors with standard strategies. These standards somehow claim low-cost data collection arrangements. The prototype sensor arrays help establish practical solutions for indoor AQI monitoring, management, and control systems [31].

Many research groups welcomed and praised the idea of cheap sensor setups for practical solutions for indoor AQI monitoring problems. The groups also low-cost sensing devices need proper and precise deployments to achieve the targeted goals. They also discuss the significant contributions of these sensor-based experiments to the body of knowledge, irrespective of the limitations of these sensors used in these experiments. A low-cost sensors arrangement needs to identify the minute measures from the field under analysis, which ultimately leads to activity and information-driven decision-making systems [32].

The smart home technology relies on remarkable atmosphere circumstances, pollution levels, house types, and individual lifestyles. Age, gender, and societal behavior of individuals also play a vital role. Smart homes are mainly acknowledged and assessed as an energy management system to limit energy expenses and time. Besides, homes with good AQI are pleasant and provide a considerable edge of energy-saving [33]. A study conducted in Singapore discussed the smart home appliances are mostly acknowledged by the respondents using saving power cost. Individuals found it inappropriate to change their living to save money even though there is a better point of interest than drawbacks. So, individual comfort is the priority [9].

To observe the ventilation rate of a chamber, a context-aware IoT system was industrialized. The framework used an Arduino-based setup and a versatile mobile sensing framework using Sensor-drone and Samsung Galaxy S4 to determine carbon dioxide levels in classrooms and halls. Arduino setup is cautiously framed depending on perception and cautious adjustment of the sensors. Carbon dioxide is used as a tracer gas, and its development and decay are observed so that ACR (h-1) and ventilation rate can be computed. Estimations are taken for every single conceivable instance of ventilation. Using this framework, corrective ventilation measures can be surveyed and proposed continuously [34].

Specifically, the decline in the expense of sensor innovations is a noteworthy accomplishment. Beginning of reasonably priced sensors, there should be a common improvement in other linked areas, such as behavioral changes in travel choices and energy and acknowledgment. To link research gaps with the advancement of sensors innovation, which, right now, seems to be relatively revolutionary. So, research in these areas will grow drastically soon [8].

3. MATERIAL AND METHODS

This section presents the architecture, equipment used, prototype deployments of sensors, and machine learning implantation details.

3.1 Architecture of Indoor Air Quality System

IAQ is a low-cost AQI monitoring system developed using Arduino, Humidity, Temperature, Carbon monoxide, Particulate Matter, Carbon dioxide, liquefied petroleum gas sensor, which is a gas leakage detection sensor. The solution is accessed by identifying the diversity of different factors such as as Humidity, Temperature, CO_2, CO, PM, and LPG leakage.

Figure 2 indicates the architecture of the suggested system. Five types of sensors are used that are connected using IoT and the block-chain system that communicates with Neural Network Algorithm (NNA) model that does processing on data taken from the sensor as input and predicts the result. The input data, processed data, and relevant information are continuously stored on a computer system and reported through warnings and indicators through different reports and signals as their confidence in the state of AQI environment to the system's user. This block-chain module was executed in java as blocks contents in a hash that is a distinctive identifier; each block can calculate a block hash, and the SHA-256 hash is calculated from it. When a threshold is attained, a block is looped over to corroborate a block's hash for the validity of the complete block-chain.

3.2 Neural Network Algorithm (NNA) Model Used for Decision Support

Neural networks are widely used in many applications successfully. They act as real word functions/models. This model predicts the control of the system. Neural networks have processing elements linked to each other in layers. Usually, two layers connect with the real world. The output from the sensor is provided to the first layer, the input layer, whereas the output is the response to the system provided by the hidden layer that holds the packet of data as a buffer for output(s) of the system.

Usually, feed-forward multilayer networks use back-propagation. A multilayer feed-forward network used in this paper is shown in Figure 3. Neurons are divided into the input layer, the output layer and the layers that are hidden. The hidden layers relay feed- forwards from the input layer to the output layer.

The training of this network is compulsory in which thresholds and weights are determined. This training is necessary to reduce the error function. The error functions are described by the LMSA (Least Means Square Algorithm).

$$E = \frac{1}{2}\sum k((T_k - O_k)^2) \tag{1}$$

where T_k and O_k are objectives and determine the output for output neuron k exclusively.

