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Research

Air quality and dust level monitoring systems in hospitals using IoT

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Received: 15 August 2024 / Accepted: 3 March 2025
Published online: 11 March 2025

Abstract
Maintaining good indoor air quality is crucial in buildings dedicated to enhancing the health and well-being of their occupants. This challenge becomes even more complex due to the diverse range of users and spaces within a single institution. Different areas, such as operating rooms and waiting rooms, require specific air quality standards, tailored to the varying health conditions of patients and visitors. Poor air quality can hinder hospital staff in performing their duties effectively and affect patients' comfort during recovery. Hospitals can now achieve indoor air quality standards cost-effectively through Internet of Things (IoT) technology. The IoT enables remote monitoring, offering greater control over indoor conditions like air quality, temperature, humidity, and dust levels. This system monitors air quality, dust concentration, temperature, and humidity within healthcare facilities, sending notifications to staff via an app and push alerts when readings exceed normal levels. It utilizes the MQ135 sensor for air quality, the GP2Y1010AU0F optical dust sensor, and the DHT11 sensor for temperature and humidity, all interfaced with NodeMCU through the Arduino IDE. Data from these sensors is stored on a cloud platform and displayed in a mobile app, with near real-time monitoring from sensors placed throughout the facility. A time-series algorithm, such as Autoregressive Integrated Moving Average (ARIMA), is used to forecast temperature and humidity trends in wards. The system alerts staff when indoor temperature exceeds 27 °C, triggers warnings when air quality surpasses 500 ppm, and issues critical alerts for levels above 650 ppm. Sensor data, sent to the cloud every 120 s, provides staff with insights to better plan actions to improve indoor air quality.

Article Highlights

- This system provides a comprehensive overview of hospital environments by tracking air quality, dust, temperature, and humidity simultaneously, offering a more complete picture of indoor conditions than systems that focus on fewer parameters.
- The use of IoT technology enables real-time monitoring and alerts, allowing hospital staff to respond immediately to any issues. Additionally, predictive analytics anticipate future changes, giving staff time to take preventive measures.
- The integration with a mobile app and cloud-based data storage ensures easy access to data, convenient monitoring, and the ability to scale the system across multiple hospital facilities, catering specifically to the unique needs of different healthcare environments.

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Keywords Air quality · Dust level · Monitoring systems in hospitals · Internet of things

1 Introduction

Hospital acquired infection (HAI) transmission has been linked to poor environmental hygiene, and increased cleanliness monitoring is currently in place to prevent further growth in this area. This project aims to lower the risk of infectious disease epidemics while improving the overall health of the population. In a hospital setting, cleanliness is essential not only in wards and operating rooms, but also in all public areas, including waiting rooms, public restrooms, cafeterias, and chapels. Hospitals are hotspots for infectious diseases because of the enormous number of individuals seeking treatment for various illnesses. In the upkeep and operation of such institutions, hygienic criteria, such as air quality and dust levels, as well as upholding safety regulations, are critical. It aids in the reduction of contagious illnesses and bacteria and pathogen transfers to unwitting inpatients, outpatients, convalescents, medical staff, visitors, and the general public. Deep IoT integration into healthcare systems is becoming a reality. A survey produced by the research company Grand View Research predicted that the worldwide healthcare sector will spend around $ 44.21 billion on IoT hardware, software, and services in 2023 [1, 25].

Hospitals are hotspots for infectious diseases due to the large inflow of patients with various illnesses seeking treatment. Monitoring hygiene parameters, such as air quality and dust levels, and maintaining safety standards plays a pivotal role in the maintenance and upkeep of such institutions. It helps reduce the rate of transmission of contagious diseases, bacteria, and pathogens to unsuspecting inpatients, outpatients, convalescents, medical staff, visitors, and the general community [2].

Hygiene monitoring, a component of environmental monitoring, ensures the effective cleaning and identification of problematic areas requiring redress to improve overall sanitation. As revealed by the scientific community, monitoring indoor air quality is crucial because it affects the health status of patients. It is a complex and dynamic process that considers the physical factors and biological and chemical contaminants generated by both indoor and outdoor environments [3]. This work proposes a model to monitor hygiene within hospital premises based on factors such as air quality and dust. The contributions of the proposed model to other models are as follows:

- Comprehensive Monitoring: Unlike many existing systems that focus on one or two environmental parameters, this system monitors four critical factors: air quality, dust levels, temperature, and humidity. This allows for a more holistic understanding of the indoor environmental conditions.
- IoT Integration for Remote Monitoring: The use of IoT technology distinguishes this system from conventional methods by providing real-time remote-monitoring capabilities. With sensors such as MQ135 (for air quality), GP2Y1010AU0F (for dust), and DHT11 (for temperature and humidity), the system continuously tracked environmental data and sent it to the cloud for analysis and storage. This ensures that data are easily accessible from any location through a mobile application.
- Real-Time Alerts: Existing systems may log data, but fail to provide timely interventions. The proposed system addresses this gap by integrating a notification system that sends in-app and pushes notifications to hospital staff whenever the monitored parameters exceed preset thresholds. This proactive approach helps staff take immediate action, minimizing potential health risks.
- Predictive Analytics: Using time-series forecasting models such as ARIMA to predict future temperature and humidity trends is another significant improvement. This anticipates potential environmental changes before they occur, providing hospital staff with enough time to adjust their air systems or take other necessary actions.
- User-Friendly Mobile Interface: The mobile application that interacts with the system provides users with easy access to environmental data, making it more convenient for hospital staff to respond to alerts or track trends over time. This adds to the practicality and scalability of the solution because it can be deployed across various facilities.
- Cloud-Based Data Storage and Analysis: Storing data on a cloud platform allows for scalability, flexibility, and better data management compared to traditional on-premise systems. It facilitates data analysis over time to identify patterns and optimize environmental conditions proactively.
- Tailored to Healthcare Environments: Unlike generic air quality monitoring systems, this system is tailored to the specific needs of healthcare facilities, where different areas (such as operating rooms, patient wards, or waiting rooms)

may have varying air quality requirements. The system adapts to these different zones, ensuring customized monitoring based on the needs of each area.

The rest of the paper on maintaining good indoor air quality in healthcare facilities using IoT technology is organized as follows. Section 2 discusses the background and related works. The system design and implementation are covered in Sect. 3, and the results are discussed in Sect. 4. Finally, Sect. 5 concludes the paper.

2 Literature survey

Hospitals are hotspots for infectious diseases due to the large inflow of patients with various illnesses seeking treatment. Hygiene parameters, such as air quality, dust levels, temperature, and humidity levels were monitored. Maintaining safety standards plays a pivotal role in the maintenance and operation of these institutions. It helps to reduce the rate of transmission of contagious diseases, bacteria, and pathogens to unsuspecting inpatients, outpatients, convalescents, medical staff, visitors, and the general community. Important work has been done in the field of medical science using IoT to monitor a patient's health [4].

In [5], propose a framework was proposed to monitor hygiene in hospitals by deploying touch sensors at prime points to monitor the frequency of usage, placing sensors to monitor air quality within the hospital premises, deploying sensors at door points to detect the number of people entering the premises, thereby monitoring the level of dust generated by footsteps, and using temperature and humidity sensors to monitor temperature and humidity levels. The model uses Raspberry Pi to control and interface the sensors. The collected data are sent to a Central Controller. A report is generated, and if any action is required, the concerned staff personnel are alerted through SMS. This system is an integrated approach to monitoring cleanliness, dust level, and air quality, thereby providing an efficient system to monitor hygiene in hospital premises.

