Real-Time Air Quality Monitoring based on IoT using the Long Short-Term Memory

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ABSTRACT
Air quality is an important factor that directly impacts human health and the environment, particularly in urban areas with high levels of pollution. This study proposes a real-time air quality prediction system based on the Internet of Things (IoT) using a time-series data approach. The system is designed using an ESP32 microcontroller integrated with a DHT22 sensor for measuring temperature and humidity, as well as an MQ135 sensor for detecting pollutant gases. Environmental data are transmitted in real time to a cloud platform for storage, visualization, and analysis. The prediction method used in this study is the Long Short-Term Memory (LSTM) algorithm, which is effective in modeling temporal patterns in time-series data and generating predictions of future air quality conditions. The system architecture consists of hardware, network communication, and a cloud-based application layer that enables continuous environmental monitoring and remote data access. In addition, a monitoring dashboard is developed to display air quality information and provide early warnings in the event of a decline in air quality. The implementation results indicate that the system is capable of performing real-time air quality monitoring while also providing predictions based on historical data with relatively low cost and high efficiency. The proposed system has the potential to serve as an alternative solution for IoT-based air quality monitoring, supporting rapid decision-making and increasing public awareness of environmental conditions.

Keywords
Air quality, Internet of Things, ESP32, time-series, LSTM, real-time prediction.

1. INTRODUCTION
Air quality is one of the key indicators that affect human health and environmental sustainability. The increase in population, urbanization, as well as industrial and transportation activities has led to a decline in air quality, particularly in urban areas. Exposure to air pollutants such as hazardous gases and fine particulate matter can increase the risk of respiratory and cardiovascular diseases, as well as premature death. Therefore, continuous air quality monitoring has become an urgent necessity to support efforts in mitigating the impacts of air pollution. Although various air quality monitoring systems have been developed, most available devices are expensive and have limited accessibility, making them difficult to implement widely, especially at the local scale or in educational institutions.[10],[11],[12]. The advancement of Internet of Things (IoT) technology offers an alternative solution through the use of low-cost sensor devices capable of performing real-time environmental monitoring and integrating with cloud services. This study proposes an IoT-based air quality monitoring and prediction system using an ESP32 microcontroller integrated with an MQ135 sensor for detecting pollutant gases and a DHT22 sensor for measuring temperature and humidity. [5],[6],[13],[14]. In addition to monitoring, the system is equipped with a prediction method based on the Long Short-Term Memory (LSTM) algorithm, which is capable of modeling time-series data patterns to estimate future air quality conditions.[1],[2],[3]. The integration of IoT technology and machine learning methods is expected to produce a system that not only performs real-time monitoring but also provides early warnings of potential air quality deterioration. Thus, this study aims to develop an air quality monitoring and prediction system that is effective, affordable, and easy to implement as an alternative solution for technology-based environmental management.

2. METHODOLOGY
2.1 Architecture Diagram
The system architecture consists of three main layers, namely the device layer, the network layer, and the application layer. In the device layer, an ESP32 microcontroller is used, connected to an MQ135 sensor to detect air quality (hazardous gases) and a DHT22 sensor to measure environmental temperature and humidity. [5],[6],[13],[14]. Sensor data are periodically read by the ESP32. In the network layer, sensor data are transmitted via a Wi-Fi connection to a cloud platform using internet communication protocols.[7],[8],[9]. The transmitted data include gas concentration, temperature, and humidity at specific time intervals. The application layer functions for data storage, visualization, and analysis. Historical data are stored in a cloud database and displayed through a monitoring dashboard. Furthermore, these data are used as input for the LSTM model to perform air quality prediction