Inputs received by the hidden node or layer and output layer are multiplied as w_{ij} and w_{jk}. The non-linear sigmoid function provides output on the hidden and output layers. Output layer known as j layer node input sum is given by Equation (2).

$$Net_j = a_j = \sum w_{ij}S_i + \theta_j \tag{2}$$

where a_j is j neuron's present output state and in w_{ij};i weight of j neuron on connections. The output sum of jth layer is given by Equation (3).

$$s_j = f(net\, j) \tag{3}$$

The threshold function is f, and by Equation (4) the sigmoid function is given.

$$f(z) = (1.0 + e^{-z})^{-1} \tag{4}$$

The output of the hidden layer is computed by Equation (5)

$$f(a_j) = \frac{1}{(1 + exp(-net_j - \theta_j))} \tag{5}$$

Layer-k node output is the sum of outputs that are described in Equation (6)

$$S_k = f(a_k) = \frac{1}{(1 + exp(-net_k - \theta_k))} \tag{6}$$

S_k is the actual performance O_k that Neural Network (NN) produces. Value of θ_j and θ_k are the bias node in

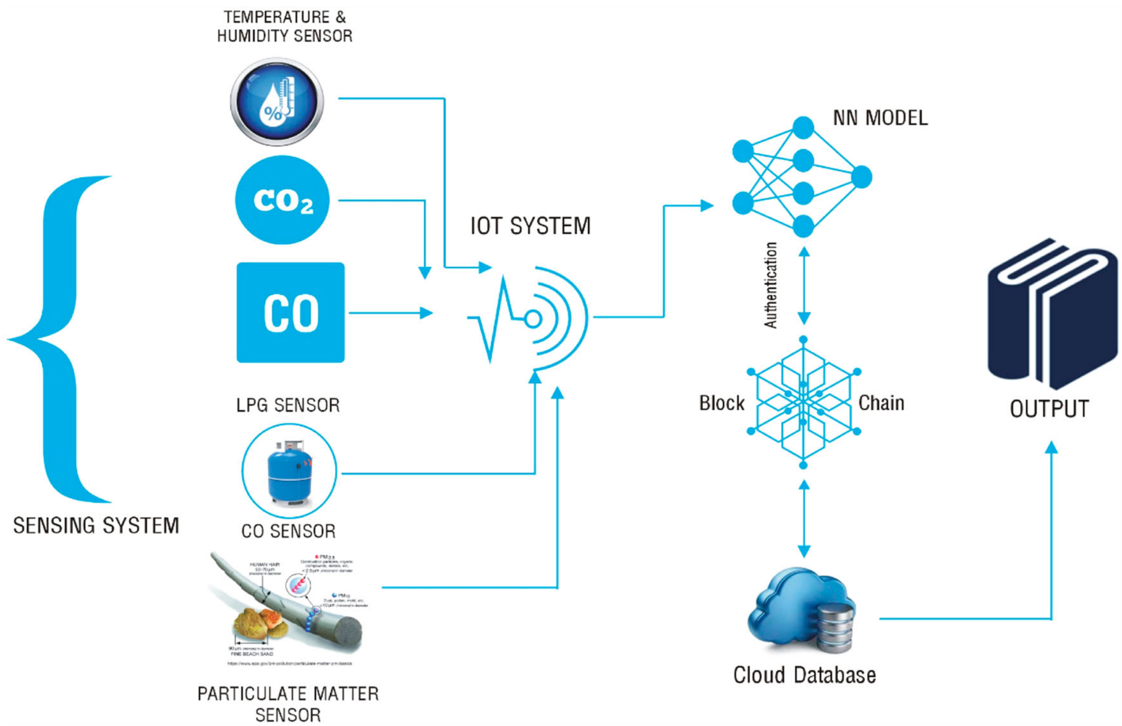

Figure 2: Architecture of the proposed system

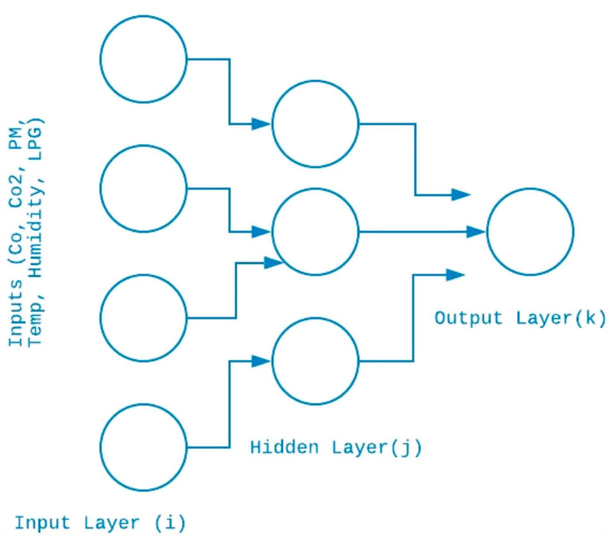

Figure 3: Block Diagram of a neural network

layer j and k. Those nodes are taken by multiplying the weight and input. The sum of all output can't be zero as it requires the iterations to proceed until termination occurs, so bias input is always constant (+1).

