IoT- based Air Quality Monitoring and Prediction System

G. Nisanthan and A.L.F. Shanaz

Abstract— Addressing the pressing global concern of air pollution, this research introduces an innovative real-time monitoring system that leverages IoT technology and deep learning for accurate air quality assessment and forecasting. The system employs an IoT device equipped with sensors to measure particulate matter (PM2.5, PM10) The system employs an IoT device equipped with sensors to measure particulate matter (PM2.5, PM10) and carbon monoxide (CO) levels, with real-time data transmitted via Wi-Fi to a centralized database for continuous monitoring of air quality conditions. and carbon monoxide (CO) levels, with real-time data transmitted via Wi-Fi to a centralized database for continuous monitoring of air quality conditions A sophisticated predictive model, integrating one-dimensional Convolutional Neural Networks (Conv1D) and Long-Short Term Memory (LSTM) algorithms, is employed to forecast the Air Quality Index (AQI) up to seven days in advance. By considering historical data patterns and external factors, the model demonstrates exceptional accuracy in predicting future air quality trends. The accuracy of the model is assessed using R-MSE and accuracy parameters. The system's user-friendly interface, accessible through a mobile application, provides real-time updates on air quality levels, allowing users to make informed decisions about their activities and health. Furthermore, the collected data serves as a valuable resource for researchers and policymakers, aiding in the development of effective strategies to mitigate air pollution and improve public health.

Index Terms – **Air Quality Index, Conv1D-LSTM, Dataset correlation, IoT Application, Multivariate-Time-Series-Forecasting.**

I. Introduction

IN recent times, global warming has led to climate changes and unusual weather patterns, impacting millions of people directly or indirectly through health issues caused by air pollution. The rise in industrialism and motor vehicle use has contributed to increased levels of greenhouse gases, posing health risks. The existing monitoring systems are insufficient for long-term future predictions to address potential hazardous situations due to air pollution. This research aims to monitor the air quality index in industrial areas, ensuring environmental air pollution levels are within acceptable limits. Additionally, the model can serve as an air pollution monitoring device for heavily polluted locations. The predictive model analyzes the air quality database, employing the CONV1D-LSTM deep learning approach to identify pollutant levels and forecast future values. Utilizing a low-cost data collection device, real-time Air Quality Index (AQI) results can be displayed via web or mobile applications. The IoT-based device provides both real-time air pollution information and predicted air pollution details for a week (7 days), encompassing low to high ranges for each day. The forecasting methodology incorporates trend and seasonal time series analysis for robust air pollution predictions. The primary objective of the proposed system is to deliver accurate predictive air pollution results for the next seven days using time series deep-learning algorithms. This involves designing a device to measure outdoor air pollution, displaying the Air Quality Index, and creating an IoT-based system to visualize and store results.

The system aims to generate reliable predictions using a CONV1D-LSTM combined deep learning algorithm while ensuring user-friendly web and mobile platforms for data visualization. However, significant research gaps persist, particularly concerning the high costs of current products and the lack of user-friendly interfaces.

Many advanced air quality monitoring systems are prohibitively expensive, limiting accessibility for smaller organizations and low-income communities. Additionally, existing platforms often lack intuitive designs that facilitate easy interpretation of data for non-experts. Addressing these gaps through affordable technology and improved user-centered design is essential for enhancing the adoption of predictive air pollution systems, ultimately contributing to better public health outcomes related to air quality management. By focusing on both cost-effectiveness and user engagement, future developments can ensure that vital air quality information is accessible to all stakeholders.

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II. Literature Review

A. Background Research

The advancement of technology and air quality analysis and monitoring systems are developing over the years. After the introduction of AI, day-by-day predictive methods are introduced in the world. Recent research in air pollution monitoring systems depict the use of wireless sensor networks, IoT framework, and artificial neural networks.

The increase in the population and the growth of industrialism are the main factors for our environmental pollution.

Air pollution is also part of it. With the development of technology, many researchers have proposed new technologies to monitor air pollution and control its effects due to that over the years. With the introduction of the Internet of Things, web-based systems got more attention than server-client-based systems. Zeba Idrees et al. [1] proposed a low-cost air pollution monitoring system with a review of the protocols and the technologies. This paper has mentioned that WSN and IoT architectures are more beneficial for Air Pollution monitoring systems. Aziz Z.A et al. [2] proposed a WSN-based air pollution monitoring system that is used to collect the data from several zones and gather it into a database and report the results using the internet. But in both cases, the real-time data is only considered to display.

