IoT based Classroom Air Quality Management Using Deep Hierarchical Cluster Analysis

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ABSTRACT

Poor classroom air quality and high levels of dust have a detrimental impact on student health, comfort, and productivity. To address this issue, we propose an IoT enabled system for monitoring and predicting classroom air quality and dust levels. The system employs multiple sensors placed inside the classroom to collect air quality data. Deep hierarchical cluster analysis is utilized to group the data at different levels of granularity, enabling the extraction of meaningful insights from large volumes of data and revealing trends and patterns that may be challenging to identify using conventional techniques. The work aims to comprehend the factors influencing classroom air quality and dust levels and develop an accurate prediction model. We leverage machine learning algorithms, specifically deep hierarchical cluster analysis, to uncover hidden patterns and relationships within the data. By applying deep hierarchical cluster analysis, we categorize the air quality and dust levels of a classroom into distinct clusters or groups based on data point similarity. Subsequently, a Long Short-Term Memory (LSTM) model is developed based on the cluster analysis results to predict air quality and dust levels. The results showed that the system is suitable for real-time implementation, indicating its potential to be used in practical applications.

Keywords: Air Quality Measurement and Prediction, IoT, Deep hierarchical cluster analysis,LSTM, Classroom environment

1. INTRODUCTION

Indoor pollution is caused by a variety of factors, including but not limited to, human exhalation, smoking, fuel burning, and the proximity of the indoor environment to surrounding outdoor sources of pollutants. Outdoor sources of pollution can include busy roads, highways, industrial regions, and other sources of industrial activity that emit harmful particulate matter and chemicals. These pollutants can accumulate in enclosed spaces, such as classrooms, and contribute to poor air quality, which can have significant health implications for occupants, particularly those with pre-existing respiratory conditions (Sharma et al., 2021). Indoor pollution can have a significant impact on a person's health by creating cardiovascular and respiratory ailments, as well as altering human cognition, because the average person spends roughly 80–90 percent of their time indoors (WHO, 2010 ;Tran et al., 2020). Students spend a significant amount of their time in classrooms, ranging from 30-40% of their time. During this period, they are exposed to a variety of pollutants, including those mentioned above. In addition, the use of chalk in classrooms can contribute to dust particles in the air, which can further exacerbate the problem. Respiratory problems and various health concerns may arise, especially among students with pre-existing conditions like asthma, as a result of extended contact with airborne pollutants and dust particles (Patel et al., 2009; Liu et al., 2018). Thus, addressing indoor air pollution in classrooms is crucial for promoting a healthy learning environment for students. Such exposure can also have an impact on human cognition, causing fatigue and decreased performance. Maintaining a healthy indoor learning environment is crucial for the well-being and academic performance of students. In order to achieve this, it is important to monitor and predict the indoor air quality regularly. The presence of pollutants such as carbon monoxide (CO), carbon dioxide (CO_2), ammonia (NH_3), sulphur (S), benzene (C_6H_6), and particulate matter (PM) like $PM_{2.5}$ and PM_{10} can significantly impact the air quality in classrooms. The concentration of these pollutants can be used to calculate the Air Quality Index (AQI). By regularly monitoring the AQI, it is possible to assess pollution levels and take appropriate actions to protect the health of students and faculty. An air quality monitoring system that employs AQI as a metric for assessing pollution levels can be highly beneficial in maintaining a healthy learning environment. Such a system can alert faculty and initiate immediate action in the event of extreme pollution levels, thereby ensuring the safety and well-being of everyone in the classroom. By continuously monitoring indoor air quality and generating alerts when necessary, this system can help prevent respiratory issues like asthma, allergies, and other health problems caused by prolonged exposure to polluted air.

This paper proposes an IoT based classroom air quality monitoring system that allows user to observe and monitor live air quality within the classroom using IoT. Sensors are used in the classroom to measure the air quality index and dust particles density. The sensed data is continuously transmitted to the server. Furthermore, sensor data is displayed on a webpage to determine the status of pollution in classroom. The data collected is used to forecast air quality and dust density. This IoT based system offers a practical and cost-effective solution for monitoring and predicting classroom air quality, ensuring a safe and healthy learning environment for students and teachers alike.

Our key contributions are as follows:

- Development of an IoT enabled system for monitoring and predicting classroom air quality and dust levels.
- Utilization of deep hierarchical cluster analysis to extract meaningful insights from large volumes of data and identify trends and patterns.
- Development of an accurate prediction model based on LSTM, enhancing proactive management of classroom environments.