2.2 System Diagram

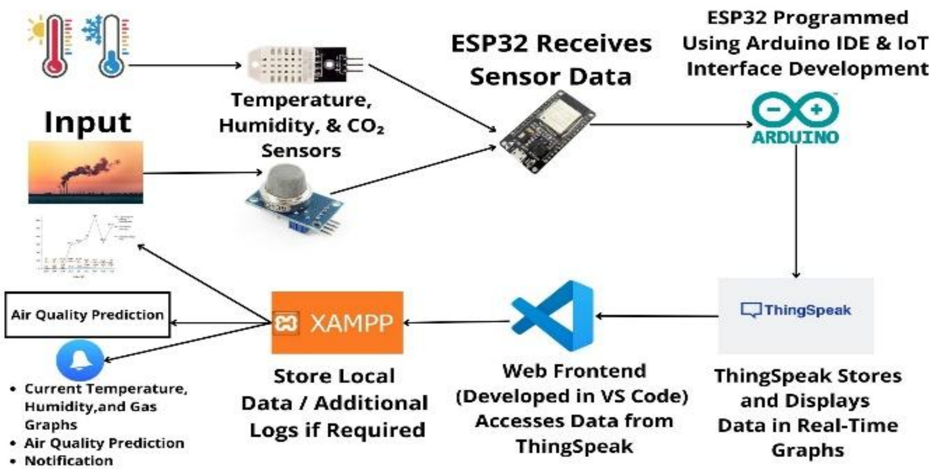

Fig 1: System Diagram

The proposed system diagram consists of several main layers, namely data acquisition, processing, transmission, visualization, and prediction. In the data acquisition layer, DHT22 and MQ135 sensors are used to measure temperature, humidity, and the concentration of air pollutant gases. The sensor data are processed by an ESP32 microcontroller as an edge device that performs data reading, initial processing, and data transmission via a Wi-Fi network. The data are then sent to a cloud-based IoT platform, namely ThingSpeak, for real-time storage and visualization. At the application layer, the data are accessed through a web interface for monitoring purposes. In addition, historical data are used as input for the Long Short-Term Memory (LSTM) model to predict future air quality conditions. The prediction results are classified into air quality categories and displayed on a dashboard along with real-time data, enabling the system to provide effective and low-cost monitoring as well as early warnings of air quality conditions.

2.3 Flowchart System

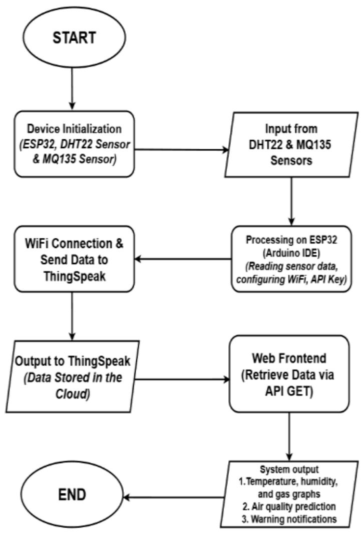

Fig 2: Flowchart System

The system flowchart illustrates the continuous process of IoT-based air quality monitoring. The process begins with the initialization of the ESP32 microcontroller along with the DHT22 and MQ135 sensors, followed by the acquisition of temperature, humidity, and gas concentration data. The data are processed locally and transmitted via a Wi-Fi connection to a cloud-based IoT platform, namely ThingSpeak, for real-time storage and visualization. Subsequently, the data are accessed through a web interface via an API and presented to users in the form of environmental condition information, monitoring graphs, and warning notifications when air quality deteriorates. This process runs continuously, enabling real-time and ongoing air quality monitoring. Monitoring graphs, and alert notifications in the event of deteriorating air quality. This process operates in a continuous loop, thereby facilitating real-time and persistent atmospheric surveillance.[10,[11],[12].

2.4 Sensors and Devices

The main tools used in this research include:
1. **ESP32 microcontroller** as the central controller and IoT communication unit.

2.**MQ135 sensor** for detecting hazardous gases and air pollution levels

3. **DHT22 sensor** for measuring temperature and humidity

4. **Wi-Fi module** (integrated into the ESP32) for internet connectivity

5. **Cloud platform** as a medium for data storage and visualization

[6],[7],[8].

2.5 IoT Architecture

The IoT architecture used adopts the concept of end-to-end data flow, in which data are collected by sensors, processed by an edge device (ESP32), transmitted through the internet network, and stored in the cloud. The cloud serves as the central hub for data management, analysis, and visualization. This system supports remote monitoring through computers or smartphones.[5],[6].

2.6 LSTM Models

The Long Short-Term Memory (LSTM) model is used to predict air quality based on the collected historical data. LSTM is a type of Recurrent Neural Network (RNN) designed to handle sequential data and long-term dependencies. The modeling stages include data preprocessing, splitting the dataset into training and testing sets, model training, and model performance evaluation. The model input consists of time-series data from air quality parameters, temperature, and humidity. The model then generates predictions of air quality conditions for the subsequent time period. The prediction results are utilized as an early warning system for potential air quality deterioration. With this methodology, the proposed system is capable of performing real-time air quality monitoring while simultaneously providing accurate predictions using an IoT and Machine Learning approach, making it an efficient and cost-effective solution for intelligent environment-based monitoring

3. RESULTS AND DISCUSSION

This section presents the results of the implementation of the IoT-based air quality monitoring and prediction system, as well as the performance evaluation of the proposed system. It includes the implementation of hardware and software, system testing, cloud integration, dashboard visualization, and the results of monitoring and prediction