In [6], a model was designed using a NodeMCU, formaldehyde sensor, dust sensor, DHT22 sensor, and Organic Light emitting diode (OLED) display. These sensors are used for the detection of various environmental parameters, such as particulate matter, carbon monoxide, carbon dioxide, temperature, humidity, and pressure. The data sensed by the sensors were continuously transmitted through the Wi-Fi module of the NodeMCU to the cloud over the Internet. The sensors also display the output of the OLED display. An online application that provides global access to measured data via any device with an internet connection is also designed to be able to readily access these values. This model is designed to be affordable, considering small-scale industries and their cost limitations.

In [7], shows how to utilize a Raspberry Pi to monitor air quality. Sensors can detect particulate matter, carbon monoxide, carbon dioxide, temperature, humidity, and pressure, among other environmental characteristics. The Raspberry Pi was connected to the Arduino Uno through a USB wire, and the sensors were attached to the Arduino Board. The Raspberry Pi continuously transmits the data collected by the sensors to the cloud. The sensors DSM501A, DHT22, and BMP180 have digital outputs and are used to measure temperature, humidity, and pressure. MQ9 (gas sensor) and MQ135 (air sensor) sensors, carbon monoxide, and carbon dioxide were measured using the analog sensors MQ9 (gas sensor) and MQ135 (air quality sensor). This configuration offers a low-power, small, and highly precise system for remotely monitoring the environment using specialized sensors from any location in the world.

In [3], a study on indoor air conditions suitable for the hospital environment was provided. From this study, we can infer that temperature in hospital wards should be above 21 °C and below 24 °C. The relative humidity in inpatient rooms, communal areas, and, if possible, hallways should have a range of 40–60 percent.

In [8], a GP2Y1010AU0F optical dust sensor and a DHT 22 temperature sensor were interfaced with an Arduino Mega 2560. An Arduino Ethernet Shield is used to connect the Arduino to the Internet. The collected data can be viewed using a mobile web application. To assess the accuracy of this system, a comparison was made with thermometer readings, and an average error of 1.06% was obtained.

In [9], explained how an IoT-based indoor air quality monitoring platform works. It comprises a web server and a device called "Smart-Air" that measures air quality. The device was designed with an expandable interface so that it could swiftly adapt to the environment because the monitoring area changed. Consequently, several types of sensors can be fitted or modified depending on their surroundings. The following sensors were employed in the investigation: a laser dust sensor, volatile organic compound (VOC) sensor, carbon monoxide (CO) sensor, carbon dioxide (CO2) sensor, and temperature-humidity sensor. A color-changing LED strip was also added to the center of the device to visualize air quality. A STMicroelectronics STM 32 F407IG microcontroller was used. The platform utilizes AWS as the server to effectively analyze Smart-Air data, visualize interior air quality, and manage and monitor numerous smart air devices at once.

In [10], examined the air samples from hospital wards designated for patients' treatment in Shahid Mustafa Khomeini Hospital wards in Ilam province, East Iran, and verified positive tests for COVID-19. During the bioaerosols sample, the study provides information on the environmental conditions of hospital wards as well as particulate matter concentrations with various aerodynamic sizes.

In [11], an in-depth study of the literature as well as IAQ assessments in nine hospitals was conducted. Because of the need for anonymity, the IAQ measurements were not included in the publication. The need to have particular administrative strategies for the installation of a hospital IAQ management system was highlighted in this study. The research also identified some pollutants that could be present in hospital air. Carbon monoxide (CO), carbon dioxide (CO2), nitrogen dioxide (NO2), ozone (O3), formaldehyde (CH2O), total volatile organic compounds (TVOC), respirable suspended particulates (RSP), radon, total bacterial count, glutaraldehyde (C5H8O2), nitrous oxide (N2O), and latex allergens are only a few examples. This study also lists and explains various mitigation techniques.

In [12], explores the scope of IoT in healthcare was explored. A variety of distributed devices in IoT-based healthcare can aggregate, analyze, and transmit real-time medical data to the cloud, enabling novel methods of data collection, storage, and analysis as well as the activation of context-based alarms. This study suggests a cloud-based solution for merging all hospital records and, as a result, keeping all patient data in one place.

In [13], the system was capable of measuring air-contaminated gases in real time, such as CO2, CO, NO2, and SO2. The air quality monitoring station and the PC successfully communicated with the sink node via machine-to-machine communication. Various gas sensor technologies were explored for the system, and electrochemical and infrared sensors were eventually chosen along with a graphical user interface (GUI) that allows end users to interact with the system easily.

In [14], this study demonstrates this because we spend almost 90% of our time indoors, on average. The quality of air we breathe determines the environment within the structures. According to scientific research, maintaining the relative humidity between 40 and 60 percent offers considerable health benefits. This humidity range is suitable for proper immune defenses.

In [15], a simple and cost-effective dust monitoring system was developed for determining fine dust levels in a given area. A fine dust sensor was connected to an Arduino-based IoT device, which sent dust-level data to a mobile application in real time. The suggested technology opens up new possibilities for mobile services, such as delivering rapid warnings to nearby customers.

In [16], a smart healthcare system that can track a patient's basic health signals in real time as well as the circumstances of the room in which the patient is now located in an IoT environment was presented. The five sensors used in this system to gather data from the hospital environment include heartbeat, body temperature, room temperature, CO, and CO_2 sensors. The error percentage of the developed scheme was within a predetermined range for each example (5 percent). Medical practitioners are informed of the patients' conditions via a gateway so that they can process and evaluate the patient's current situation.

In [17], iAQ Wi-Fi, an Internet of Things-based solution for indoor air quality monitoring, was proposed. This solution consisted of a hardware prototype for ambient data collection and web/smartphone compatibility for data consultation. The sensing components of this system are a temperature and humidity sensor, CO2 sensor, dust sensor, and digital light sensor. The processing component of the system was an open-source Arduino UNO, and the communication component was an ESP8266 for Wi-Fi 2.4 GHz.

In [18], collected various records and information, the IoT-based Remote Health Monitoring (RHM) system primarily employs both AI and machine learning (ML). On the other hand, ML approaches are widely utilized to construct analytic representations and have been integrated into clinical decision support systems and a variety of healthcare service forms. Patients are offered one-of-a-kind treatment, lifestyle guidance, and care strategy after clinical decision support systems meticulously examine each issue. A patient record system that interacts well with the required sensing devices and gathers structured and unstructured data for machine learning (ML) analysis in a smart city is part of remote health monitoring (RHM) technology and architecture.

Suriano and Prato [27], focus on low-cost particulate matter (PM) sensors, specifically the PMS5003 and SPS30 models. The study highlights how these sensors, though economical and easy to use, have performance limitations such as sensitivity to humidity, which can distort readings. By applying correction factors to account for humidity, the researchers were able to improve sensor accuracy. The paper also uses EPA guidelines to classify sensor applications, showing that PMS5003 sensors can be used for regulatory network supplementation, while SPS30 sensors are more suitable for informal monitoring applications.

Suriano and Penza [28], investigate low-cost gas sensors used for indoor air quality monitoring. They explore calibration techniques to improve the performance of these sensors, which often suffer from issues like cross-sensitivity and instability at zero levels. Their findings show that with appropriate calibration, these low-cost sensors can be made more reliable, even in complex indoor environments.

