

Article

Assessment of Indoor Air Quality in Academic Buildings Using IoT and Deep Learning

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Abstract: Humans spend most of their lifetime indoors; thus, it is important to keep indoor air quality within acceptable levels. As a result, many initiatives have been developed by multiple research centers or through academic studies to address the harmful effects of increased indoor pollutants on public health. This research introduces a system for monitoring different air parameters to evaluate the indoor air quality (IAQ) and to provide real-time readings. The proposed system aims to enhance planning and controlling measures and increase both safety and occupants' comfort. The system combines microcontrollers and electronic sensors to form an Internet of Things (IoT) solution that collects different indoor readings. The readings are then compared with outdoor readings for the same experiment period and prepared for further processing using artificial intelligence (AI) models. The results showed the high effectiveness of the IoT device in transferring data via Wi-Fi with minimum disruptions and missing data. The average readings for temperature, humidity, air pressure, CO₂, CO, and PM_{2.5} in the presented case study are 30 °C, 42%, 100,422 pa, 460 ppm, 2.2 ppm, and 15.3 µ/m³, respectively. The developed model was able to predict multiple air parameters with acceptable accuracy. It can be concluded that the proposed system proved itself as a powerful forecasting and management tool for monitoring and controlling IAQ.



Citation: Marzouk, M.; Atef, M. Assessment of Indoor Air Quality in Academic Buildings Using IoT and Deep Learning. *Sustainability* **2022**, *14*, 7015. <https://doi.org/10.3390/su14127015>

Academic Editor: Farid Shirazi

Received: 16 April 2022

Accepted: 25 May 2022

Published: 8 June 2022

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Keywords: indoor air quality; Internet of Things; artificial intelligence; buildings environment; deep learning

1. Introduction

According to the US Environmental Protection Agency [1], poor indoor air quality (IAQ) is considered a major risk to human health. People spend most of their lifetime indoors, where some pollutant concentrations are as high as five times more than the pollutants outdoors. In recent years, pollutant concentrations have increased due to a lack of ventilation and the extensive use of synthetic materials in both residential and commercial buildings that hinder air exchange, certain occupant behaviors, and chemicals used in personal products. Those who are affected the most are young adults and those with respiratory diseases. Weather conditions and building quality represent an additional concern, since the outdoor air can easily flow inside through cracks and windows, affecting different rooms and spaces inside; even those under controlled ventilation remain vulnerable to air pollutants. The ultimate goal of any building is to improve quality of life and to provide occupants with a sustainable, healthy environment. Building studies show that many health problems are caused by poor indoor air quality and the economic value of a building is badly affected if the building is known for its poor performance in air quality [2]. Indoor air quality and sustainability management have become vital considerations in today's human lives. Buildings that are unique in nature, such as hospitals, are in need of adequate control of their indoor environment, and in such cases, a sustainable approach is highly required to continuously evaluate and control any risks that may affect patient

health [3]. The term “sustainability development” is often used to describe an approach to improve quality of life, thus providing a healthy environment and enhancing both social and economic conditions for generations to come [4].

There is growing attention given to indoor air quality (IAQ) due to its effects on occupants’ comfort and productivity. Indoor air quality depends on parameters that are not easily measured, and such a challenge requires a fundamental innovation. The Internet of things (IoT) can be used as an alternative to measure predefined indoor air parameters, but it is associated with technical details (i.e., sensor availability and Wi-Fi connectivity). Since the IAQ parameters will depend on continuous monitoring for managing and controlling later, cloud services can be a good option to effectively store and capture trends from data. However, choosing a suitable cloud for IoT applications remain a challenging task. The main objective of this research is to develop a methodology for measuring different indoor parameters with the ability to store large amounts of data and use prediction models to enhance both forecasting and controlling ability. This paper’s objectives include both evaluating and predicting indoor air quality in buildings. It reduces the gap of studying the relationship between indoor and outdoor air quality. The study identifies IAQ parameters and their different detection technologies in order to investigate how IoT technology can be utilized. Finally, an IoT system is developed to provide real-time measurements with the ability to store large amounts of data for the application of prediction models.

2. Literature Review

Over the last five decades, the human population has increased rapidly and urban areas have expanded as a result. Such an increase has a significant impact on our environment. The extensive use of transportation and manufacturing activities has caused a significant increase in greenhouse gases (GHGs) and a continual increase in Earth’s temperature. The last decades witnessed a continuous improvement in air quality monitoring technologies, which facilitated further studies to inspect the relationship between air quality and climate changes. Air quality studies from the past and present will improve our understanding of air pollution, health effects, and ecosystem viability [5]. In Europe, different scenarios have been applied, including the effects of fuel consumption as a result of factories and transportation activities, in order to evaluate air quality policies. Crippa et al. [6] concluded that air quality measures and policies, if accurately implemented, can control pollution and, subsequently, health is enhanced. In India, Rajak et al. [7] presented a comprehensive review regarding short- and long-term exposure to air pollution and its effects on human health. It was noted that despite air pollution exposure occurring in both urban and rural areas, air pollution monitoring systems mainly collect data from mega cities, which implies that many cases in rural areas are frequently neglected. Arsic et al. [8] also predicted ozone concentrations depending on different air quality parameters, including CO, H₂S, and SO₂. Other factors were also investigated, including wind speed, wind direction, and air pressure. The study utilized multiple linear regression analysis and compared the results with an artificial neural network (ANN). The results showed that the ANN demonstrated better performance when incorporating different primary concentrations and meteorological factors. It was concluded that predicting air quality variables is better modeled by ANNs to consider any nonlinear relationships.

Tran et al. [9] presented a procedure to assess personal exposure (PE) to airborne particulate matter (PM) across diverse microenvironments (MEs). The procedure was performed over 24 h. Considering different exposure scenarios is necessary to identify appropriate strategies to improve urban air quality and mitigate the health effects of PM. The researchers concluded that there are potential carcinogenic risks associated with long-term exposure to elevated levels of PM_{2.5}-bound toxic trace elements. Zhou and Ooka [10] studied the feasibility of adopting deep neural networks (DNNs) for predicting indoor airflow distribution; they investigated the influence of DNN architecture on prediction performance, considering two DNNs for different prediction strategies. The performance of the two DNN architectures was tested on both a training dataset and a test dataset,

which were compared. Qiu et al. [11] performed an experiment to continuously monitor the variability of indoor particulate matter in six office buildings in Chengdu, Sichuan Province. Four out of the six buildings showed a reduction in indoor PM_{2.5} during work hours, suggesting functional filtration systems. The results indicated that the daily accumulation of indoor CO₂ was due to ineffective ventilation. Khaniabadi et al. [12] modeled air quality for health risk assessment and focused on selected parameters such as sulfur compounds and fine particles. Data collected hourly were used to accurately calculate the average daily concentrations. The study concluded that mitigation policies are needed to be taken by governments to control air pollution, especially fine particles. Steinemann et al. [13] illustrated that green buildings might not result in better IAQ. Many developers in recent years have aimed to certify their building as a green building. Although certificates have minimum requirements in order to gain IAQ credits, it was noticed that many buildings may obtain certification without satisfying the IAQ requirements. Luo et al. [14] shed some light on the relationship between occupants' indoor climate experience and their thermal comfort expectations in buildings. The study emphasized the need for physical measurements, and encouraged the review of the current indoor environment standards. It is usually claimed that ventilation will lead to better IAQ. Francisco et al. [15] conducted an in-depth study of ventilation effects on IAQ and occupants' health in households. It was concluded that more studies are needed in order to discover the relationship between ventilation and IAQ. In New Zealand, Bennett et al. [16] studied sources of pollution for the indoor environment, and it was concluded that school location highly affected the IAQ. Hesarakı and Huda [17] analyzed and discussed radiant low-temperature heating (LTH) and high-temperature cooling (HTC) systems based on their results on energy usage, thermal comfort, indoor air quality, design, and control. The authors concluded that LTH/HTC systems can save between 10% and 30% energy and provide better thermal comfort in comparison with all-air systems.