The back-propagation algorithm informs on the error produced by the neural network, o_k to w_{ij}. Equations (7) and (8) show the back-propagation algorithms

$$\Delta w_{ij} = \eta \delta_j S_i, \rho > 0 \tag{7}$$

$$\delta_k = (T_k - O_k) O_k (1 - O_k), k = 1, 2, 3 \tag{8}$$

Equation (10) determines the error in prediction

$$\delta_j = S_j (1 - S_j) \sum \delta k w_{jk} \tag{9}$$

In T_k, k represents the dimension. The term in Equation (7) is known as momentum. It has the effect of speeding up the learning speed. The momentum is also useful to define the effect of last used weight changes. If Equation (7) is modified into Equation (10), we get.

$$\Delta w_{ij}(n+1) = \eta \delta_j S_i + \alpha \Delta w_{ij}(n) \tag{10}$$

The learning rate of NN is represented as constant. The large value means speedy learning of the neural network [28,29].

3.3 IAQ System Components and its Organization

The IQA system is designed and implemented using Arduino integrated development environment. The Arduino is used to collect the sensor data. These sensors are placed in different locations to react as input for the neural network decision support system. The sensors, deployed for data collection in the proposed system, are discussed in the following sections.

The IQA proposed system has a set of sensors with an Arduino microcontroller. The DHT22AM2302 sensor is

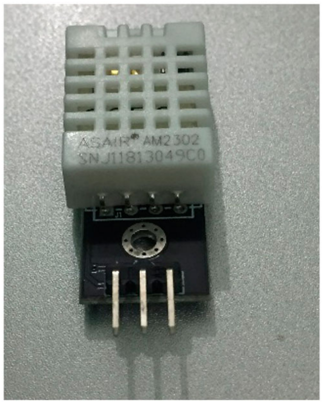

Figure 4: The Humidity and Temperature sensor DHT22AM2302

used to measure the temperature and humidity of the subject location. MG-811 sensor collects the information on carbon dioxide (Co2). MQ5 contains LPG values. MQ7 is a gas sensor that collects carbon monoxide concentrations in the environment. SPS30 is used to collect information on particulate matter. The important characteristics of these sensors are given in the following section.

3.3.1 The Temperature and Humidity Sensor DHT22AM2302

The temperature and humidity sensor model AM2302 DHT22 collects data for humidity and temperature of the air in the subject program. It is a simple, common, cheap, and easy-to-use sensor. In this current experimental setup, the AM2302 model of the DHT22 sensor was used. The DHT22 is used due to its accuracy and calibrated output. Figure 4 shows the used sensor for temperature and humidity measurement.

3.3.2 MQ5 Liquefied Petroleum Gas Sensor

In Figure 5 MQ5 LPG sensor is shown that detects concentrations from 0 to 10000 ppm. Input voltage is 5 VDC, and the power used is 150 mA. The sensor provides a digital output voltage from 0.1 and 5 V that is TTL digital of 0 and 1. If the analog output voltage is relatively clean, then the voltage is between 0.1 and 0.3 V and if the output has a high concentration voltage is 4 V. The sensor board size is $32 \times 20 \times 22$ mm and has 4 pins with 0.1″ spacing.

3.3.3 MQ7 Carbon Monoxide Gas Sensor

MQ7 CO sensor shown in Figure 6 detects concentrations from 0 to 10000 ppm. Power is between 2.5 and 5 V. Sensor provides a digital output voltage from 0.1 to 5 V that is TTL digital of 0 and 1. If the analog output voltage is relatively clean, then the voltage is between 0.1 and 0.3 V and if the output has a high concentration voltage

Figure 5: LPG Sensor MQ5

Figure 6: CO Sensor MQ7

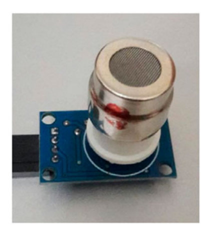

Figure 7: CO_2 Sensor MG-8 1 1

is 4 V. The sensor board size is 40.0 mm $*$ 21.0 mm and has 4 pins with 0.1″ spacing.

3.3.4 MG-811 CO2 gas Sensor

MG-811 CO2sensor provides analog and digital output with a simple drive circuit. The sensor also provides a trigger Level configuration Potentiometer that adjusts the output level transition. The Operating Voltage is DC 6 V, and Preheat Duration is 20 s. Figure 7 shows the used sensor for carbon dioxide.