The pursuit of a better life is correlated with one's health. Owing to several factors, including inadequate health services, significant disparities between rural and urban areas, and physician and nurse shortages at crucial moments, the global health crisis has unfortunately caused a conundrum. Hospitals and other healthcare facilities now use healthcare monitoring systems more frequently, and portable healthcare monitoring devices based on emerging technologies are a serious concern for many governments worldwide. Internet of Things (IoT) technology has facilitated the transition of healthcare from face-to-face consultations to telemedicine.

3 Design and implementation

This study follows a structured, process-oriented approach in which the entire project is broken down into a series of smaller modules. The problem is well-defined and carefully analyzed to produce a complete and unambiguous specification of what the model is required to do. The software development life cycle follows a sequential manner, with the development progressing through several distinct phases. The model follows a data-flow architectural style, in which the input data are transformed into output data through a series of computational manipulative components [20]. Here, the input data were obtained in real time from the sensors. These data pass through various components of the model and are displayed through the mobile application, as shown in Fig. 1.

Figure 2 shows the User Interface Mockup design. The application communicates with the Node MCU via a network connection and wirelessly receives sensor data after processing [19]. Users can examine current Air, Dust, Temperature, and Humidity levels by retrieving data from the Node MCU in real time. The most recent data are presented on the home screen once the users push the refresh button. Once the dangerous levels of any of the parameters are detected, the application turns red to notify the user that there are unsafe conditions in the hospital. On clicking the circular value indicator for any of the parameters, a graph will pop up, showing the most recent data collected by the sensor in real time as well as the model-predicted data.

Figure 3 it shows the procedure in which the project will be implemented. The NodeMCU, which is the Central Controller, connects to the cloud through the Wi-Fi module. The collected data is uploaded to the cloud which has been trained using ML. The data is compared with the trained dataset and if the pattern observed is outside of normal, the concerned hospital staff are alerted to take the required action through the mobile application. The data here refers to the monitored sensor values.

The framework for hygiene monitoring in medical facilities is described in this study based on various variables, including air quality, dust levels, temperature, and humidity levels. The sensors are positioned at the Prime Points to gather data, which is then relayed to the Central Controller, who analyzes it and generates an hourly report. The mobile application then receives this data and uses it to provide the user with the current temperature, humidity, air quality, and dust readings. Through an integrated approach to cleaning, dust levels, and air quality monitoring, the system offers an efficient way to manage hygiene in medical buildings. When harmful amounts are detected, the system sends an alarm to the personnel involved. We suggest using more sensors in the future to collect more environmental data for the improved monitoring of hospital conditions.

A time-series machine learning model was trained using the temperature and humidity readings that were gathered and stored in the cloud and used to predict temperature and humidity levels in the future. The seasonal autoregressive integrated moving average (SARIMA) [19], autoregressive integrated moving average (ARIMA) [19], One-Step Prediction, Multi-Step Prediction, and Autoregressive Integrated Moving Average (ARIMA) models were trained to find the model that predicts with the fewest errors. With root mean squared error levels of 0.67 for temperature forecasts and 2.39 for humidity, the ARIMA model produced results with the lowest errors for both temperature and humidity.

Fig. 1 Proposed system

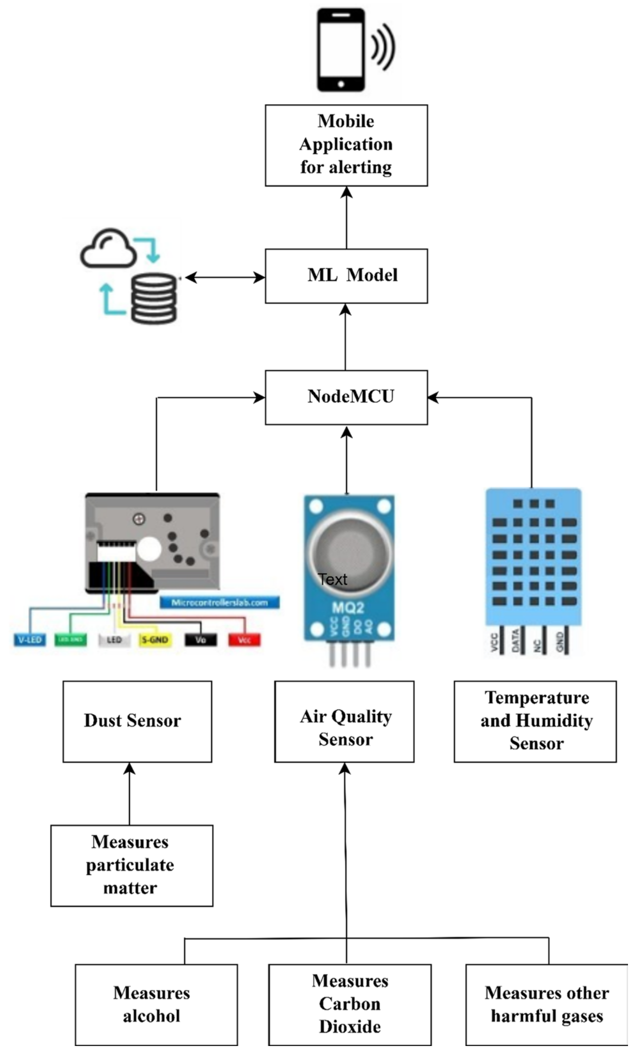
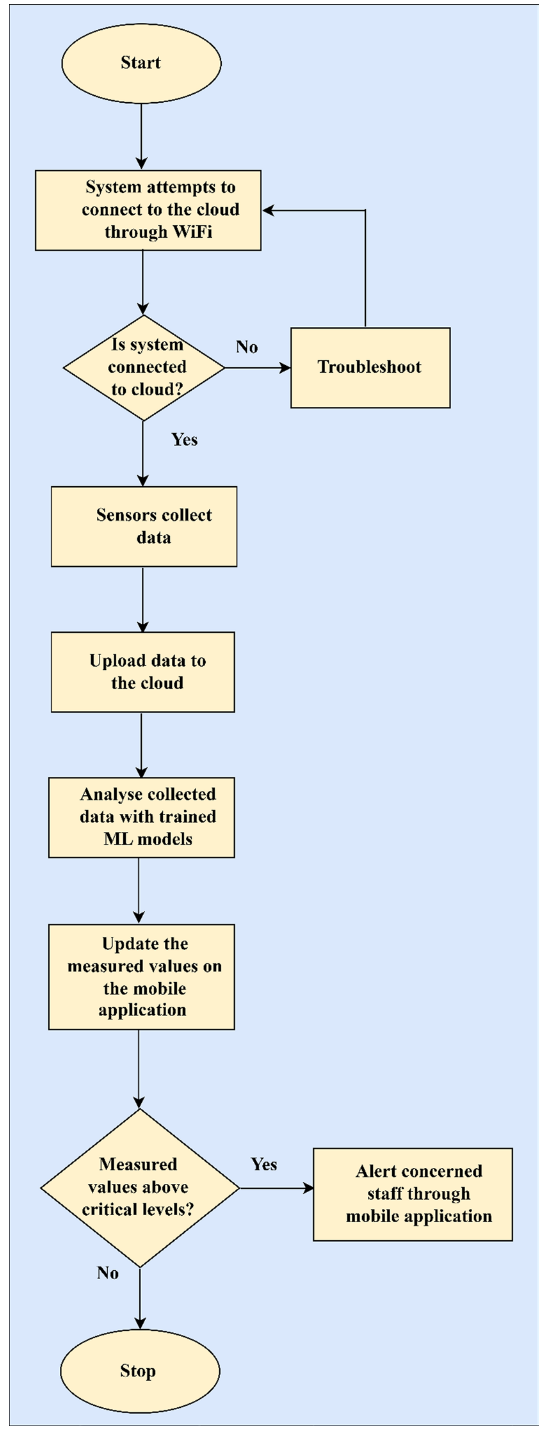