3.1 Software Implementation

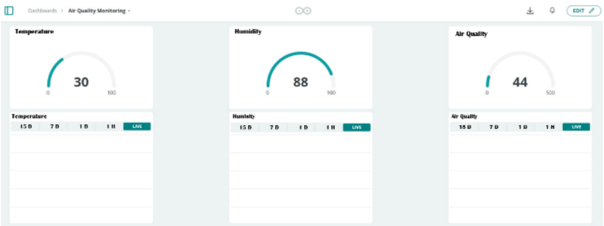

Fig 3: Air Monitoring Quality Dashboard

The software is developed using the Arduino IDE for programming the ESP32, which is responsible for reading sensor data, performing initial processing, and transmitting the data to a cloud server via a Wi-Fi connection. In addition, a web-based interface is developed to display monitoring data using web technologies. The software system also includes a prediction module based on the Long Short-Term Memory (LSTM) model, which utilizes historical data as input to predict future air quality conditions.

3.2 Cloud and Dashboard Integration

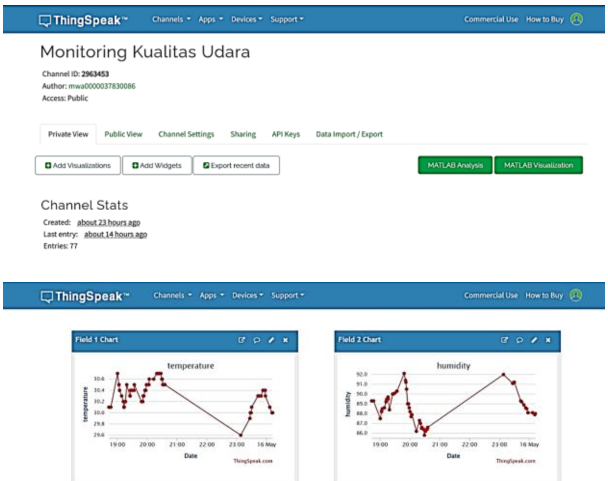

Fig 4: Data Storage Dashboard Using ThingSpeak

The collected sensor data are transmitted to a cloud-based IoT platform, namely ThingSpeak, for storage and visualization. This platform enables real-time data monitoring through graphs of temperature, humidity, and gas concentration. The monitoring dashboard displays current environmental conditions as well as historical data, which can be accessed by users via computers or smartphones.[1],[2],[3].

3.3 System Testing

System testing was conducted to ensure that all components function properly, including sensor data acquisition, data transmission, cloud storage, and dashboard visualization. The test results indicate that the system is capable of transmitting data reliably over a Wi-Fi network with low latency. Furthermore, the system can operate continuously for long-term monitoring.

3.4 Monitoring Reesults

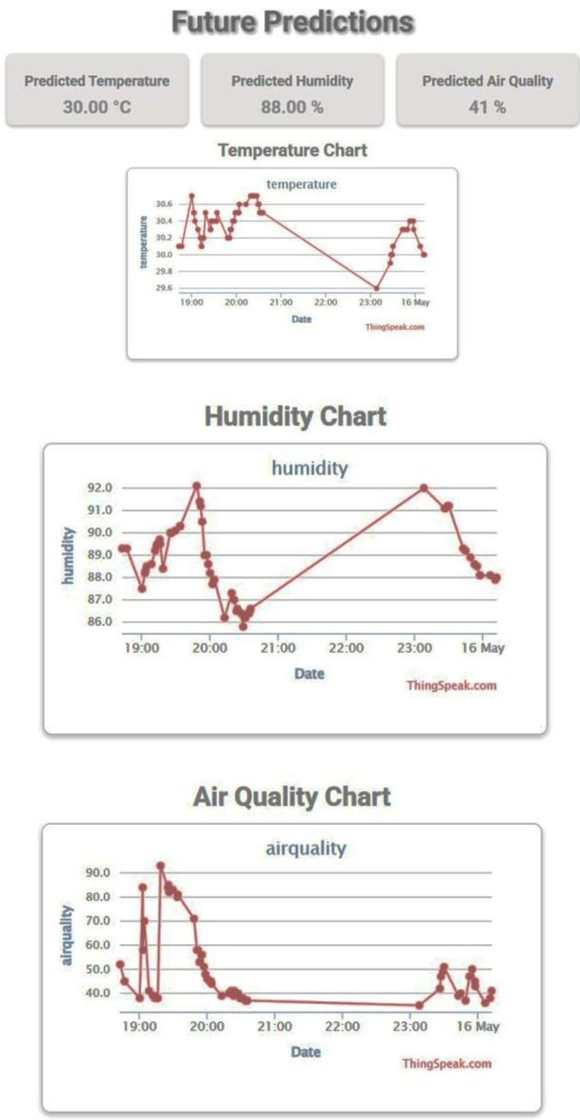

Fig 5: System Monitoring Results Using the Website

The system successfully displays real-time environmental metrics, including temperature, humidity, and pollutant levels. These temporal visualizations facilitate immediate assessment of air quality fluctuations and ambient conditions.