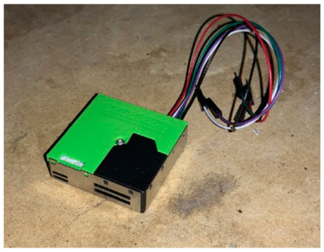

Figure 8: Particulate Matter Sensor SPS3 0

Figure 9: Arduino UNO Microcontroller

3.3.5 SPS30 Sensor

The Particulate Matter Sensor SPS30, as shown in Figure 8, is a lightweight, high-quality, optical particle sensor using laser scattering and advanced contamination resistance technology to achieve superior binning and particle measurements. This sensor makes users calculate mass concentration and number of particles of 1, 2.5, 4, and 10 μg/m^3.

3.3.6 Arduino UNO

Arduino microcontroller has 6 input/output pins and 14 digital pins, as shown in Figure 9. These pins are programmed to Arduino IDE according to sensors.

4. RESULTS AND DISCUSSION

The IAQ system based on the NN decision-making component is intelligent and smart. Intelligent IAQ systems are a novel idea due to their usage and design. To test the proposed system's performance, five measures were collected from a room: Carbon Mono Oxide, Carbon Di Oxide, LPG, Particulate Matter, temperature, and humidity.

The temperature and humidity sensor collects real-time values of temperature, which ranges from -40 Celsius to $+125$ Celsius. In Table 1, the authors try to classify these temperature measures in five different levels to train our NN algorithm.

Table 1: Five Classifications of Temperature for Training Dataset

Temperature (°C)	Class
> 40	Very High
30–40	High
20–30	Normal
10–20	Low
< 10	Very Low

Table 2: Classes of humidity

Humidity (%)	Class
$> 80\%$	Dangerous
70–80%	Threatening
50–70%	Healthy
35–50%	Normal
$< 35\%$	Satisfactory

Table 3: Classes of Carbon Monoxide

CO (PPM)	Class
> 2000	Dangerous
1000–2000	Threatening
250–1000	Healthy
100–250	Normal
< 100	Satisfactory

Table 4: Classes of Carbon Dioxide

CO2 (PPM)	Class
> 2000	Dangerous
1000–2000	Threatening
250–1000	Healthy
100–250	Normal
< 100	Satisfactory

Table 2 shows five classes (Dangerous, Threatening, Healthy, Normal, and Satisfactory) for various humidity levels detected by the AM2302 DHT22 sensor. A standard AM2302 DHT22 sensor provides real-time moisture values ranging from 0% to 100%.

Table 3 shows five classes (Dangerous, Threatening, Healthy, Normal, and Satisfactory) for various levels of carbon dioxide detected by the MQ7 Carbon Monoxide Gas sensor. A typical MQ7 carbon monoxide gas sensor provides real-time carbon monoxide values ranging from 0 to 2000.

Table 4 shows five classes (Dangerous, Threatening, Healthy, Normal, and Satisfactory) for various levels of carbon dioxide detected by the MG-811 CO2 gas sensor. A typical MG-811 CO2 gas sensor provides real-time carbon dioxide values ranging from 0 to 2000 ppm.

Table 5 shows five classes (Dangerous, Threatening, Healthy, Normal, and Satisfactory) for levels of LPG

Table 5: Classes of LPG

LPG (PPM)	Class
> 3000	Dangerous
1500–3000	Threatening
350–1500	Healthy
100–350	Normal
< 100	Satisfactory

Table 6: Classes of particulate matter

PM (PPM)	Class
> 2000	Dangerous
1000–2000	Threatening
250–1000	Healthy
100–250	Normal
< 100	Satisfactory

gas sensed by the MQ5 Liquefied petroleum gas sensor. A typical MQ5 sensor provides real-time liquefied petroleum gas values ranging from 0 to 3000 ppm.

Table 6 shows five classes (Dangerous, Threatening, Healthy, Normal, and Satisfactory) for levels of particulate matter detected by the SPS30 particulate matter sensor. A typical SPS30 sensor provides real-time particulate matter values ranging from 0 to 2000 ppm.

A training dataset was classified manually according to the five classes, as discussed in Table 6. Rapid miner is used for training dataset using a neural network model. Then the input of the sensors is tested on the trained neural network process to predict the AQI by showing confidence in five classes. A testing dataset collected in the worse environment of the room was provided to the system, and then the confidence on these inputs indicates the AQI, as shown in Figure 10. The confidence in the values is used to indicate the AQI.

To assess AQI using IoT-based electronic-nose, the selection of experimental area is house residence, and data have been collected from 4 days with 10 min time intervals. The residence region measurement is 200 m^2. The measurement of rooms was 18 m^2, and the dimensions were carried from a height of 1.3 m. The seven-member of the house has used a central heating system. Although there were changes in the number of occupants during the day, there were no less than three people always present in the household. There was no air-cleaning mechanism in the house. The ventilation of the climate was possible by opening the windows. The entry gate in the family was not shut during the estimation, and in this manner, the air was homogeneous throughout the house. Ventilation was completed once per day for a period of 60 min. Ventilation began at 12:00 right from the start and at 08:00 on different days.