Jin et al. [18] investigated the relationship between lung cancer and poor indoor environment to provide a base for future studies related to IAQ. The results showed that the pollution sources linked directly to lung cancer are smoking, indirect smoking, oil fumes, coal used for cooking, and solid fuel used for heating. In Egypt, Osman et al. [19] studied IAQ in hospitals as the indoor environment is highly critical and needs to be continuously monitored and controlled. It was concluded that further studies need to investigate the dispersion of different contaminants. Maesano et al. [20] studied the relationship between pollution sources and health effects. It was observed that there is a lack of studies for IAQ in educational buildings, and a poor indoor environment greatly affects students' performance. Chang et al. [21] studied indoor decoration materials and their relationship with IAQ, and concluded that sources of indoor pollution included wall decorations, panel furniture, and latex paints. The study concluded that an increase in temperature will lead to an increase in pollutant concentrations, and ventilation will positively decrease concentrations. Mutis et al. [22] utilized IR sensors to detect indoor motion and to predict the occupants' activities using deep learning to balance between the energy consumption and the indoor environment through optimizing the working hours of the HVAC systems. Jang et al. [23] developed a neural network that enhanced the use of a building energy management system (BEMS) to overcome the lack of historical data for prediction and provide better thermal control. Heracleous et al. [24] investigated the indoor comfort conditions in classrooms by collecting and analyzing in situ measurements of relative humidity, temperature, and CO₂. The recommendations included the need for natural ventilation at a low air change rate to keep the indoor air quality within the limits provided by international standards.

Amoatey et al. [25] reviewed IAQ studies from the Gulf Cooperation Council (GCC) countries. People from this area spend most of their time indoors due to dust storms, inconvenient temperatures, and relatively high humidity. The review results showed that mitigation studies and IAQ modeling are urgently needed. The recommendations included studying the effect of multiple pollutants on health compared to a single pollutant, and

that future studies should focus on rural areas instead of only concentrating on urban areas. Cao et al. [26] studied the associations between air pollution, outdoor activities, and symptoms of wheeze and rhinitis for pre-school children in Wuhan and the surrounding cities. The research provided a guide to the design of outdoor activities and outdoor courses for pre-school children during the process of urban construction.

Jin et al. [27] monitored unauthorized intrusion on construction sites to reduce safety incidents using IoT-based methodology. They developed a monitoring system and provided means to plan countermeasures such as a reward and punishment mechanism. Rafsanjani [28] proposed an approach to control occupant energy-use behavior through combining IoT technologies with behavior intervention techniques to enhance energy savings. The study was able to track individual occupants' energy-use actions to identify inefficient behaviors, and to drive energy-saving behaviors. Boje et al. [29] investigated the integration between building information modeling (BIM) and digital twin (DT) concepts to revolutionize the construction industry. The study also stated that the cyber-security of large-scale infrastructure concerns will remain an issue for years to come. Asif et al. [30] utilized system dynamics tools to report the indoor CO₂, temperature, and relative humidity levels within naturally ventilated classrooms, and the records of ventilation rates were presented. The study concluded that the CO₂ levels remain almost the same when comparing between summer and winter seasons. Lei et al. [31] investigated the use of different neural networks to evaluate the air quality within shopping malls, and compared the results between the fuzzy neural network and Elman neural network to test the use of a wavelet neural network. The study proved that the wavelet network is optimized by the use of a rough set to reduce the redundant attributes, and can accurately evaluate buildings' IAQ.

Zhou et al. [32] proposed a multi-output neural network to improve air quality forecasts. The model depended on multiple input sources from different monitoring stations. The factors measured included PM_{2.5}, PM₁₀, and NO compounds. The model used long short-term memory (LSTM) in the network architecture for adding memory capabilities to the network. The network proved effective in recognizing complex air quality patterns compared to shallow networks. Khazaei et al. [33] presented a network to predict carbon dioxide (CO₂) concentrations for indoor air based on room parameters. The results showed that CO₂ can be accurately estimated based on temperature and humidity measurements; thus, a strong relationship exists between these air quality parameters. The study indicated that such results can improve ventilation studies and the control of indoor environments. For further studies, it was suggested that more rooms should be monitored to collect more data and to study other air parameters, as these may affect CO₂ concentrations. Johnston et al. [34] also applied a system that is able to measure fine particles. The system is considered a low-cost option, since it costs less than USD 100. Although the developed system showed accurate results, its lack of mobility, due to the need for a continuous power supply, is considered a major limitation for scalability.

Previous research efforts have either concentrated on the IoT solutions without performing a reading analysis, or focused on the IAQ processing and prediction models, which are based on previously collected data, without considering either real-time readings or outdoor environment effects on the indoor environment. Any applied solution for assessing IAQ needs to provide the continuous monitoring of critical parameters with easy access to the collected historical data. IoT technologies are a promising method for collecting environmental measurements, but in order to develop a full comprehension, advanced modeling is required. The literature presented different modeling techniques for predicting IAQ, but frequently failed to include outdoor variables within their inputs.

3. Air Quality Parameters

The following sub-sections identify the main parameters that are essential to evaluate the IAQ. Thermal comfort, including temperature and relative humidity, varies based on occupants' preferences. Air pressure is a main component in order to control the

indoor environment. Carbon dioxide concentrations indicate the air circulation rate within confined spaces. Carbon monoxide is a toxic gas that causes poisoning. Fine air particles can accumulate in the human lungs, causing different respiratory diseases. Finally, the relationship between the outdoor and indoor environment is a crucial factor for controlling internal spaces.

3.1. Thermal Comfort

According to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE Standard 55-2017 [35]), thermal comfort is an expression of satisfaction with the surrounding thermal environment, and that satisfaction is evaluated subjectively according to the human condition of mind. Thermal comfort is greatly affected by clothes, air temperature, relative humidity, and air speed. In addition, the occupant's expectation is considered an important psychological factor. In buildings, improvement in indoor air quality greatly increases productivity and contributes towards the provision of a healthy environment [36]. Thus, keeping the surrounding environment within an acceptable range of temperature and relative humidity is one of the objectives to control IAQ.

3.2. Air Pressure

Air pressure is the weight of air molecules that press on objects. Temperature and wind have a significant influence on building pressure. All controlling systems and mechanisms installed in buildings to provide thermal comfort either result in high pressure in buildings or low pressure. A slightly higher pressure will keep hot air outside of the building during summer, and in winter, low pressure will allow outside air inside, which will stabilize the humidity. Controlling air pressure inside the building is key to a comfortable indoor environment.

3.3. Carbon Dioxide

Carbon dioxide (CO_2) is a gas with no color that consists of one carbon and two oxygen atoms. The gas results from aerobic organisms as they metabolize carbohydrates and lipids. Other sources of the gas include volcanoes and hot springs. It is the main component of the surrounding air and is essential to all forms of life. It is also a versatile gas that can be used for different industrial purposes. Since the industrial revolution, the concentration of CO_2 has been increasing rapidly, leading to global warming and the acidification of oceans and seas. According to the National Oceanic and Atmospheric Administration [37], the concentration of CO_2 gas reached 417 ppm in 2019. The growth rate in 2019 was 2.2 ppm, which is highest rate for the last 10 years.