B. Monitoring Device

Network transmission is one of the highly developing industries around the world. But in the scenario of WSN transmissions, most of the devices have relied on GSM or Wi-Fi controllers. Those systems are sufficient to maintain the data but with the speed and quality of the latest IoT platforms, the performance of those network elements is not enough to fulfil. Virendra Baror et al [3] proposed a QoS Enabled IoT-based Low-Cost Air Quality Monitoring System with power consumption optimization. The model was designed for low power consumption on the monitoring device. The proposed network used Node MCU with parametric sensors as a micro-control unit, but their data transmission unit is quite slow in their system. Candia A et al [4] proposed a real-time air quality monitoring system.

C. Prediction Model

A system has been proposed by Han Y. et al. [22] that foresees air quality for the next 48 hours (about 2 days) through the application of domain-specific knowledge within the Bayesian deep learning approach. The historical data of the area and a sample weather forecasting dataset were used to improve the accuracy of the model. Kalaplieski J. et al. proposed the CNN Deep learning approach to train the model and predict the air quality within the 6 categories of air quality. The nearby weather data and the camera images were used as inputs. This method shows some deep learning techniques to analyze the image results and whether they matched with the results then it will have proceeded. Chang Y. et al. [5] proposed an LSTM-based aggregated model for Air Pollution Forecasting. In this model, three types of datasets are used in data processing to predict air quality results. Those datasets are the Local Station Dataset, Neighbour area dataset and abroad area dataset. These datasets are processed into the LSTM model and the aggregated result will be displayed as forecasted air quality. The results were also analyzed by MAPE, MAE and RMSE. This module is the advanced version of the LSTM model which merged all the results. Neither does the previous system consider the present data for the analysis. The CNN-LSTM-based model for time series forecasting has been compared with different models in Halil. E et al. [6].

D. Limitations in current systems

Current IoT-based air quality monitoring systems face several limitations that hinder their effectiveness in providing timely and accurate data. Many existing systems rely on traditional sensor networks that are expensive and often require extensive maintenance, leading to limited coverage and high operational costs. Additionally, these systems usually offer real-time data without strong forecasting capabilities—a necessary component of proactive air quality management. Prediction accuracy has improved when deep learning models, like Conv1D-LSTM, are integrated into these systems; however, these models' complexity and resource requirements can be problematic when implemented on low-cost IoT devices. This results in a trade-off between the accuracy of predictions and the cost-effectiveness of the monitoring system, limiting widespread adoption.

The proposed system aims to address these limitations by offering a low-cost, straightforward solution that delivers air quality index (AQI) results through a web application while incorporating predictive capabilities for future air quality levels. By combining an efficient Conv1D-LSTM model with IoT technology, this system seeks to provide accurate AQI forecasts for the upcoming days, enhancing decision-making processes for users. However, challenges remain in optimizing the model for deployment on resource-constrained devices while ensuring real-time data processing and user-friendly interfaces. Additionally, achieving high accuracy in predictions without compromising system performance or incurring excessive costs presents a significant research gap that needs to be addressed to improve air quality monitoring and forecasting systems effectively.

III. Methodology

The air pollution monitoring system is highly demanding and important for both present and future generations. With the development of IoT and AI systems, air pollution can be predicted. This project consists of two parts.

The first part is dedicated to displaying real-time air pollution data, while the second part focuses on forecasting future results. The air pollution monitoring system is highly demanding and important for both present and future generations. With the development of IoT and AI systems, air pollution can be predicted.

A. Device Prototype

The prototype model is connected through an Arduino microcontroller with parametric sensors to measure PM10, PM2.5, CO_2, Temperature, and Humidity. The data transmission process will be done using a Wi-Fi network and using the IoT cloud to maintain the database.

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The data flow diagram below (Fig. 1) illustrates the device's input and output parameters of this device.