Fig. 2 User interface design for the proposed system

Fig. 3 Workflow of the system



Algorithm Environmental Monitoring and Alert System

1. **Start**
2. **Deploy Systems**
   2.1 Deploy monitoring Systems in prime locations to measure temperature, humidity, dust, and air quality levels.
3. **Initialize Connection**
   3.1 Connect each monitoring system to the cloud via WiFi.
4. **Verify Connection**
   4.1 Check if the system is successfully connected to the cloud.
   4.2 **If the connection is successful**:
   4.2.1 Collect data are collected from the sensors.
   4.3 **Else**:
   4.3.1, Troubleshoot connection issue.
   4.3.2 Attempt to reconnect to cloud storage.
5. **Data Upload**
   5.1 Upload the collected data to the cloud server.
6. **Mobile Application Update**
   6.1 Update the sensor values on the mobile application.
7. **Data Analysis**
   7.1 Analyze the collected data using a Machine Learning (ML) model.
8. **Prediction Generation**
   8.1 Generate predicted values based on analysis.
   8.2 Display the predicted values are displayed on the mobile application.
9. **Critical Level Check**
   9.1 Check if the predicted values exceed the critical levels.
   9.2 **If the values are above critical levels**:
   9.2.1 Alert the concerned staff via the mobile application.
   9.3 **Else**:
   9.3.1 Proceed to collect the next set of sensor values.
   9.3.2 Generate and update the report.
10. **End**

The forecasting intervals for temperature and humidity can significantly impact the utility and effectiveness of the predictions made by the ARIMA model. A well-defined interval helps determine the appropriate planning and response strategies for hospital management.

- Short-term forecasting typically refers to predictions made hours to a few days ahead, which can be particularly useful for immediate operational decisions, such as adjusting HVAC systems to maintain optimal conditions for patient comfort and safety. This can aid in managing daily fluctuations owing to changes in occupancy or external weather conditions.
- Long-term forecasting, On the other hand, long-term forecasting usually covers periods from weeks to months and can provide insights into broader trends, such as seasonal variations in temperature and humidity. This information is essential for strategic planning, such as budgeting for energy costs and preparing for expected changes in patient flow, which might require adjustments to environmental controls.

The utility of predicting temperature and humidity trends lies in enhancing the overall patient care and operational efficiency. Accurate forecasts enable hospital staff to proactively address potential environmental issues before they become critical, thereby ensuring that indoor conditions remain within safe and comfortable ranges. Additionally, by understanding the expected trends, hospitals can implement preventative measures, optimize resource allocation, and enhance their response strategies, ultimately leading to improved patient outcomes and more effective facility management.

3.1 Implementation modules

3.1.1 Air quality module

The MQ-135 Gas sensor can detect gases, such as ammonia (NH3), sulfur (S), benzene (C6H6), CO2, and other harmful gases and smoke. It is used to measure air quality in terms of parts per million (ppm) and is interfaced with the NodeMCU using an Arduino IDE. Figure 4 depicts the connection between the central controller and sensor.

- MQ-135 is for gas detection.
- GP2Y1014AU0F is for dust (particulate matter) detection.

These sensors can be combined to create a comprehensive air quality monitoring system that detects harmful gases and dust levels.

3.1.2 Temperature and humidity module

A basic and inexpensive digital temperature and humidity sensor was a DHT11. It is a serially connected, single-wire, digital humidity and temperature sensor that outputs humidity and temperature measurements. Temperature was measured in terms of degrees Celsius and humidity was measured in terms of percentages. It is interfaced with the NodeMCU using the Arduino IDE [26]. Figure 5 depicts the connection established between the DHT11 sensor and the NodeMCU.

3.1.3 Dust module

The SHARP GP2Y1014AU0F Dust Sensor Module particulate sensor employs an LED to reflect airborne dust particles, similar to how sunlight illuminates the space and makes it easy to detect how dirty the air is. It measures dust in micrograms per cubic metre. It is interfaced with the NodeMCU using the Arduino IDE. Figure 6 depicts the connection between the central controller and optical dust sensor.

3.1.4 Machine learning module

The collected data were also used for training time series models to forecast future values, particularly temperature and humidity values, as these readings tend to vary with time. One-step prediction, multi-step prediction, Seasonal Autoregressive Integrated Moving Average (SARIMA) [21], and Autoregressive Integrated Moving Average (ARIMA) models [22–24]