3.4. Carbon Monoxide

Carbon Monoxide (CO) consists of one carbon atom bonded with one oxygen atom. It is a colorless and odorless gas. The gas is known for its toxicity to all beings that depend on hemoglobin to carry oxygen through the blood stream. CO is generated from the partial oxidation of carbon compounds. During the burning process, the carbon compounds are decomposed to CO_2 , but the lack of oxygen during the burning process leads to the formation of CO gas. According to Omaye [38], fatal air poisoning in many countries is mainly caused by CO poisoning.

3.5. Fine Particles

According to the United States Environmental Protection Agency [39], fine particles (also known as particulate matter) are a mixture of tiny solid and liquid particles that exist in the air. Particles such as dust may be seen by normal eyes, but other particles may need a microscope to be seen. Both the size and shape of the particles vary greatly. Particles are emitted directly from fires, unpaved roads, and construction activities. Other sources of particulate matter (PM) include chemical reactions in the atmosphere and industry emissions. The most common PM types are PM_{10} and $\text{PM}_{2.5}$, which are classified based on the

diameter of the particle, being either greater than 10 micrometers or 2.5 micrometers. The classification is important, since particles less than 2.5 micrometers can easily accumulate in the lungs and enter the blood stream.

3.6. Relationship between Indoor and Outdoor Air Quality

The relationship between indoor and outdoor air quality is represented in the literature either as a model or a conducted experiment. The modeling approach often depends on computer simulation or attempting to develop a comprehensive relationship starting from basic mathematical equations. On the other hand, the experimental approach typically requires sampling using advanced instruments and a controlled environment in order to acquire accurate results. Software is available to simulate the relationship between the indoor and outdoor environments to predict pollutant concentrations in small spaces, but it is also able to simulate the air flow and provide pollutant predictions for entire buildings or complex projects. Such a methodology provides guidelines for designers to integrate the results with designs and to improve HVAC performance. The disadvantage of modeling is that during the facility operation, the simulation might not be that useful for controlling the indoor environment, and there will be a need for further experiments to account for the actual activities of the occupants and changes to the outdoor environment. Thus, in order to control the IAQ, there is a need to link the sampling and software simulation to better improve decision making.

4. Research Method

The proposed system activities for evaluating IAQ in academic buildings are depicted in Figure 1. These tasks can be grouped into four main phases, including developing the IoT module (Phase 1), which consists of microcontrollers connected with sensors; then, the data are transferred (Phase 2) via Wi-Fi to a designated cloud to be accumulated for deep-learning model application (Phase 3) to enhance the prediction and visualization of IAQ (Phase 4) analysis.

4.1. IoT Module

Internet of Things (IoT) technologies are rapidly developing and provide huge possibilities in terms of satisfying our changing needs. IoT applications are being integrated into all aspects of our life, from Smart Cities to controlling small equipment in factories. The technology facilitates the collection and analysis of huge amounts of data and supports the decision maker with real-time information to maximize the output results. IoT technology includes the following five steps:

- Data ingestion: IoT devices collect data from different environments.
- Data transmission: the collected data are then transmitted to a cloud via an internet service.
- Data processing: once the data are collected and transmitted, the IoT platform contains different algorithms to analyze the data.
- Data visualization: the information that results from processing is then provided to the end user in an interface or as an alert via text messages or emails.
- Data prediction: over time, the accumulated data can be used to provide trends and to introduce predictions.

An IoT application typically consists of microcontrollers attached to sensors, which collect different readings from the surrounding environment and send them to an IoT platform via an internet service. Monitoring air parameters has been a goal for IoT developers. The measurement and evaluation of air conditions were being investigated a long time ago, but with the innovation of IoT technology, providing real-time information is possible and responses to events have become faster than ever.

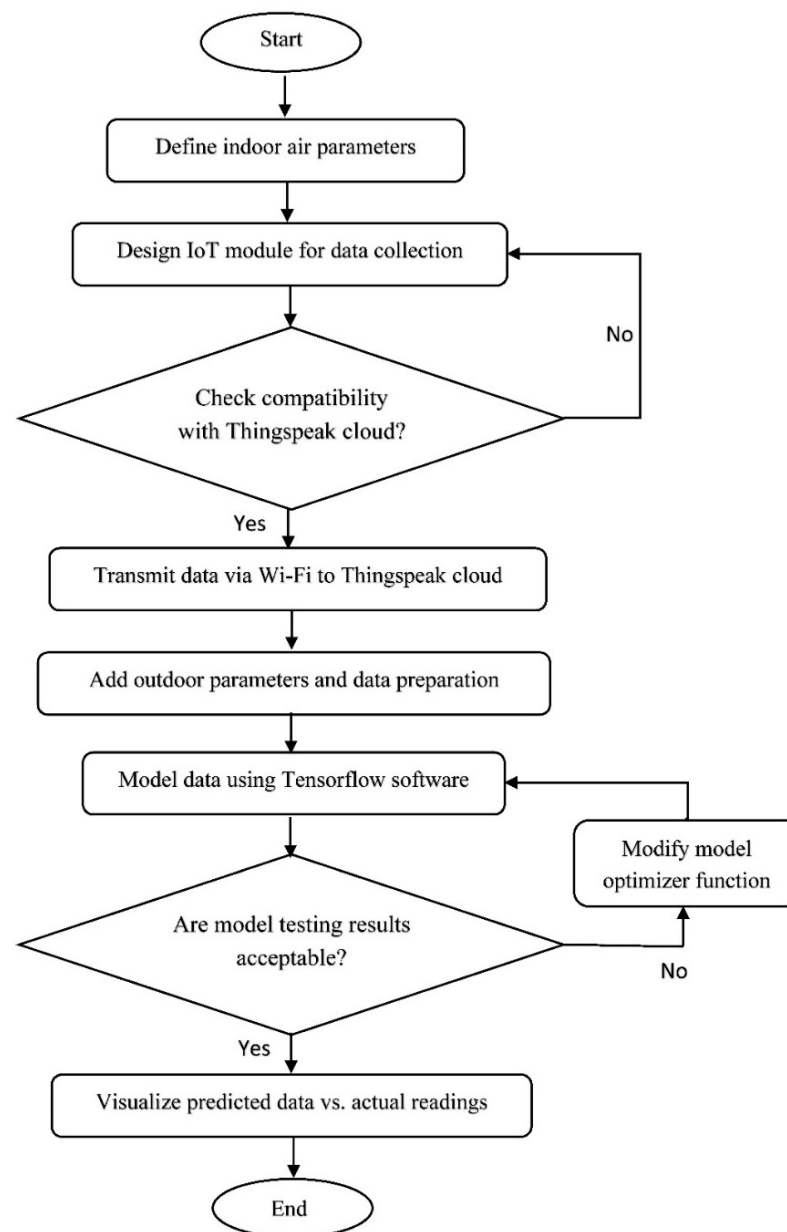


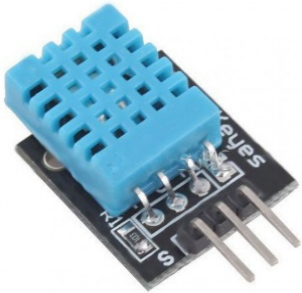
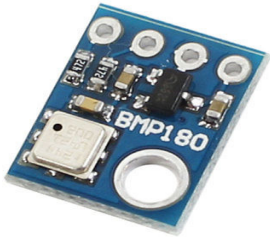
Figure 1. IAQ system flowchart.