The confidence in the values is used to indicate the AQI.

Figure 11 shows the 5 days' measurement graph representing the relationships between Co_2 – Humidity. Figure 11 represents the indoor humidity, and CO_2 fluctuated depending on the number of household people and particular exercise. Natural ventilation toward the beginning of the day hours reduced humidity and CO_2 gas intensity.

Figure 12 describes the 4 days' measurement graph, showing the relationships between Co_2 and CO. The graph represents that the indoorCO_2 and CO gas concentrations fluctuated depending on the number of household people and particular exercise. Natural ventilation toward the beginning of the day hours reduced CO, and CO_2 gas concentrations.

Figure 13 reveals the 5 days' measurement graph specifies the relationships between PM_{10} and CO. The graph indicates the indoor PM_{10} and CO gas concentrations fluctuated depending on the number of household people and particular exercise. Natural ventilation toward the beginning of the day hours reduced CO gas concentrations. During the start of the day, the intensity of the PM_{10} is increased during the daily routine work of the household members. The 37% rate has been increased during the household member activity.

Figure 14 displays PM10 intensity over 3 days. The graph displays that the indoor PM_{10} fluctuated depending on the number of household people and particular routine exercise. During the start of the day the intensity of the PM_{10} increased during the daily routine work of the household members. Figure 13 represents the daily variations of PM_{10} and CO amount. Time-period1 (00:00–08:00), Time-period 2 (08:00–16:00) and Time-period 3 (16:00–00:00) are observed during the whole day. Time-period 1 represents the sleeping activity in the house; time-period 2 represents the daily routine exercise in the household (cooking, cleaning, etc.) of the individuals have performed; and the time-period 3 shows the activity of eating and resting of the household members.

Figure 15 represents the CO2 measurements over 5 days. The shows that the indoor CO_2 gas concentrations fluctuated depending on the number of household people and particular routine exercise. During the start of the day the intensity of the CO_2 gas concentrations is low. Figures 11, 12 and 13 displays the everyday changes of temperature, humidity, PM_{10}, CO, and CO2 values. Time-period1 (00:00–08:00), Time-period 2 (08:00–16:00) and Time-period 3 (16:00–00:00) are observed during the whole