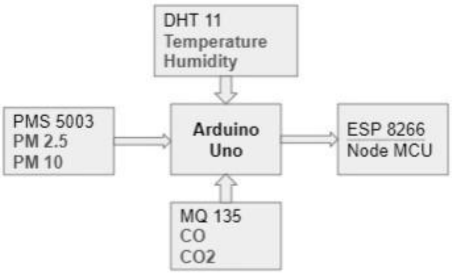

Fig. 1. Data flow diagram of the device prototype

1) Sensor Modules

By considering the factors that affect air pollution, we find that numerous toxic gases are created by both natural causes and human activities. These parameters have already been discussed in section I(A). Above are the sensor modules and microcontroller that will be used in this project.

2) Connection with NodeMCU

ESP 8266 is one of the fastest data transmission systems used for Arduino projects. This is connected with the Arduino board using U-ART connection. This means interconnection between the transmission (Tx) and receiver (Rx) pins of both devices. This device can transfer the sensor data to the IoT platform using JSON packaging.

3) ThingSpeak visualization

The ***ThingSpeak*** is an open-source platform that provides a set of open tools and a global, open network to build an IoT application at a low cost, with maximum security and a user-friendly approach. ***StreamLit*** & ***Heroku*** are used to make a real-time web platform for this entire system.

B. CONV1D-LSTM Based Prediction Model

Our proposed system for the prediction part will be based on CONV1D–LSTM-based hybrid model. First, the training data will be processed with recent similar data into the 1D-CNN block and the utilized output will be combined with the real-time data from the sensors in the LSTM model and the predicted results will be published through the IoT framework.

First the data added to the data frames and then data cleaning has been made to remove the Nan valued data. In this process the NaN values replaced by the mean of the remaining data. Then to remove outliers,

In the preprocessing phase of our study, we employed the StandardScaler method to standardize the dataset and mitigate the influence of outliers. StandardScaler operates by removing the mean and scaling the features to unit variance, transforming the data into a distribution characterized by a mean of 0 and a standard deviation of 1. This normalization process is particularly critical when dealing with datasets that exhibit outliers, as it helps to reduce their impact on model performance. By centering the data, StandardScaler effectively diminishes the skewness introduced by outliers, thereby enabling the model to learn more accurately from the underlying patterns present in the dataset.

While StandardScaler proves effective in many contexts, it is important to acknowledge that it does not completely eliminate outliers; rather, it adjusts their influence within the dataset. In scenarios where outliers are significantly divergent from the rest of the data, using z-score analysis the outliers can be identified and isolated.

Here the model is developed as a multivariate time series prediction model. Many air pollution prediction research studies are based on a single parameter. However, better results can be achieved by combining two parameters. Due to mechanical errors or signaling errors, there is a chance that some data from a single parameter may be missing. Nevertheless, combining well-correlated parameters can resolve these types of issues.

Layer	Parameters
`Conv1D`	`filters=32, kernel_size=2, padding="causal", strides=1, activation="relu"`
`Conv1D`	`filters=32, kernel_size=2, padding="causal", strides=1, activation="relu"`
`MaxPool1D`	
`Bidirectional(LSTM)`	`units=32, return_sequences=True`
`LSTM`	`units=64, return_sequences=True`
`Bidirectional(LSTM)`	`units=32, return_sequences=False`
`Dense`	`units=1`
`Dense`	`units=1`
`Lambda`	`function=lambda x: x * 200`

Fig. 2. Convolution-LSTM Layers and parameters

The above image refers to the layers which used in the Conv1D-LSTM model after the number of trail and errors to get the high perfomance with the right combination of the layers. The proposed architecture integrates multiple layers designed for effective feature extraction and sequence modeling, culminating in a tailored output prediction mechanism. Initially, two Conv1D layers are employed, each comprising 32 filters with a kernel size of 2, utilizing "causal" padding and ReLU activation functions. This configuration facilitates the extraction of temporal features while maintaining the order of input sequences.

Following the convolutional layers, a MaxPool1D layer is introduced to downsample the output, enhancing computational efficiency and emphasizing significant features. The architecture then incorporates a Bidirectional LSTM layer with 32 units that returns sequences, allowing the model to capture dependencies from both past and future contexts. This is succeeded by a standard LSTM layer with 64 units, which also returns sequences, further enriching the temporal representation. A second Bidirectional LSTM layer, configured with 32 units but set to return only the final output, consolidates the learned information for subsequent processing.