Thingspeak [40] is an open-source IoT platform established in 2010 that aims to revolutionize IoT applications by providing cloud services to improve applications' scalability. Thingspeak is divided into channels, where each channel contains eight fields that collect data from sensors and present real-time data visualization. There are some key capabilities that make Thingspeak unique among other common IoT platforms. The following are some of Thingspeak's characteristics, which enable IoT designers to:

- Easily set up devices to directly connect to the cloud services.
- Present collected sensor data in different charts according to each field.
- Use the powerful features of MATLAB to deeply analyze the sensor data.
- Schedule specific analytics to run based on certain events.
- Prototype IoT applications without the need for any web or server programming.

Table 1 lists the components and their respective designated functions of the proposed IoT application. Figure 2 illustrates sensors connection with ESP32 Microcontroller.

Table 1. Designated functions of IoT application components.

Component	Function	Illustration
ESP32 Microcontroller	ESP series, especially ESP32, provide the designer with unique abilities including Bluetooth and Wi-Fi connections to enable the board to act not only as a microcontroller, but also as gateway for different IoT applications.	
DHT 11	DHT 11 is used to measure both temperature and relative humidity, and then it changes the received analog signal to a digital signal. This simplifies the use of the sensor and enables compatibility with any microcontroller with no need for prior calibration, as it gives a calibrated digital signal output [41]. The sensor is tested when attached with an ESP32, and the uploaded code contains specific lines to allow the sending of readings directly to the Thingspeak platform. Sensor error: max. 5% for humidity and 2 °C for temperature.	
BMP180	Pressure sensors that are compatible with microcontrollers usually adopt a three- or four-pin interface connected to a ground (Gnd) pin, power (Vcc) pin, and data pin. BMP180 is a highly accurate barometric pressure sensor with an embedded temperature sensor for different purposes, and is fully calibrated by the manufacturer as a ready-to-use sensor [42]. Sensor error: max. 0.12 hpa.	
MQ135	MQ135 is an electrochemical sensor designed specifically for IAQ applications. The device is highly sensitive to CO ₂ gas and is known for its stability and long life. Reliability and calibration of the sensor was evaluated and integrated with the operating code according to Abbas et al. [43]. Sensor error: Chemical sensor errors depend on compound concentrations and vary according to the case study.	
MQ7	MQ7 is specialized in detecting CO and providing accurate readings in parts per million (PPM). It is larger in size and widely used for air quality applications. The sensor's calculations were integrated within the code, as illustrated by Modaresi et al. [44]. Sensor error: Chemical sensor errors depend on compound concentrations and vary according to the case study.	
GP2Y1010AU0F	GP2Y1010AU0F sensor is manufactured by Sharp industries and is well known for its accuracy and durability. It is an optical sensor that uses a laser, as it calculates the number of particles according to their wavelengths. Hsu et al. [45] studied occupants' comfort within indoor environments to evaluate Smart Buildings in Taiwan, and GP2Y1010AU0F was utilized to collect dust measurements. Sensor error: max. 0.1 mg/m ³ .	

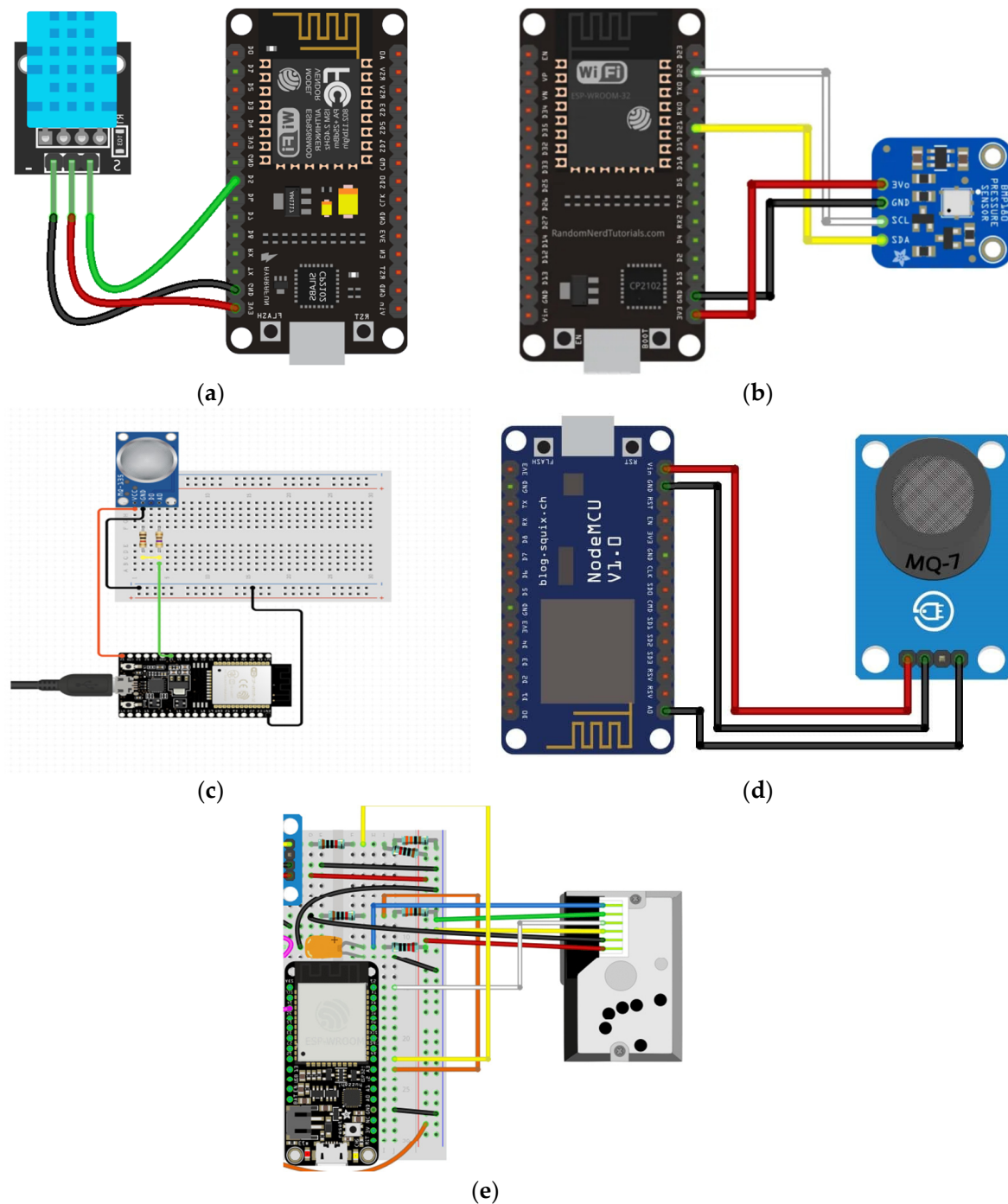


Figure 2. Sensors connected with ESP32. (a) DHT 11, (b) BMP180, (c) MQ 135, (d) MQ 7, (e) GP2Y1010AU0F.