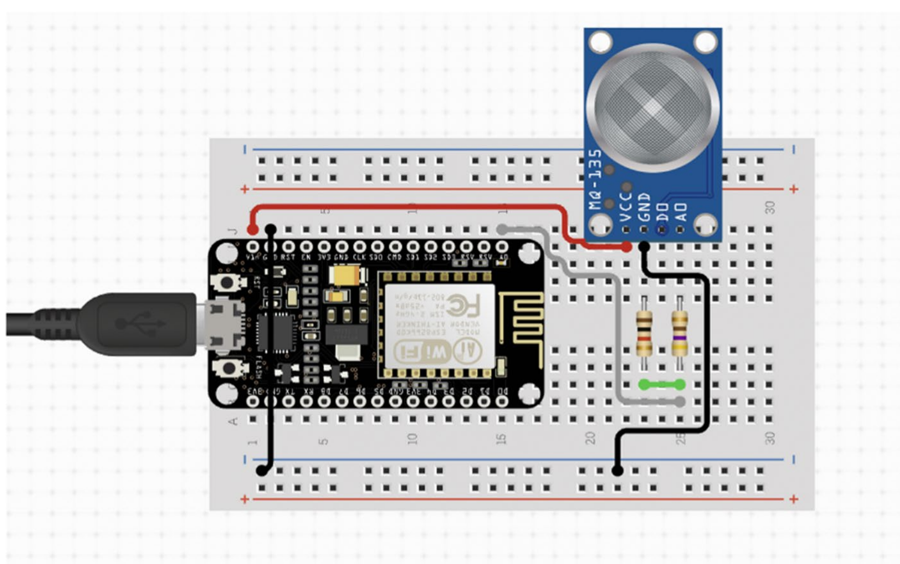


Fig. 4 Connection between NodeMCU and MQ135

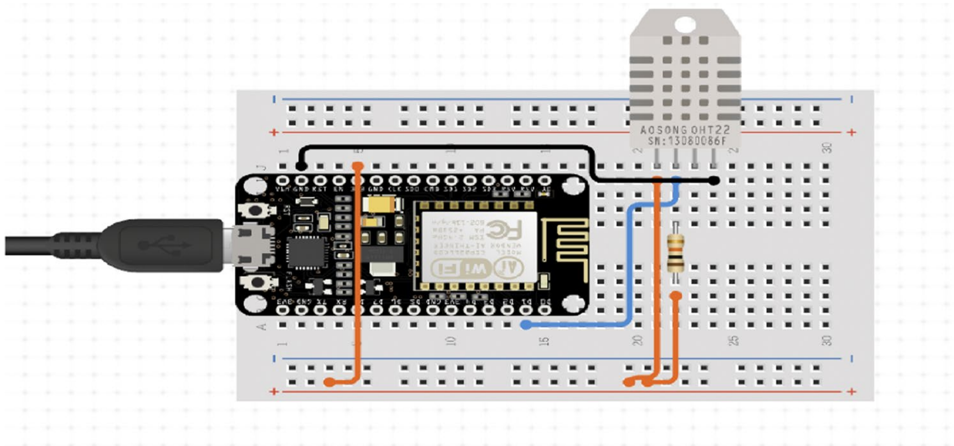


Fig. 5 Connection between NodeMCU and DHT11

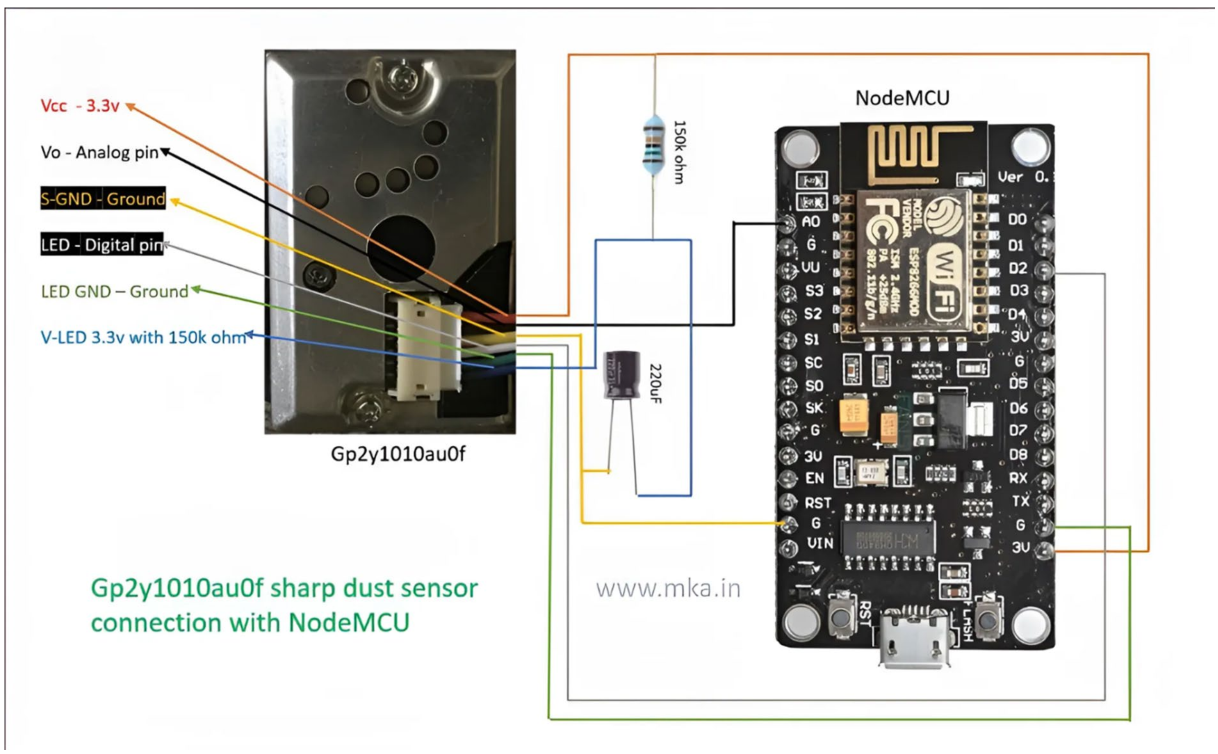


Fig. 6 Connection between NodeMCU and GP2Y1014AU0F

were trained to identify the model that predicted the least errors. The proposed system is implemented using the Arduino IDE to interface the different sensors with the NodeMCU, which is the central controller. The connections to the respective pins were established by connecting wires and a breadboard. The data collected from the various sensors were transferred to the cloud using the built-in WiFi module of the central controller, and the data were later displayed to the hospital staff using a mobile application.

3.1.4.1 One-step prediction One-step prediction refers to forecasting the next value in a time series, given current and past values. In this approach, the model is trained to predict the next value y'_{t+1} based on the current and past observations $y_t, y_{t-1}, \ldots, y_{t-p}$

Mathematically, a simple one-step prediction can be represented as:

$$y'_{t+1} = f\left(y_t, y_{t-1}, \ldots, y_{t-p}\right)$$

where f is the function learned by the model, and p is the number of past observations considered.

3.1.4.2 Multi-step prediction Multistep prediction involves forecasting multiple future values of a time series. There are two main strategies for multistep predictions.

- Recursive Strategy: The model predicts the next value and then uses this predicted value as an input to predict further into the future.

Mathematically, for a two-step prediction:

$$y'_{t+1} = f\left(y_t, y_{t-1}, \dots, y_{t-p}\right)$$
$$y'_{t+2} = f\left(y'_{t+1}, y_t, \dots, y_{t-p+1}\right)$$

- Direct Strategy: Separate models are trained to predict each future step directly.

Mathematically:

$$y'_{t+1} = f_1\left(y_t, y_{t-1}, \dots, y_{t-p}\right)$$
$$y'_{t+2} = f_2\left(y_t, y_{t-1}, \dots, y_{t-p}\right)$$

3.1.4.3 Autoregressive integrated moving average (ARIMA) ARIMA is a popular statistical model used for time series forecasting. It combines three components: autoregressive (AR), integration (I), and Moving Average (MA).

Autoregressive (AR): The AR part of ARIMA models the relationship between an observation and the number of lagged observations (previous values).

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t$$

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t$$

where are $\phi_1, \phi_2, \dots, \phi_p$ the parameters of the model, and ϵ_t is white noise

Integrated (I): The integration part involves differencing observations to make the time series stationary.

$$y'_t = y_t - y_{t-1}$$

Moving Average (MA): The MA part models the error as a linear combination of error terms from previous time steps.

$$y_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q}$$

where $\theta_1, \theta_2, \dots, \theta_q$ are the parameters of the model.

The full ARIMA model is written as:

ARIMA (p, d, q)

where p is the order of the autoregressive part, d is the order of differencing, and q is the order of the moving average.

3.1.4.4 Seasonal autoregressive integrated moving average (SARIMA) SARIMA extends ARIMA to handle seasonality in time series data. It includes seasonal components in the AR, I, and MA components of the model.

The full SARIMA model is written as:

$$\text{SARIMA}(p, d, q) \times (P, D, Q)_s$$

where:

- p, d, q are the non-seasonal ARIMA parameters.
- P, D, Q are seasonal ARIMA parameters (seasonal AR, seasonal differencing, and seasonal MA).
- s is the length of the seasonal cycle.

The SARIMA model equation can be expressed as:

$$\Phi_P\left(B^s\right)y_t = \Theta_Q\left(B^s\right)\epsilon_t + \text{ARIMA}(p, d, q)$$

where $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ represent the seasonal components of the model.

In the context of maintaining good indoor air quality in healthcare facilities, time-series models such as ARIMA and SARIMA, along with one-step and two-step predictions, play a crucial role in forecasting environmental parameters such as temperature and humidity. How these models and prediction methods work.

1 One-Step Prediction

One-step prediction refers to forecasting the value of a time-series variable (e.g., temperature or humidity) for the next time interval based on past observations. In this system, a one-step prediction can forecast the temperature for the next 120 s using previous temperature readings. It is highly useful for real-time monitoring where immediate predictions are needed, allowing the system to alert hospital staff if the temperature is expected to exceed the set threshold.