The model concludes with two Dense layers, each containing a single unit, facilitating the final output prediction. Notably, a Lambda layer applies a custom

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function that scales the output by multiplying it by 200, thereby adjusting the model's predictions to meet specific requirements. This architecture effectively combines convolutional and recurrent methodologies to optimize performance in tasks requiring both feature extraction and sequential analysis.

The model utilizes Stochastic Gradient Descent (SGD) as its optimization algorithm, which is favored for its ability to handle large datasets and its straightforward implementation. When selecting a learning rate for SGD, it is crucial to balance convergence speed with stability; an effective approximation for the learning rate can be derived from empirical observations using the equation:

$$\eta = \frac{1}{\sqrt{t}}$$

where ηη represents the learning rate and tt denotes the iteration number. This adaptive approach allows the learning rate to decrease over time, facilitating more refined updates as the model approaches convergence.

By integrating ReLU activations with SGD optimization and a strategically selected learning rate, the architecture is well-equipped to tackle complex tasks in various domains, enhancing both training efficiency and model performance.

IV. Results

A. *Real-Time Air Quality Monitoring Device*

The real-time air pollution parameters and air quality index are monitored using this device. This device is named *Make Em' Green - Air Quality Monitor*, the prototype of this device is used for the spot data collection. The device is considered a low-budget energy saving device. By using the prototype many features can be easily identified.

The device prototype has been designed using an Arduino Uno microcontroller. The parametric sensors related to that, and the data was sent to the ThingSpeak platform through the ESP8266 Wi-Fi module.

Fig. 3. Model of the prototype

Powering- Due to outdoor usage, we have developed a solar powering module for powering the device. The 5V solar cell is used to charge the 3.7V battery which will store around 2600mH current and transfer it to the device. Using a DC-DC boosting converter we again get the values up to 5.5-7 v towards the Arduino model.

TABLE I
ARDUINO PINOUTS

Devices	Parameter/ Purpose	Connected Pins
PMS5003	PM 2.5, PM10	Rx, Tx (UART/TTL) (In NodeMCU)
MQ 135	CO_2, CO	A0
DHT11	Temperature, Humidity	D2
ESP 8266 12E NodeMCU	Connectivity	5,6 (s/w serial)
B. *Powering Model*	Powering the device	Vin, Gnd

C. *Data Collection & Visualization*

The data collected from our air quality monitoring system is transmitted via Wi-Fi and subsequently stored in the ThingSpeak database. This data will be regularly updated to synchronize with our primary data storage system.

Data visualization is implemented through two primary channels: the ThingSpeak platform and a dedicated mobile application. The mobile application, which is part of this project's development, offers a user-friendly interface for accessing air quality data. It provides notifications to users, allowing them to monitor daily air quality conditions effectively. Furthermore, users can view predictive results regarding air quality within the same application.

The Air Quality Index (AQI) serves as the standard method for presenting results in our web application. This globally recognized metric indicates the level of air pollution, with various countries employing different indexing methods and formulas. Our proposed monitoring application calculates AQI levels based on the average values of particulate matter (PM 2.5 and PM 10) and carbon monoxide (CO) in parts per million (ppm) This approach not only enhances user understanding of air quality conditions but also aligns with international standards for air quality assessment. The following equation is used to calculate AQI from particulate matters.

$$AQI = AQI_{min} + \left[\frac{PM_{obs} - PM_{min}}{PM_{max} - PM_{min}} \times (AQI_{max} - AQI_{min})\right]$$

where:

- PM_{obs} = Observed 24-hour average concentration in µg/m3
- PM_{max} = Maximum concentration of AQI color category that contains PM_{obs}
- PM_{min} = Minimum concentration of AQI color category that contains PM_{obs}
- AQI_{max} = Maximum AQI value for the color category that corresponds to PM_{max}
- AQI_{min} = Minimum AQI value for the color category that corresponds to PM_{min}

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Table II shows the details from the US standards of AQI ranges according to the other parametric ranges.

TABLE II
The US Standard AQI ranges for PM 2.5 & PM 10

AQI Ranges	PM 2.5 Ranges	PM 10 Ranges	CO (ppm) Ranges
0-50	0-54	0-12	0-4.5
50-100	54-154	12-35.4	4.5-9.5
100-150	154-254	35.4-55.4	9.5-12.5
150-200	254-354	55.4-150.4	12.5-15.5
200-300	354-424	150.4-350.4	15.5-30.5

Many countries utilize the Air Quality Index (AQI) standards established by the United States Environmental Protection Agency (EPA) for calculating air quality values, despite the existence of various international standards. This widespread adoption can be attributed to the comprehensive nature of the US system, which is backed by extensive research and regulatory frameworks.