A wooden box of size 27 cm $\times$ 15 cm was designed and created to contain all of the sensors and microcontrollers to create an air-quality monitoring device, as depicted in Figure 3. An IoT box was provided with a moving mechanism at the bottom to allow the sensors, microcontrollers, and batteries to fit in easily as clearly shown in Figure 4. After the box was assembled, tests were performed to make sure that the sensors were sending readings to their specific channel on the Thingspeak platform.

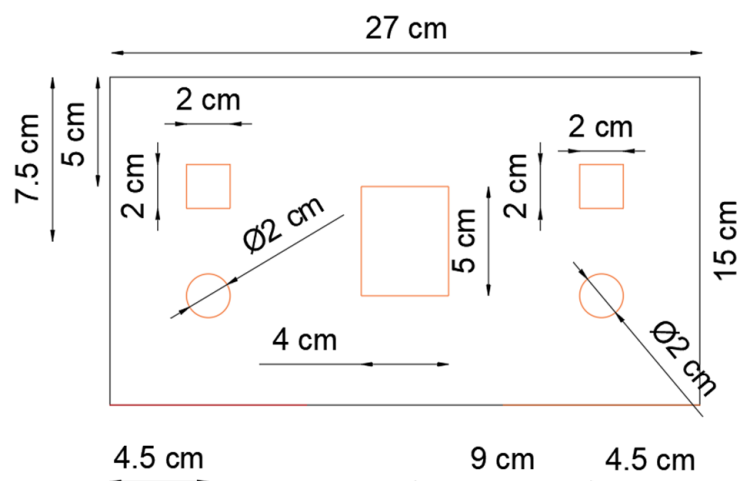


Figure 3. IoT wooden box.



Figure 4. Assembled IoT box.

4.2. Data Transmission

For data transmission, the floor of a university building was chosen to conduct the experiment in different rooms for several days. Figure 5 shows the floor plan and dimensions. For every room, a code was given (for example R1), and a channel was created on the Thingspeak platform. Multiple IoT boxes were assembled so that every room had a box to effectively monitor the IAQ, and all sensors were put at a reasonable height (as close to the middle as possible) and not close to walls and windows. The microcontrollers were programmed to send a reading every 10 min. Each reading contained measurements for temperature, humidity, air pressure, CO₂, CO, and PM. All boxes sent their data via Wi-Fi and the Thingspeak channels were tested to receive the readings. The measurements were collected from all rooms and uploaded to the Thingspeak platform during July and August 2019. Figure 6 shows the monitoring of the collected readings on Thingspeak for the case study.

After collecting readings for 9 days, from 1:00 PM on the 29 July to 1:00 PM on the 7 August, the number of readings totaled 16,764 for 13 different spaces. Many readings were lost due to Wi-Fi instability and the checking of the connectivity of the devices from time to time. Table 2 illustrates the average reading for each day for the whole floor. It can be noticed that the average of the readings varies for temperature and humidity on a daily basis, but for other variables, the readings show steady averages for the floor.

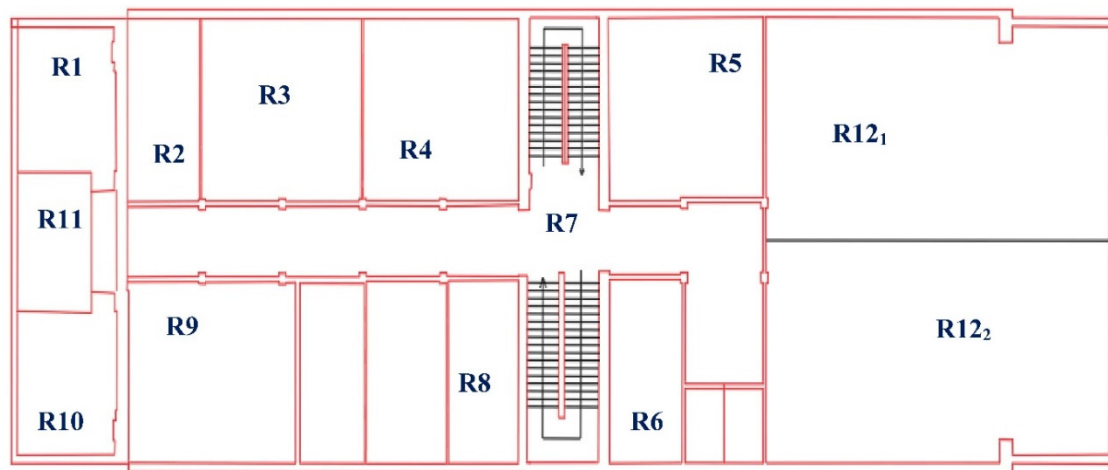


Figure 5. Academic building floor plan.