2 Two-Step Prediction

The two-step prediction extends the one-step approach by predicting the value of a time series for two consecutive future points. For instance, it might predict the temperature not just for the next 120 s but for the following two intervals (240 s). This method provides a short-term forecast that enables staff to anticipate changes slightly further ahead, allowing them to take preemptive actions if the environmental conditions are expected to degrade.

3 ARIMA (AutoRegressive Integrated Moving Average)

ARIMA is a time series forecasting model that combines three components: autoregression (AR), differencing (I for "Integrated"), and moving average (MA). In this healthcare setting, ARIMA is trained on historical data of parameters, such as temperature and humidity, to forecast future values. For example:

- Autoregression (AR) considers past temperature values to predict the next one.
- Differencing (I) was used to make the time series stationary by removing trends or seasonality.
- The moving Average (MA) smoothed out the noise in the data using past forecast errors.

This model can predict future temperature or humidity levels based on past patterns, giving the system the ability to forecast upcoming environmental conditions and send alerts before the thresholds are crossed.

4 SARIMA (Seasonal ARIMA)

SARIMA is an extension of ARIMA, which handles seasonality in time-series data. In healthcare facilities, environmental parameters, such as temperature and humidity, might follow seasonal patterns (e.g., higher temperatures in summer). SARIMA adds a seasonal component to ARIMA, making it better suited to such periodic patterns. It forecasts both short-term trends and longer-term seasonal cycles, helping the facility anticipate changes due to external factors such as weather or seasonal fluctuations.

3.2 Application in indoor air quality monitoring

By implementing these models:

- One-step and two-step predictions allow the system to provide short-term forecasts for immediate decision making.
- ARIMA predicts general trends in temperature and humidity over time, helping the staff monitor gradual changes.
- SARIMA accounts for seasonal variations, enabling better preparation for environmental shifts owing to seasonal factors.

4 Results and discussions

Figure 7 shows the User Interface with Alerts, on air quality.

The Fig. 7 displays real-time data for three environmental parameters through mobile application interface used for monitoring hygiene within hospital premises such as Temperature, Humidity, Air Quality. The system alerts staff when indoor temperature exceeds 27 °C, triggers warnings when air quality surpasses 500 ppm, and issues critical alerts for levels above 650 ppm. Sensor data, sent to the cloud every 120 s.

The Fig. 8 depicts X-Axis (Timestamp): The x-axis represents the time, with the data points indicating specific timestamps. Y-Axis (Temperature in Celsius): The y-axis indicates the temperature in degrees Celsius.

Observed Data (Blue Line): The blue line represents actual observed temperature data over time. This shows how the temperature varies across different timestamps.

ARIMA Forecast (Orange Line): The orange line represents the predicted temperature values generated by an ARIMA (AutoRegressive Integrated Moving Average) model. This line indicates the forecasted temperature values of the model based on past observations. Confidence Interval (Gray Shaded Area): The grey shaded area around the forecast line represents the confidence interval, providing a range within which the true temperature values are expected to lie with a certain level of confidence. A wider shaded area suggests a greater uncertainty in the forecast. The observed temperature data show two prominent peaks around timestamps 20 and 40, indicating significant increases in temperature during these periods. The ARIMA forecast line closely follows the observed data, indicating that the model effectively captures the trend and seasonality of the data. The confidence interval provides a measure of uncertainty, with the observed data generally falling within this range, suggesting that the model predictions are reasonably accurate.

Figure 9 depicts X-Axis (Date): represents the time axis, denoted as "Date," indicating the sequence of data points collected over time. Y-Axis (Humidity % RH): relative humidity values as a percentage (% RH). Observed Data (Blue Line): The blue line indicates the actual observed humidity levels recorded over time. This line represents the ground truth for the data. ARIMA Forecast (Orange Line): The orange line represents the humidity values forecasted by the ARIMA model. This line shows the predicted humidity based on historical data. Confidence Interval (Gray Shaded Area): The grey shaded