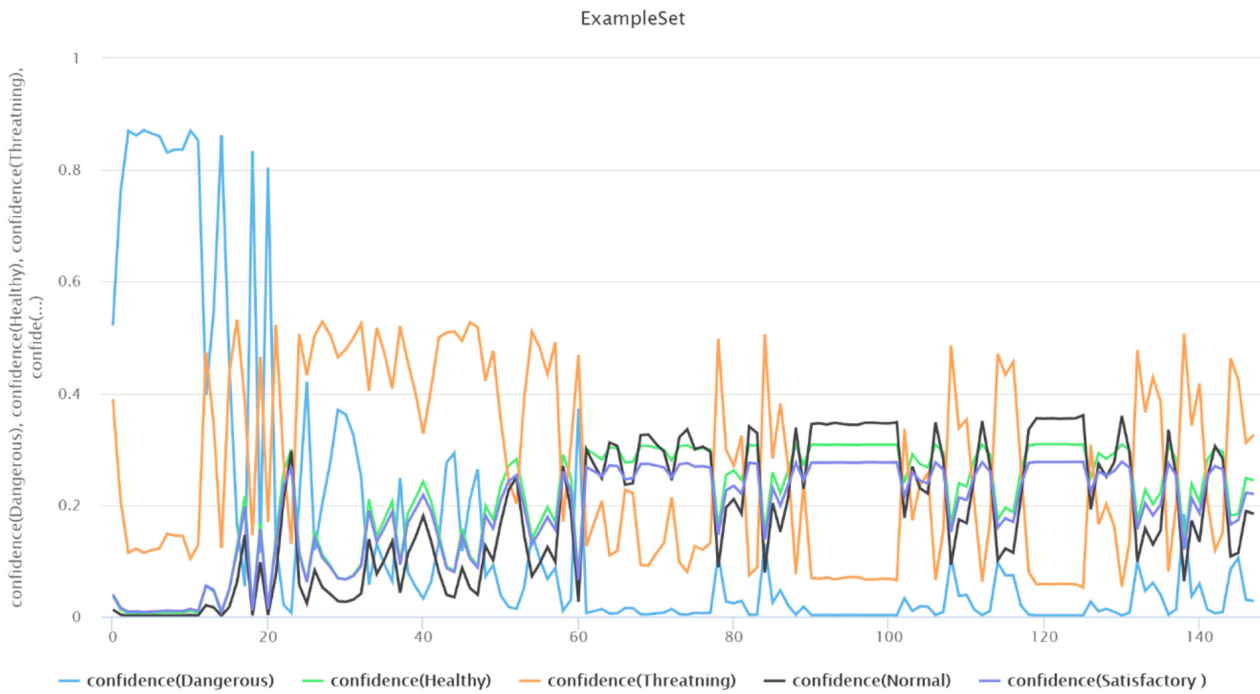

Figure 10: Confidence on the input dataset

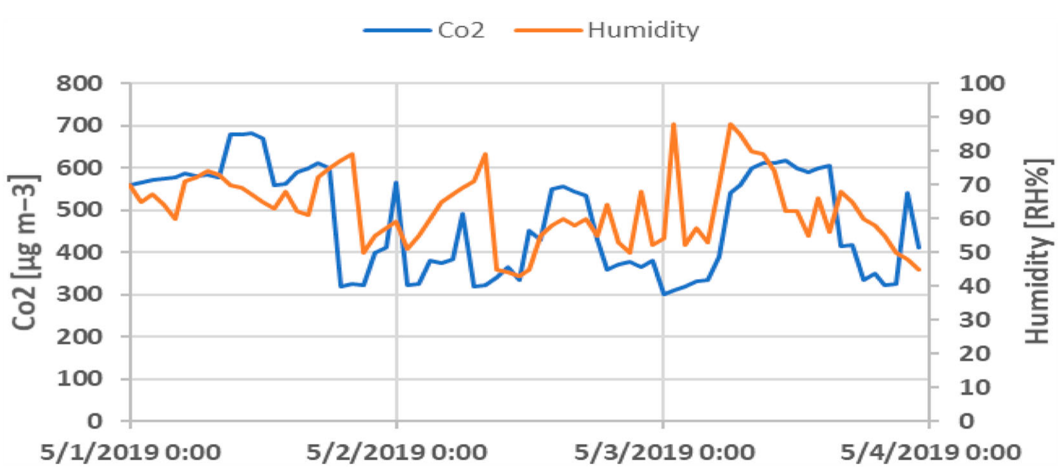

Figure 11: Relationship between CO_2 and Humidity

day. Ttime-period 1 represents the sleeping activity in the house, time-period 2 represents the daily routine exercise in the household (cooking, cleaning, etc.) of the individuals have performed, and the time-period 3 shows the activity of eating and resting of the household members.

Figure 16 represents the intensity of CO over 3 days. Figure 16 represents that the indoor CO gas concentrations fluctuated depending on the number of household people and particular routine exercise. The start of the day hours caused a decrease in the intensity of CO gas concentrations. Figures 11, 12 and 13 display the day-to-day variations of temperature, humidity, PM10, CO, and CO2 values. Time-period1 (00:00–08:00), Time-period 2 (08:00–16:00) and Time-period 3 (16:00–00:00) are observed during the whole day. Time-period 1 represents the sleeping activity in the house, time-period 2 represents the daily routine exercise in the household (cooking, cleaning, etc.) of the individuals have performed, and the time-period 3 shows the activity of eating and resting of the household-members.

4.1 Performance of Artificial Neural Network

Performance of the Artificial Neural Network is focused in terms of accuracy, precision, recall, and f-measure.