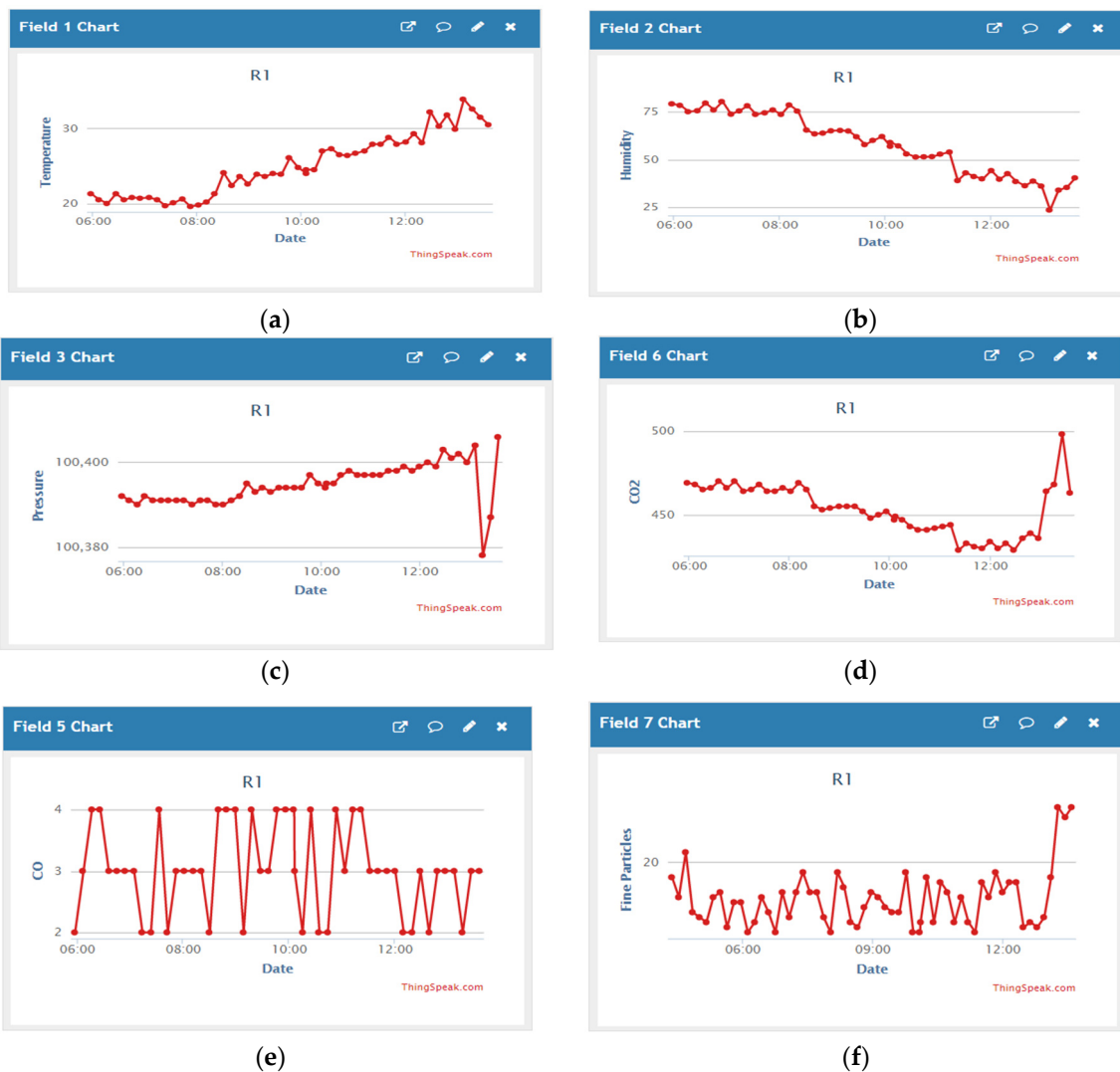


Figure 6. Collected readings on Thingspeak for the considered case study. (a) Temperature field test, (b) humidity field test, (c) pressure field test, (d) CO₂ field test, (e) CO field test, (f) fine particles field test.

Table 2. Average daily readings of the case.

Day	Avg. Temp. (°C)	Avg. Humidity (%)	Avg. Air Pressure (Pascal)	Avg. CO (PPM)	Avg. CO ₂ (PPM)	Avg. PM (μ/m ³)
29 July	34.0	24.1	100,403.2	2.4	463.20	15.30
30 July	29.8	40.0	100,404.3	2.4	460.10	14.20
31 July	29.1	50.3	100,409.1	2.4	474.30	15.90
1 August	28.9	48.2	100,406.7	2.4	477.90	16.80
2 August	30.5	39.5	100,405.9	2.4	448.70	15.20
3 August	30.8	38.6	100,407.2	2.4	459.10	16.50
4 August	30.5	42.3	100,403.3	2.4	471.80	17.20
5 August	29.9	45.6	100,403.8	2.4	461.10	13.50
6 August	28.4	43.8	100,404.1	2.5	459.30	13.70
7 August	24.2	61.9	100,406.7	2.5	460.20	15.10

Table 3 provides more details for each of the studied academic building rooms, and it can be noticed that the space with the code R7 is the hottest in terms of temperature with an average of 31.7 °C, while R2 is considered the coldest. The average CO₂ concentration in room R2 was 475.3 ppm, and since the average in this is the highest, it can be concluded that R2 is the worst in terms of ventilation. R3 contained the least number of fine particles and this was not expected, as R9 is not used on a regular basis and it was expected to have the lowest concentration. The maximum CO reading was 5 ppm, and this was detected in R1, R4, R7, R12₁, and R12₂. In general, the rooms show acceptable readings for CO and particulate matter, and varied for CO₂ according to the ventilation mechanism for each room. The relationship between temperature and humidity can be observed in both R8 and R11, which have one of the lowest temperature averages and the highest average humidity. To extract more information about the rooms, further analysis is needed to develop a comprehensive conclusion about the IAQ.

4.3. Deep-Learning Module

After successfully utilizing the IoT for collecting IAQ measurements, raw data were downloaded from the cloud to be labeled and prepared for modeling. In order to fully understand the indoor environment, outdoor air parameters must be considered; thus, outdoor measurements were added. The Meteoblue [46] database was utilized in this study for collecting outdoor environment historical data. Multiple columns were added, including outdoor temperature, outdoor humidity, outdoor wind velocity, and outdoor wind direction. It can be noticed from Table 4 that CO and dust were excluded from the readings, as their concentrations depend on the occupants' behavior, which is not considered in this study. The table provides a sample of the readings collected from 29 July to 7 August. The total number of readings is 16,764 records. The model inputs include all outdoor variables and the indoor pressure due to the physical relationship between temperature and pressure. The outputs that the model predicts are indoor temperature, humidity, and CO₂ for the 13 different rooms considered in the case study. To facilitate the training process, the outdoor wind direction from Meteoblue was selected to be in degrees rather than text directions (N, E, S, and W) to provide maximum accuracy and the fastest training performance. Moreover, blank readings or missing variables were excluded so that all collected readings contained all variables. Once all of the data were ready, they were saved as Excel sheet files to be imported later to TensorFlow.

Table 3. IAQ readings for the academic building rooms.

Room ID	No. of Readings	Temperature (°C)			Humidity (%)			Air Pressure (Pa)			Carbon Dioxide (PPM)			Carbon Monoxide (PPM)			Particulate Matter (µ/m³)		
		Min	Avg.	Max.	Min	Avg.	Max.	Min	Avg.	Max.	Min	Avg.	Max.	Min	Avg.	Max.	Min	Avg.	Max.
R1	1318	19.3	29.5	39.7	7.3	41.6	82.8	100,390	100,407.1	100,418	422	460.1	511	1	3.3	5	7	14.3	19
R2	1302	20.3	28.2	39.4	8.9	43.4	79.6	100,389	100,405.3	100,423	442	475.3	548	2	2.1	4	5	17.2	21
R3	1285	18.2	30.3	38.5	10.6	45.5	91.3	100,386	100,403.5	100,420	393	440.1	505	0	1.9	3	7	12.9	19
R4	1310	20.8	31.4	38.9	9.7	42.7	85.6	100,389	100,406.2	100,422	416	462.8	514	2	2.4	5	8	16.1	21
R5	1296	21.5	30.5	40.3	8.4	44.8	77.2	100,391	100,407.8	100,426	404	451.3	514	2	3.3	4	10	15.2	21
R6	1300	22.6	29.3	41.6	10.1	45.7	89.7	100,387	100,404.1	100,422	441	473.2	551	1	2.1	3	9	17.8	25
R7	1293	19.7	31.7	37.9	5.2	43.8	85.8	100,390	100,407.7	100,424	428	461.9	538	3	2.2	5	14	13.2	20
R8	1291	21.8	28.8	39.1	7.8	46.4	79.6	100,389	100,407.1	100,425	422	467.1	524	0	2.8	4	4	16.7	21
R9	1275	22.1	30.6	40.5	6.3	45.3	83.9	100,389	100,406.4	100,422	435	471.8	522	1	1.7	4	5	16.3	23
R10	1286	20.4	31.2	39.5	8.5	42.1	79.8	100,391	100,408.7	100,425	413	455.2	527	0	3.2	3	11	15.1	22
R11	1294	19.9	29.7	37.8	5.6	46.4	90.3	100,388	100,405.2	100,423	434	464.7	542	0	2.9	3	9	13.9	20
R12 ₁	1272	21.2	30.9	41.8	7.2	44.4	84.6	100,391	100,408.3	100,426	423	470.1	529	1	2.2	5	13	16.4	21
R12 ₂	1242	20.7	30.5	41.4	7.9	44.2	89.3	100,387	100,404.1	100,421	422	472.3	549	1	2.3	4	12	15.9	20

Table 4. Readings after adding outdoor parameters.