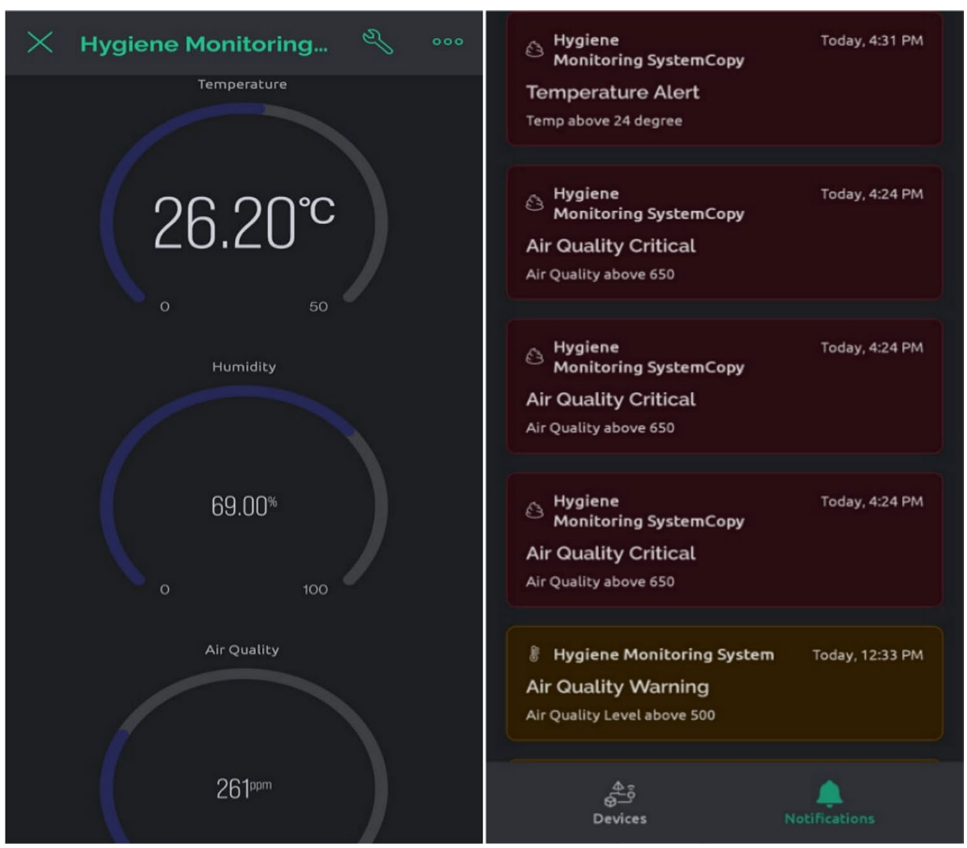


Fig. 7 User Interface with Alerts

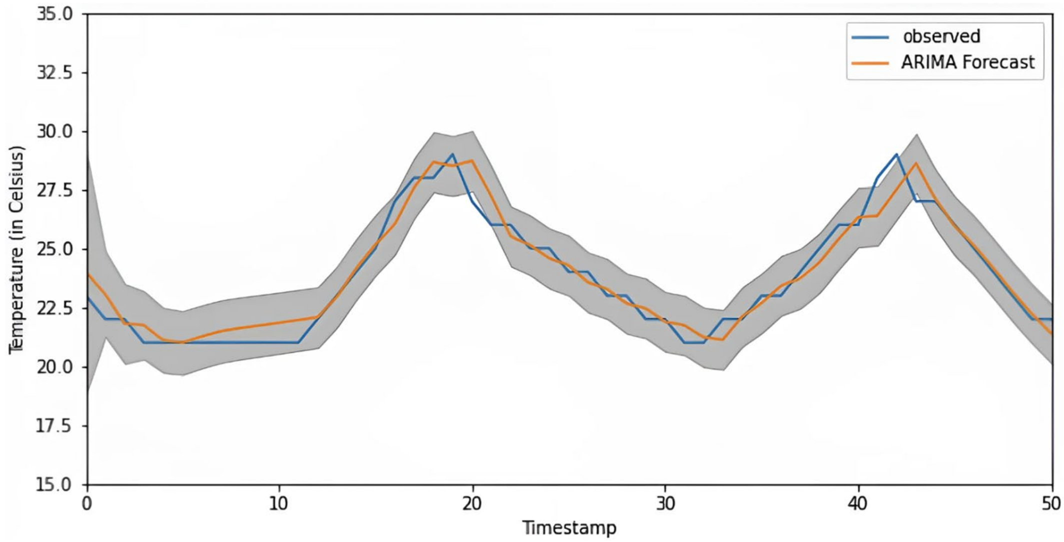


Fig. 8 Comparison between actual and ARIMA forecasted temperature values

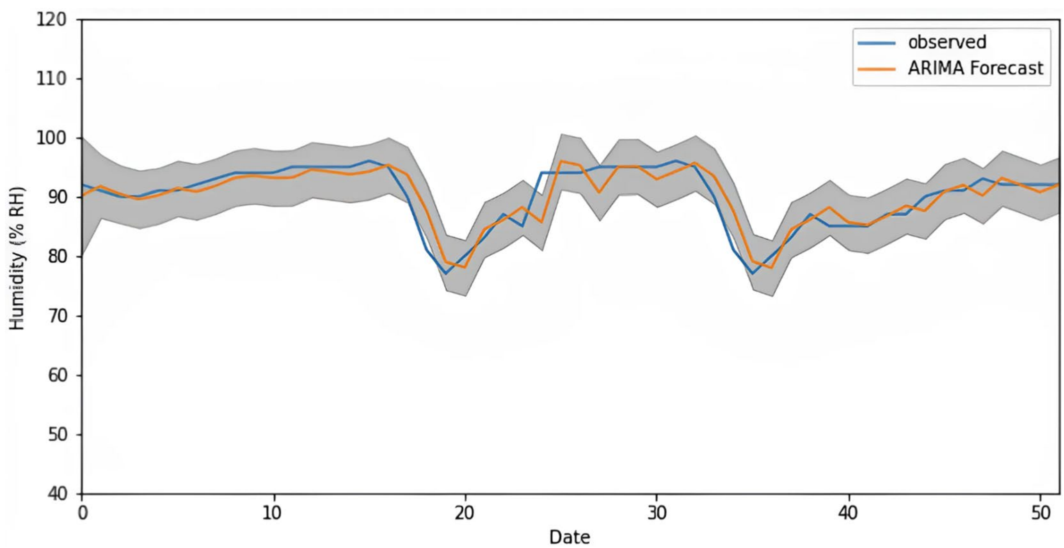


Fig. 9 Comparison between actual and ARIMA forecasted humidity values

area around the forecast line represents the confidence interval, which provides a range within which the true humidity values are expected to lie with a certain level of confidence. The width of the shaded area indicates the uncertainty of the forecast, with wider areas indicating greater uncertainty.

Trends and Patterns: Both observed and forecasted humidity levels showed similar trends and patterns, including peaks and troughs. This indicates that the ARIMA model effectively captures the underlying seasonality and trends in the humidity data.

Peaks and Troughs: Notable dips in humidity can be observed around timestamps 20 and 40, which are reflected in both observed and forecasted data. The ARIMA model accurately predicted these changes.

Forecast Accuracy: The observed humidity values generally fell within the gray confidence interval, suggesting that the model's predictions were reasonably accurate. The closeness of the forecast line to the observed line indicated that the ARIMA model provided a good fit to the actual data. Uncertainty: The confidence interval width varies, indicating the model's varying confidence in its predictions. Narrower intervals suggest higher confidence, whereas wider intervals suggest greater uncertainty.

The observed values in the graph were extracted from real-time sensor data that recorded humidity levels at regular intervals. These data are typically collected using a humidity sensor, such as the DHT11, which measures the

Table 1 Comparison of RMSE (root mean squared error)

Algorithm used	RMSE observed (for temperature predictions)	RMSE observed (for humidity predictions)
One-step prediction	0.907	2.910
Two-step prediction	1.477	4.896
SARIMA	3.51	14.59
ARIMA	0.67	2.39

relative humidity and transmits these readings to a storage system, either locally or in the cloud. Once the data are gathered, they undergo preprocessing, which includes cleaning for missing or noisy values and organizing them into a time series format. The preprocessed humidity readings were then plotted on the graph as the "observed" values (blue line), with time represented on the x-axis and humidity levels on the y-axis. This line reflects the actual recorded values and serves as a benchmark against which the ARIMA model forecast (orange line) is compared.

The Comparison of RMSE for the algorithms used is shown in the Table 1.

Temperature Predictions: The ARIMA model achieved the lowest RMSE of 0.67, indicating that it provided the most accurate temperature forecasts. The one-step prediction method also performed well with an RMSE of 0.907. Despite its complexity, has a relatively higher RMSE, suggesting that it may not have captured the temperature patterns as effectively as ARIMA.

Humidity Predictions: The ARIMA model again showed the best performance with the lowest RMSE of 2.39, followed by the one-step prediction with an RMSE of 2.910. The SARIMA model has the highest RMSE of 14.59, indicating that it is less accurate in predicting humidity levels. Overall, the ARIMA model consistently outperformed the other methods in terms of both temperature and humidity predictions, as indicated by the lowest RMSE values. The data suggest that simpler models, such as ARIMA, may sometimes outperform more complex models, such as SARIMA, especially when the latter does not adequately capture the underlying data patterns. The reason that SARIMA has a higher RMSE than ARIMA for humidity forecasting is likely due to either the absence or weak presence of seasonality in the humidity data. ARIMA, which is simpler and more focused on trend-based prediction, outperforms SARIMA when seasonal effects are minimal.

In all healthcare settings, hygiene monitoring is essential to prevent infection. Hospital hygiene is anticipated to improve because of automated electronic monitoring systems. Hospital hygiene monitoring is essential for preventing patients from contracting serious infections and diseases as well as for preventing the spread of germs and bacteria to visitors and the general public. Ensuring that the patient has a comfortable recovery is as important as treating them for their ailments.

5 Conclusions

Technology development has led to several exciting developments in the medical industry. Studies have shown that the rates of hygiene compliance among medical staff members before and after interaction with patients and the surrounding environment have dramatically increased after the implementation of the IoT management system. This research outlines a framework for hygiene monitoring in medical facilities based on different factors, such as air quality, dust level, temperature, and humidity levels. The sensors are placed at the Prime Points to collect the data, which are then sent to the Central Controller, which analyzes the data and produces a report on an hourly basis. These data are then sent to the Mobile Application, which acts as a user interface and provides the user with current values of temperature, humidity, air quality, and dust. The system offers an effective way to monitor hygiene in hospital buildings through an integrated approach to cleaning, dust level, and air quality monitoring. The system also generates an alert to concerned personnel when dangerous levels are detected.

One limitation of maintaining a good indoor air quality in diverse spaces is the varying air quality criteria for different areas within a healthcare facility, which makes it challenging to apply a uniform monitoring approach. Additionally, IoT sensors, while cost-effective, may suffer from accuracy issues or require frequent calibration, which could affect the reliability of the data collected. Furthermore, the system's reliance on periodic data updates (every 120 s) may not be sufficient for rapidly changing conditions in critical areas such as operating rooms.