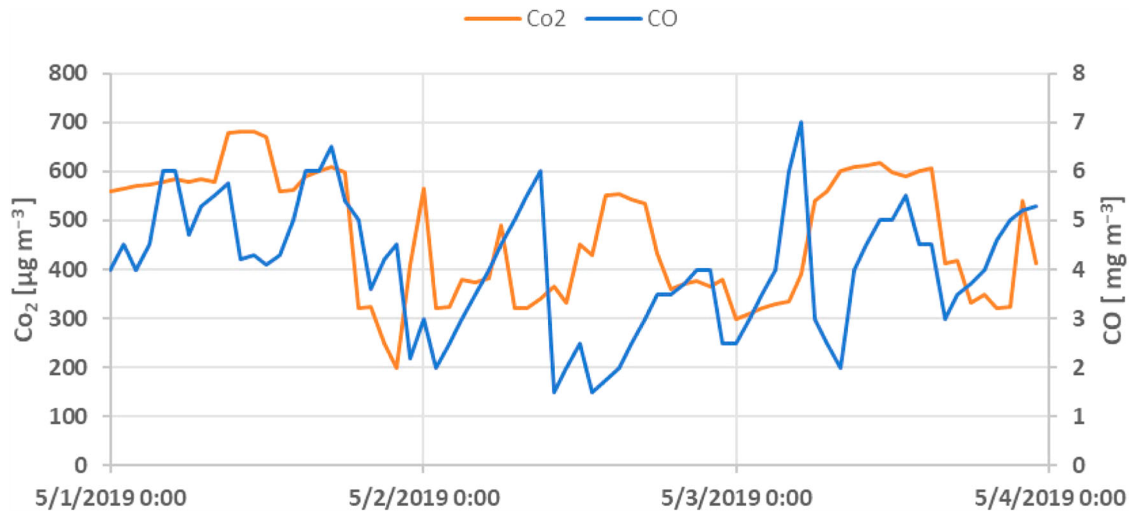

Figure 12: Relationship between CO_2 and CO

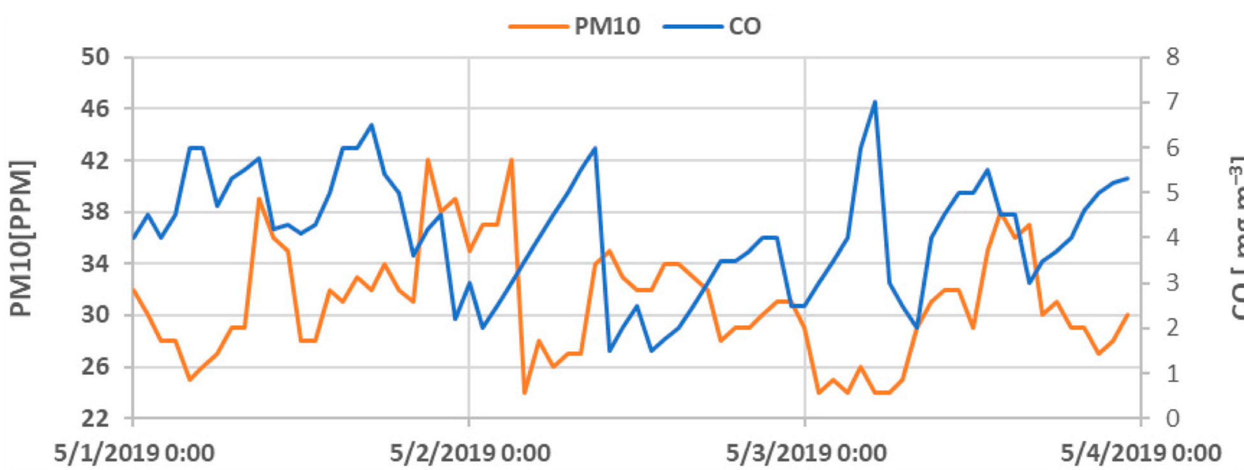

Figure 13: Relationship between PM10 and CO

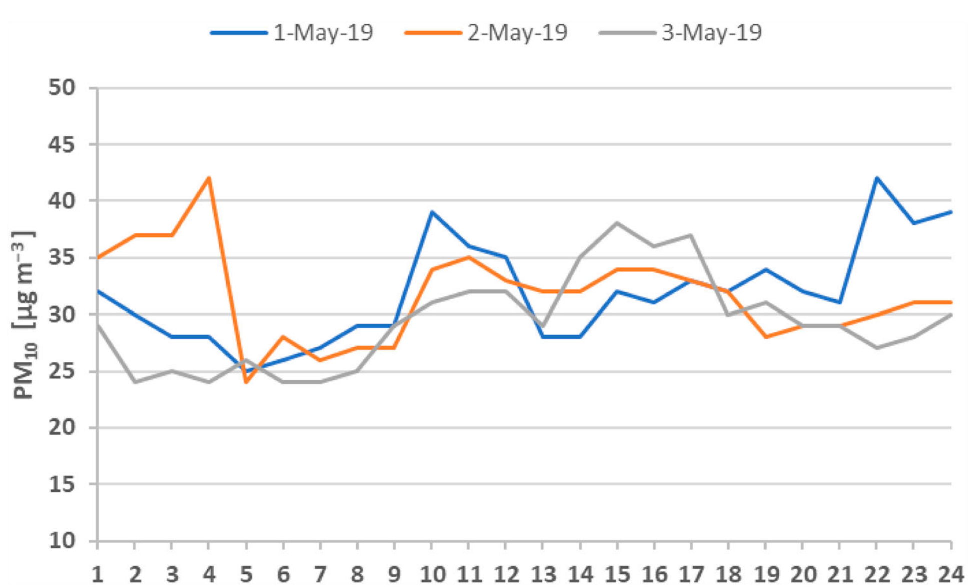

Figure 14: Daily changes of PM10

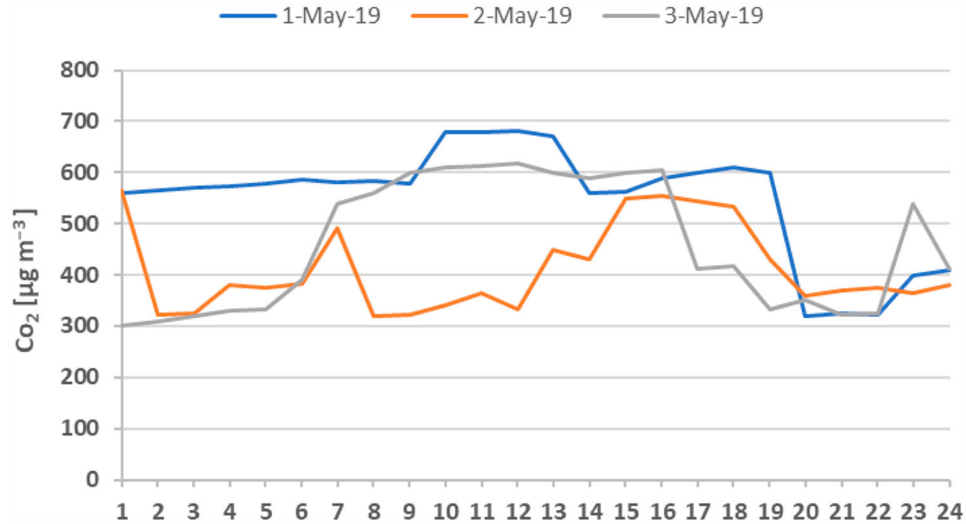

Figure 15: Daily changes of CO2

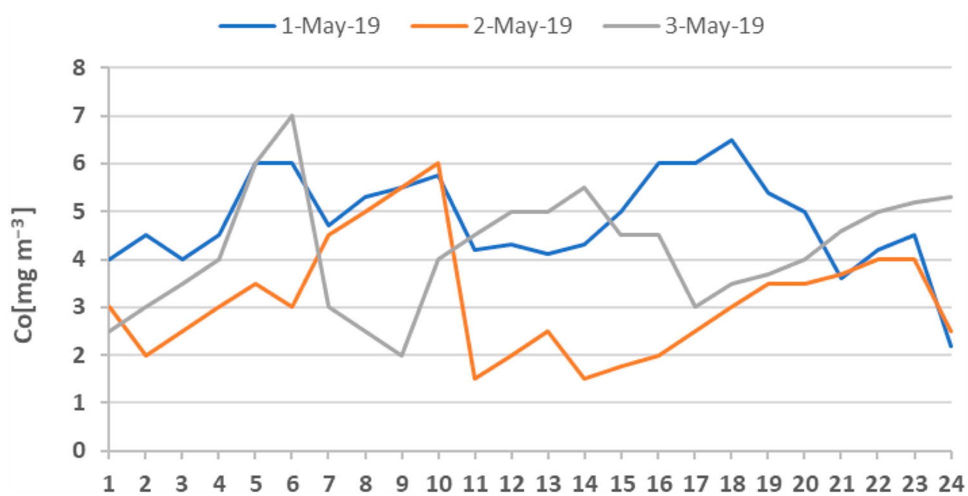

Figure 16: Daily changes of CO

Table 7: Precision, recall and f1 measure for predictive features

Predictive class	F1	Recall	Precision
Dangerous	0.931	0.945	0.956
Threatening	0.671	0.767	0.589
Healthy	0.677	0.747	0.698
Normal	0.698	0.946	0.616
Satisfactory	0.997	0.912	1.000

Precision is the fraction of the correct prediction out of the total prediction made, and recall is the ratio of the accurate prediction to all the predictions in the binary class. The tool used for the execution of Artificial Neural Network is rapid minor. The achievement of the Artificial Neural Network algorithm in terms of accuracy 92.88% and high f1, precision, and recall, are the different predictive features, as shown in Table 7.

5. CONCLUSION AND FUTURE WORK

An indoor AQI monitoring and prediction system was presented in this research using IoT, block-chain and Neural Network Algorithm. Six measurements (temperature, humidity, CO2, CO, PM and LPG) were collected from three sensors. The Arduino microprocessor is used to collect the information from sensors. Then the secured collected information through the block-chain is used to train a neural network Algorithm to predict the AQI for an indoor home or workplace environment. There were five classification models for the indoor environment for temperature, humidity, carbon monoxide, particulate matter, carbon dioxide and LPG to help the NN model to correctly predict the situation. The system performs equally reasonably for the room, workplace, and kitchen and predicts hazardous situations for users. The proposed system is useful and secure for inhabitants of closed-door environments. The future work for this research is to extend for infant care, indoor pet health monitoring; indoor plants care management system, patient care, and management system. The system is also extendable to kitchen gasses leakage control and monitoring system.

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DISCLOSURE STATEMENT

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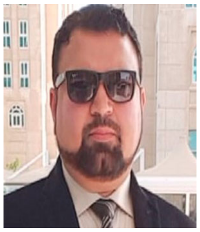

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