Date/Time	Indoor				Outdoor			
	Temp. (°C)	Humidity (%)	Air Pressure (Pa)	CO ₂ (PPM)	Temp. (°C)	Humidity (%)	Wind Velocity (Km/hr.)	Wind Direction (Degree)
7/29 01:01 PM	30	22.6	100,408.0	430.0	37.3	21.0	16.0	340.6
7/29 01:11 PM	29.8	17.9	100,410.0	431.2				
7/29 01:20 PM	31.1	16.9	100,407.0	430.2				
7/29 01:30 PM	29.1	22.1	100,410.0	430.2				
7/29 01:39 PM	29.3	15.1	100,411.0	430.2				
7/29 01:49 PM	30.6	21.3	100,407.0	430.8				
7/29 01:58 PM	30.3	15.8	100,407.0	431.0				

5. Results Visualization

The Anaconda software interface is an open-source platform for data scientists that provides different libraries and various applications to model and analyze data. The platform supports programming languages including Python and R to facilitate different statistical operations. In this study, the TensorFlow library and Jupyter Notebook web application were loaded through the Anaconda platform to provide essential machine learning functions and to facilitate sharing codes and visualizing the simulation results.

The following libraries and functions were used during the modeling process:

- The *pandas* library provides operations to manipulate data within tables and to import the numerical readings into Excel or csv formats.
- *NumPy* contains high-level mathematical operations, which are essential before loading TensorFlow.
- *Sklearn* provides statistical operations and is used to provide data normalization functions.
- *Matplotlib* is imported to visualize data and modeling results in various graph presentations and comparisons.
- *MinMaxScaler* is used for data normalization.
- *TensorFlow* is imported to start the modeling process.
- The *Keras* library, which operates within the TensorFlow system, is imported for quick modeling, allowing multiple architectures to be tested for better results.

After conducting trials with multiple proportions, the percentages of the data used for training and testing were 80% and 20%, respectively. A validation set was used to independently check the performance of the ANN weights obtained in the training process. This was conducted to ensure that the ANN model had not simply overfitted or memorized the relationship between the training data and the output, but actually developed the capability to make a prediction for an unseen set of data. Figure 7 depicts the predicted (orange line) results against actual (blue line) humidity data of room R7 for the training and testing data, respectively.

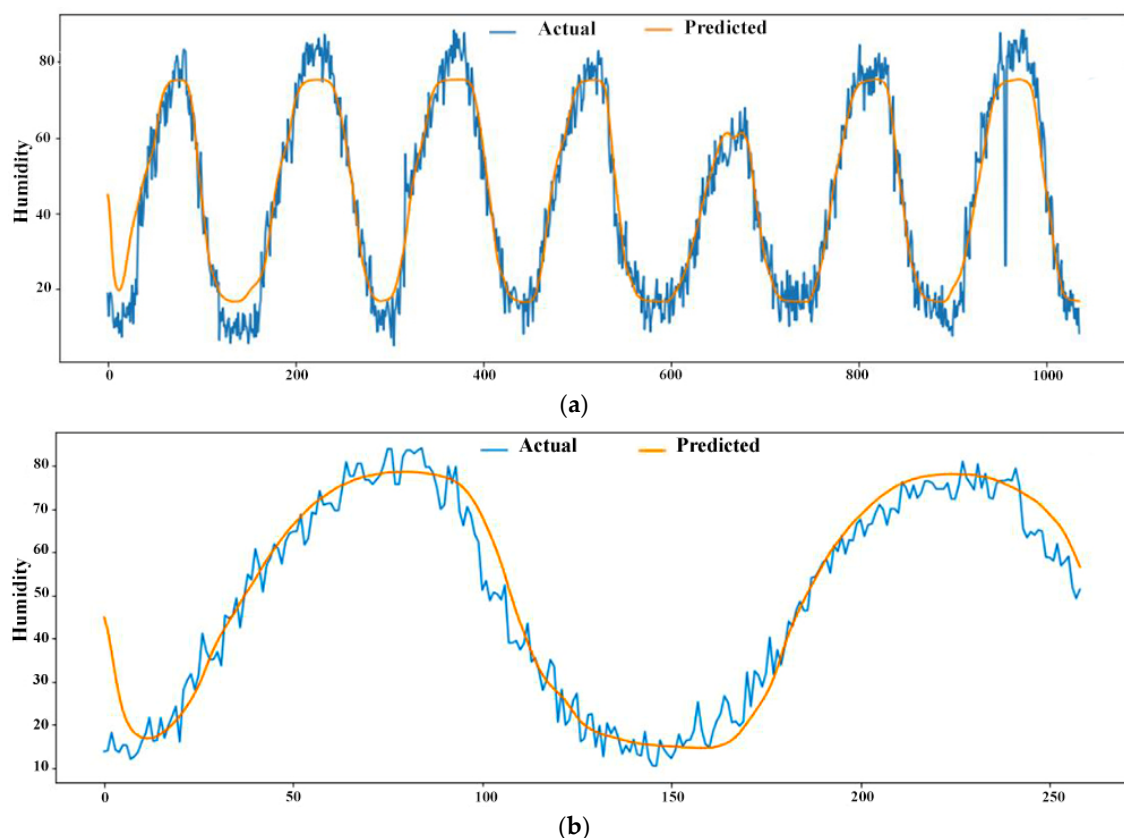


Figure 7. Predicted vs. actual humidity data for R7. (a) Training data, (b) testing data.

6. System Validation

The validation of this research is based on experimental data obtained from the case study, which was previously conducted using IoT technology. It should be noted that despite the model effectiveness in providing acceptable predictions, the model capabilities are limited, as it was developed based on readings collected within a relatively short period of time and during the summer season in different spaces for the same building due to the lack of any formal datasets regarding IAQ in Egypt. In order to enhance the model's predictions and to expand its capabilities, readings should be collected over a long period to cover different seasons and to apply the model to multiple buildings with different uses.

Table 5 lists the model results when applied to different rooms. It can be noted that, in general, the training accuracy is higher than both the validation and testing. In addition, the rooms R1, R3, and R4, which are on the eastern side of the building, provided higher accuracy. However, R2 was exceptional as the use of air conditioning affected the readings and disrupted the relationship between the data, resulting in 80.94%, which is the lowest model accuracy for the testing dataset. In general, the testing accuracy was less than the validation accuracy, but it was noted that rooms R4, R8, and R12₂ provided higher accuracy for testing comparing to the validation datasets. The rooms that provided the lowest test accuracy were R2, R5, R10, R11, R12₁, and R12₂. Despite R12₁ and R12₂ being within the same space (Lecture Hall), the results' accuracy varied, indicating that wide spaces should be divided into smaller areas and that more sensors should be provided to cover the entire area. The average accuracy for training, validation, and testing was 91.07, 87.28, and 85.95, respectively, for the entire floor, but as the model reacted differently for each room, it is important to emphasize the need to study rooms separately when evaluating IAQ in buildings.

Table 5. Model accuracy for training, validating, and testing.

Room No.	No. of Readings	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
R1	1318	93.87	91.21	90.56
R2	1302	86.21	83.15	80.94
R3	1285	92.54	89.26	88.17
R4	1310	93.83	90.11	91.12
R5	1296	90.56	86.17	84.31
R6	1300	89.28	87.49	85.67
R7	1293	91.47	88.51	85.19
R8	1291	89.68	86.30	86.72
R9	1275	90.29	85.64	85.35
R10	1286	91.36	85.78	84.28
R11	1294	87.48	84.93	82.17
R12 ₁	1272	92.75	87.88	84.68
R12 ₂	1242	94.64	88.19	88.23

7. Results and Discussion

After running the model on the 13 room readings collected from the sensors, it is concluded that the model outputs varied for each room, indicating that rooms need to be studied separately, as every room possesses different characteristics including the number of windows, opening measurements, and usage. Moreover, it was noted that the model provided lower accuracy in Room 2 due to the use of air-conditioning systems by the room's occupants, which indicates the need for occupants' behavior to be integrated into the model to enhance the prediction accuracy, as depicted in Figure 8.