Countries like Canada and those in Asia have adapted these standards to fit local environmental conditions, facilitating international comparisons and enhancing public health advisories related to air quality. However, while many nations align with US standards, local adaptations are often necessary to address specific regional issues and health guidelines, underscoring the complexity of establishing a universally applicable AQI system.

D. Prediction Model

The prediction model is combined with Conv1D and LSTM algorithms. After reading some research on behaviours of PM2.5 with PM10 parameters, this model is developed as a multivariate time series model. Of the limited number of data, this model is given very average accuracy. But after comparing the model with some variations, this model gives better performance in terms of the RMSE and R2-Score comparisons.

The multivariate movement has highly boosted the results also it gives more data for the prediction. The correlation was found in both hourly and daily datasets. As a result, the daily dataset has a better correlation than hourly data, but both do not have big differences.

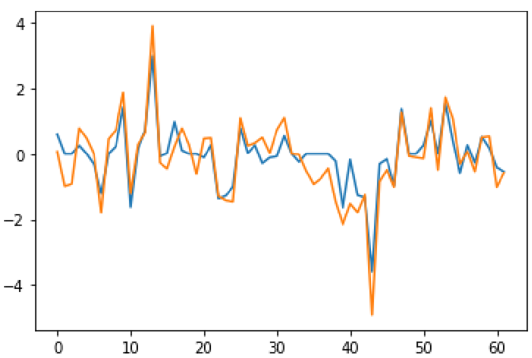

Fig. 4. Correlation between PM2.5(o) & PM10(b)

The above picture shows the correlation between PM 2.5 & PM 10 which are the parameters selected for the prediction of Air Quality data. According to Fig. 4 PM 2.5 data indicated in orange and the PM 10 indicated in blue. The results are showed in the table below.

TABLE III
COMPARISON OF CORRELATION BETWEEN HOURLY AND DAILY DATA

Dataset	Parameters	Correlation between
Hourly dataset	PM2.5 & PM10	0.88
Daily dataset	PM2.5 & PM10	0.90

Due to needing a larger dataset, the hourly dataset has been selected for the prediction. The selected dataset was trained using the Conv1D-LSTM model. The results are satisfied that the hourly data has lower MSE and Accuracy.

TABLE IV
COMPARISON OF ACCURACY BETWEEN HOURLY AND DAILY DATA

Dataset	MSE	Accuracy
Daily dataset	1.5408	0.1516
Hourly dataset	1.0214	0.2399

The model is compared with the results from the LSTM & S-ARIMA models. By comparing those results this multivariate combined model is giving good results even within the limited data.

TABLE V
COMPARISON OF ACCURACY BETWEEN LSTM, S-ARIMA & CONV1D-LSTM MODELS

Model	RMSE	Accuracy
LSTM	0.419	0.152
S-ARIMA	0.348	0.024
Conv1D-LSTM	0.218	0.239

The prediction results are adequate by comparison with other models. Our model gives a 0.218 R-MSE value and 23.99% accuracy which are better than the other prediction models.

Based on the facts in Table III and IV, the long run of the complete system and the large set of data will give higher accuracy on Conv1D-LSTM prediction. Since no any other regular models were given better results, our proposed model is recommended for this multivariate time-series forecasting system.

V. Conclusion And Future Works

Real-time air quality monitoring & prediction systems will help to identify air pollution conditions. The Conv1D-LSTM time series model gives higher accuracy for the results

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compared to ARIMA & LSTM models. Also, for future works, this prediction process will be enhanced for a long period of forecasting. The air pollution monitoring system is a highly needed project to raise awareness among urban people.

This IoT-based system provides prediction facilities along with real-time monitoring ability. The data transmission is also to be replaced by the LoRa connection because of its high-speed transmission and durability. And the devices must be connected as a network that shows where and how much air pollution is occurring from just a mobile app. Also, we must improve the Air Pollution monitoring device with GPS techniques to find the location of the device. Also, it needed to increase the model accuracy by applying deep learning techniques.

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