3.5 Prediction Results

Table 1. Table air quality measurement

No	Temp (°C)	Huminity (%)	Air Quality
1	30.5	89.0	-30.73
2	31.0	90.0	-31.1
3	31.5	91.0	-31.46
4	32.0	92.0	-31.83
5	32.5	93.0	-32.2

Step-by-step calculation of LSTM-based water quality prediction using the data presented in Table 1 (time step 5);

- $x_t=[Temp, Humidity, AirQuality]$
- $x_t=[32.50, 93.00, -32.20]$

Assumsing;

- Previous hidden state s $h_{t-1}=0.5$ *(asumsi)*
- Cell state sebelumnya $C_{t-1}=0.3$ *(asumsi)*

Combined input;

$$[h_{t-1},x_t]=[0.5, 32.5, 93.0, -32.2]$$

Determining weight;

- $W_f=[0.01,0.02,0.01,0.03]$, $b_f=0.1$
- $W_i=[0.02,0.01,0.03,0.01]$, $b_i=0.1$
- $W_c=[0.03,0.02,0.01,0.02]$, $b_c=0$
- $W_o=[0.01,0.03,0.02,0.01]$, $b_o=0.1$

Forget Gate f_t

- $f_t=\sigma(0.01(0.5)+0.02(32.5)+0.01(93)+0.03(-32.2)+0.1)$
- $=\sigma(0.005+0.65+0.93-0.966+0.1)$
- $=\sigma(0.719)\approx0.672$

Input Gate i_t

- $i_t=\sigma(0.02(0.5)+0.01(32.5)+0.03(93)+0.01(-32.2)+0.1)$
- $=\sigma(0.01+0.325+2.79-0.322+0.1)$
- $=\sigma(2.903)\approx0.948$

Candidate Cell $C\sim t$

- $C\sim t=\tanh(0.03(0.5)+0.02(32.5)+0.01(93)+0.02(-32.2))$
- $=\tanh(0.015+0.65+0.93-0.644)$
- $=\tanh(0.951)\approx0.740$

Cell State C_t

- $C_t=(0.672\times0.3)+(0.948\times0.740)$
- $=0.2016+0.7015$
- $=0.9031$

Hidden State h_t

- $h_t=0.932\times\tanh(0.9031)$
- $\tanh(0.9031)\approx0.718$
- $h_t=0.932\times0.718=0.669$

Based on the upward trend observed in the time-series data, the LSTM model predicts the air quality value for the subsequent time step. The predicted Air Quality (t+1) is -32.60

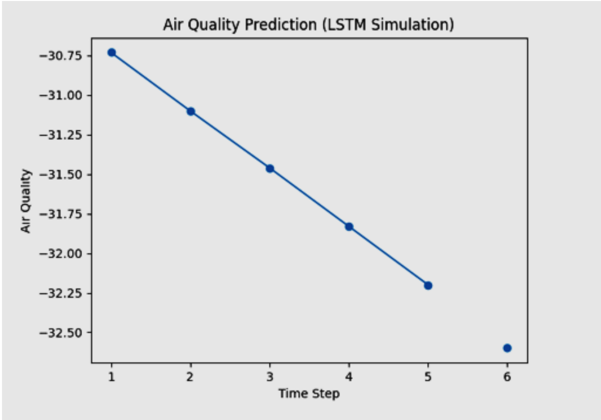

Fig 6: Prediction chart

4. SECTIONS

This study proposes the design and implementation of a real-time air quality monitoring and prediction system based on Internet of Things (IoT) technology. The integration of the ESP32 microcontroller with DHT22 and MQ135 sensors enables continuous environmental data acquisition, including temperature, humidity, and the concentration of air pollutant gases. The system is also capable of transmitting data to a cloud platform, namely ThingSpeak, allowing remote monitoring through a web-based interface. In addition, the implementation of the Long Short-Term Memory (LSTM) algorithm enables the system to predict future air quality conditions based on historical data. This predictive capability provides early information on potential air quality deterioration, thereby supporting preventive actions. Overall, the proposed system demonstrates an efficient, scalable, and low-cost solution for real-time environmental monitoring

5. ACKNOWLEDGMENTS

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