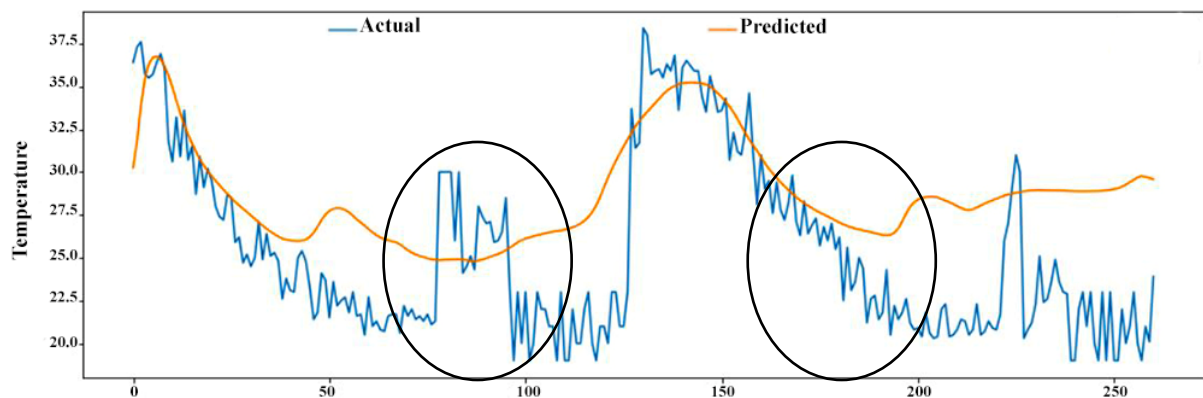


Figure 8. Comparison between actual and predicted temperature for R2.

Another observation was made with respect to the loss of readings, which is attributed to wireless interruptions. Thus, such losses are represented by the discontinuity of the data and disruption over time, which affected the prediction accuracy (see Figure 9). It is worth noting that the accuracy of the model differed based on the rooms' readings and provided, in several rooms, more than 90% accuracy for the predicted data. The high accuracy is regarded as being connected to the case study conditions (low volatile environment during summer), indicating the need to collect more readings during other seasons.

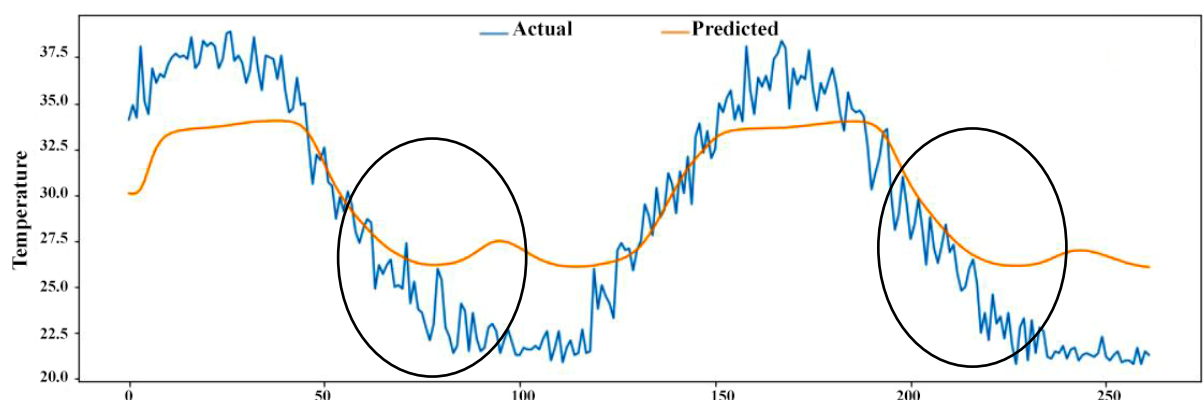


Figure 9. Discontinuity of data and disruptions due to loss of readings for R5.

8. Conclusions

Indoor air quality is the study of air quality within and around different structures. The effects of poor IAQ include health issues, productivity loss, and occupant discomfort. The construction industry is yet to improve IAQ measures and procedures to reduce these harmful effects, as the subject is not adequately addressed within the industry. The most dominant causes of indoor pollution include lack of indoor ventilation, the outdoor environment, building materials, and occupants' behavior. The addressed pollutants in the literature involved temperature, humidity, CO₂ concentrations, CO concentrations, and fine particles (PM_{2.5}). Collecting IAQ measurements requires advanced equipment and significant effort; thus, there is a need for sustainable, reliable, and innovative solutions, which are provided in this study through the Internet of Things (IoT). This research presented a solution to continuously monitor IAQ to assess and evaluate the indoor environment in an educational building using the IoT. The innovative application consists of multiple sensors to collect indoor measurements with the ability to communicate and connect with different microcontrollers. Once the readings are collected, the microcontroller sends them to a cloud via wireless connection. After the collection of the readings, a deep-learning model is developed, where inputs and outputs are identified to train a model in order to discover the embedded relationships between different air quality variables. The integration of

continuous monitoring and the ability to provide numerical relationships between air quality variables paved the way for providing an improved understanding of the interactions within the building's indoor environment.

An academic building was used to test the IoT application, where 13 stations were prepared and positioned in rooms to cover the entire floor. After the experiment was conducted, the readings were prepared and labeled for modeling using TensorFlow, a machine learning library to predict the indoor environment of rooms over time. Outdoor readings were also added to enhance the model for better reliability.

It was concluded that the model should be enhanced with occupants' behavior, as the logical relationships between readings were disrupted. Despite the case study having limitations due to the experiment being conducted during the summer, the model was able to provide highly accurate predictions for the selected deep-learning architecture. Therefore, utilizing the IoT and deep-learning techniques provided an innovative solution to investigate buildings' IAQ, and provided a foundation for developing IAQ standards within the Egyptian construction industry. The research in hand is one of the few available studies that not only provide a solution for collecting real-time readings of multiple IAQ parameters, but also utilize deep-learning techniques to create a prediction model that considers outdoor parameters. Hence, a comprehensive overview was presented to accurately evaluate the IAQ of the investigated indoor spaces. This research can be extended in the future by modeling the effect of occupants' behavior, which influences indoor environments, and providing guidelines to be followed by occupants to cope with indoor air pollution. In addition, more sensors can be integrated to measure more indoor environment parameters such as volatile organic compounds (VOCs), ammonia (NH₃), and ozone (O₃). As such, quantitative analysis can be conducted to provide a benchmark with the results obtained in this research. Furthermore, a digital twin can be used to allow the continuous monitoring of physical facilities and reflect the results in a digital prototype.

Author Contributions: Conceptualization, M.M.; Data curation, M.A.; Formal analysis, M.A.; Funding acquisition, M.M.; Investigation, M.A.; Methodology, M.M. and M.A.; Project administration, M.M.; Validation, M.A.; Visualization, M.A.; Writing – review & editing, M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Academy of Scientific Research and Technology (ASRT), Egypt, JESOR Development Program—Project ID: 5251.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Acknowledgments: The support of the Construction Engineering Technology Lab (CETL)—Faculty of Engineering, Cairo University, is acknowledged. The collaboration with the Ministry of Housing, Utilities and Urban Communities is acknowledged.

Conflicts of Interest: The authors declare no conflict of interest.

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