Acknowledgements Authors acknowledge the support from MSRIT, REVA University, NCET, Brainware University, Rao Bahadur Y. Mahabaleswarappa Engineering College for the facilities provided to carry out the research.

Author contributions Authors 1st and 2nd – Parkavi A, Sowmya B J: Initial problem identification, writeup, analysis, comparison, sections identification, and drafting of the initial manuscript. Author 3rd—Sini Anna Alex: Helped in Complexity analysis of the review work, and evaluation of the review work. Authors 6th and 7th, 8th– Rohith S, Sudipta chatterjee and Lingaraj k: Literature survey, drafting of the final manuscript, and helped in the initial review process. Authors 4th and 5th—S. Supreeth and G. Shruthi: Final English correction, technical improvement, and final images drawing using the draw.io tool, applied to the journal.

Funding There were no grants from funding organizations for this research.

Data availability The labelled datasets used to support the findings of this study can be obtained from the corresponding author upon request.

Declarations

Competing interests The authors declare no competing interests.

References

1. Internet of Things In Healthcare Market Size Report. 2030. https://www.grandviewresearch.com/industry-analysis/internet-of-things-iot-healthcare-market. Accessed 7 May 2024.
2. Paul J. Respiratory tract infections. Dis Causing Microbes. 2024. https://doi.org/10.1007/978-3-031-28567-7_3.
3. Gola M, Settimo G, Capolongo S. Indoor Air quality in inpatient environments: a systematic review on factors that influence chemical pollution in inpatient wards. J Healthc Eng. 2019. https://doi.org/10.1155/2019/8358306.
4. Liem L, Shofwan S, Janitra G, Rhatomy S. Infection control. Complicat Pain-Relieving Proced An Illus Guid. 2023. https://doi.org/10.1002/9781119757306.ch12.
5. Bevish Jinila Y, Joshua Thomas J and Priestly Shan B. Internet of things enabled approach for hygiene monitoring in hospitals. 4th Int Conf Comput Commun Signal Process. ICCCSP 2020, 2020. https://doi.org/10.1109/ICCCSP49186.2020.9315242.
6. J. M. N, Air Quality and Dust Level Monitoring using IoT. Int Res J Eng Technol. 2019. www.irjet.net. Accessed 5 May 2024.
7. Kumar S and Jasuja A. Air quality monitoring system based on IoT using Raspberry Pi. Proceeding—IEEE Int Conf Comput Commun Autom ICCCA 2017, 2017; 2017: 1341–1346. https://doi.org/10.1109/CCAA.2017.8230005.
8. Pangestu A, Yusro M, Djatmiko W, Jaenul A. The monitoring system of indoor air quality based on internet of things. Spektra J Fis dan Apl. 2020;5(2):141–52. https://doi.org/10.21009/SPEKTRA.052.06.
9. Jo J, Jo B, Kim J, Kim S, Han W. Development of an IoT-Based indoor air quality monitoring platform. J Sensors. 2020. https://doi.org/10.1155/2020/8749764.
10. Kenarkoohi A, et al. Hospital indoor air quality monitoring for the detection of SARS-CoV-2 (COVID-19) virus. Sci Total Environ. 2020. https://doi.org/10.1016/J.SCITOTENV.2020.141324.
11. Leung M and Chan AH. Control and management of hospital indoor air quality. http://www.medscimonit.com/fulltxt.php?IDMAN=6641. Accessed 7 May 2024.
12. Kodali RK, Swamy G, and Lakshmi B. An implementation of IoT for healthcare. 2015 IEEE Recent Adv. Intell. Comput. Syst. RAICS 2015, 2016; pp. 411–416. https://doi.org/10.1109/RAICS.2015.7488451
13. Phala KSE, Kumar A, Hancke GP. Air quality monitoring system based on ISO/IEC/IEEE 21451 standards. IEEE Sens J. 2016;16(12):5037–45. https://doi.org/10.1109/JSEN.2016.2555935.
14. Wolkoff P. Indoor air humidity, air quality, and health—An overview. Int J Hyg Environ Health. 2018;221(3):376–90. https://doi.org/10.1016/J.IJHEH.2018.01.015.
15. Chang S and Jeong K. A mobile application for fine dust monitoring system. Proc—18th IEEE Int Conf Mob Data Manag. MDM 2017. 2017. https://doi.org/10.1109/MDM.2017.55.
16. Islam MM, Rahaman A, Islam MR. Development of smart healthcare monitoring system in IoT environment. SN Comput Sci. 2020;1(3):1–11. https://doi.org/10.1007/S42979-020-00195-Y/FIGURES/6.
17. Marques G, Pitarma R. Monitoring health factors in indoor living environments using internet of things. Adv Intell Syst Comput. 2017;570:785–94. https://doi.org/10.1007/978-3-319-56538-5_79.
18 Alshamrani M. IoT and artificial intelligence implementations for remote healthcare monitoring systems: a survey. J King Saud Univ Comput Inf Sci. 2022;34(8):4687–701. https://doi.org/10.1016/J.JKSUCI.2021.06.005.

19. Lezcano A, Supervisor S, and Benítez R, IoT environmental monitoring system using Arduino and NODE MCU ESP8266. 2024. https://upcommons.upc.edu/handle/2117/405973. Accessed 7 May 2024.
20. Khan MB, Khan AR, Alkahtani H. Exploring the approaches to data flow computing. Comput Mater Cont. 2022;71(2):2333–46. https://doi.org/10.32604/cmc.2022.020623.
21. Fitriani I, Arum PR, Amri S. Pemodelan seasonal autoregressive integrated moving average (SARIMA) untuk Meramalkan Volume Angkutan Barang Kereta Api di Pulau Jawa Tahun 2021: memberikan prediksi volume angkutan barang kereta api di pulau jawa untuk masa mendatang. J Data Insights. 2024;2(1):26–35.
22. Wang J, Pei ZK, Wang Y, Qin Z. An investigation of income inequality through autoregressive integrated moving average and regression analysis. Healthcare Anal. 2024;5:100287. https://doi.org/10.1016/j.health.2023.100287.
23. Karasinghe N, Peiris S, Jayathilaka R, Dharmasena T. Forecasting weekly dengue incidence in Sri Lanka: modified autoregressive integrated moving average modeling approach. PLoS ONE. 2024;19(3): e0299953. https://doi.org/10.1371/journal.pone.0299953.
24. Fang Y, Shi X, Chen Y, He J. Quantity prediction of construction and demolition waste using weighted combined grey theory and autoregressive integrated moving average model. Sustainability. 2024;16(12):5255. https://doi.org/10.3390/su16125255.
25. Islam F, Akand T, Kabir S. Energy efficient real-time E-healthcare system based on fog computing. J Comput Cognit Eng. 2023. https://doi.org/10.47852/bonviewjcce32021070.
26. Singh J, et al. IoT weather data acquisition and automation system. AIP Conf Proc AIP Pub. 2024. https://doi.org/10.1063/5.0195741.
27. Suriano D, Prato M. An investigation on the possible application areas of low-cost PM sensors for air quality monitoring. Sensors. 2023;23(8):3976. https://doi.org/10.3390/s23083976.
28. Suriano D, Penza M. Assessment of the performance of a low-cost air quality monitor in an indoor environment through different calibration models. Atmosphere. 2022;13(4):567. https://doi.org/10.3390/atmos13040567.