The remainder of the paper is arranged as follows: Section 2 focuses on recent work in the field of monitoring and forecasting classroom/indoor air quality. Section 3 describes the proposed system as well as its measurement and prediction capabilities. In section 4, the proposed system's outcomes are shown. Section 5 concludes with a summary of the findings and recommendations for future research.

2. RELATED WORKS

This section highlights the overview of existing works in the domain of IoT enabled classroom and indoor air quality, dust density monitoring and forecasting system.

2.1. Indoor air quality monitoring and prediction system

Ha et al., 2018 proposes an air quality management system that combines the indoor air quality index and humidity index into an improved indoor air quality index using real-time sensor data. A network of sensors, including a humidity sensor, detects indoor air pollution levels using an extended fractional-order Kalman filter (EFKF). Timely air quality alerts are delivered to enhance prediction accuracy and performance in dealing with measurement noise and nonlinearity. The use of expensive multi-sensors to measure many parameters raises the system's cost in real-time implementation.

Toluene, xylene, and formaldehyde are volatile organic compounds (VOCs) that can be detrimental to human health and pose a challenge to indoor air quality (IAQ) management (Hung et al., 2020). The study proposes the utilization of a comprehensive control technique, the fuzzy genetic multi-layer control scheme (FGMLCS), to regulate IAQ. The proposed multilayer control structure incorporates fuzzy logic, evolutionary algorithms, and multi-objective optimization to achieve optimal control and improve IAQ.

AbdulWahhab, 2020 proposed an Internet of Things (IoT) device that forecasts atmospheric pollution levels using the autoregressive integrated moving average (ARIMA) method. Real-time and accurate measurements are provided by this system, which has a substantial positive impact on environmental safety and public health.

In (Ge et al., 2019), a DBU-LSTM neural network model is introduced, which effectively captures temporal and spatial correlations in time series data bidirectionally. This model utilizes diverse data sources like points of interest (POI) and road networks to evaluate similarities among metropolitan regions. To address incomplete air quality data from previous monitoring stations, a tensor decomposition technique is employed. However, it is worth noting that the model's drawback lies in its less accurate predictions and high computational power requirements.

In (Rastogi et al., 2020), the authors proposed an indoor air quality monitoring and forecasting system based on an Internet of Things (IoT) and discrete-time Markov chain (Privault,2018). PM_{10}, $PM_{2.5}$, and CO levels are used as features for forecasting within the

Markov chain. However, the accuracy of both measured and forecasted values needs improvement.

2.2. Classroom air quality monitoring and prediction system

The work by Tagliabue et al., 2021 presents a monitoring and prediction system for air quality in educational institutions. Environmental data such as CO_2 concentration, relative humidity, and temperature are collected through sensors in an indoor laboratory setting. The researchers utilized an Artificial Neural Network (ANN) to estimate CO_2 levels, achieving a prediction accuracy of approximately 10.6 percent.

CO_2 and $PM_{2.5}$ are detected by using low-cost sensors (Sharma et al., 2021). Multi-Layer Perceptron (MLP) and eXtream Gradient Boosting Regression (XGBR) are used to estimate the air quality in rooms that don't have sensors in real-time. Moreover, a modified Long Short-Term Memory (LSTM) model is used to forecast the air quality of rooms, which has an estimation accuracy of around 95 percent and a forecasting accuracy of around 96 percent.

CO_2, PM_{10}, and $PM_{2.5}$ levels have been measured and predicted in a school environment (Cho et al., 2022). The prediction algorithm is based on a multi-objective genetic algorithm that avoids false regression by excluding irrelevant input variables from prediction. $PM_{2.5}$ levels in school environments have been measured and predicted (Baharfar et al., 2021). The use of a 7-class regression model to predict $PM_{2.5}$ levels has an accuracy of 80%.

3. Material and Methods

3.1. Description of classrooms

We select a classroom in our institution for our experiment. We select the classrooms from Computer science block of our institution. A brief description of classroom specification is mentioned in Table 1.

Table 1. Specifications of the Experimental Setup

Specification	Classroom
Position	First floor
No. of Fans	5
No. of Doors	1
No. of Windows	4
Dimension (feet)	600
No. of Occupants	60

3.2. Data acquisition

Data collection is the most important step for evaluating our proposed system, and it is achieved by creating an IoT-based device to track indoor dust and the air quality index. The developed device is cost-effective, portable and easy to use. Additionally, a web application has been developed for collection data from the classroom and the data has been stored in the cloud. The block diagram of the proposed system is shown in Figure 1.

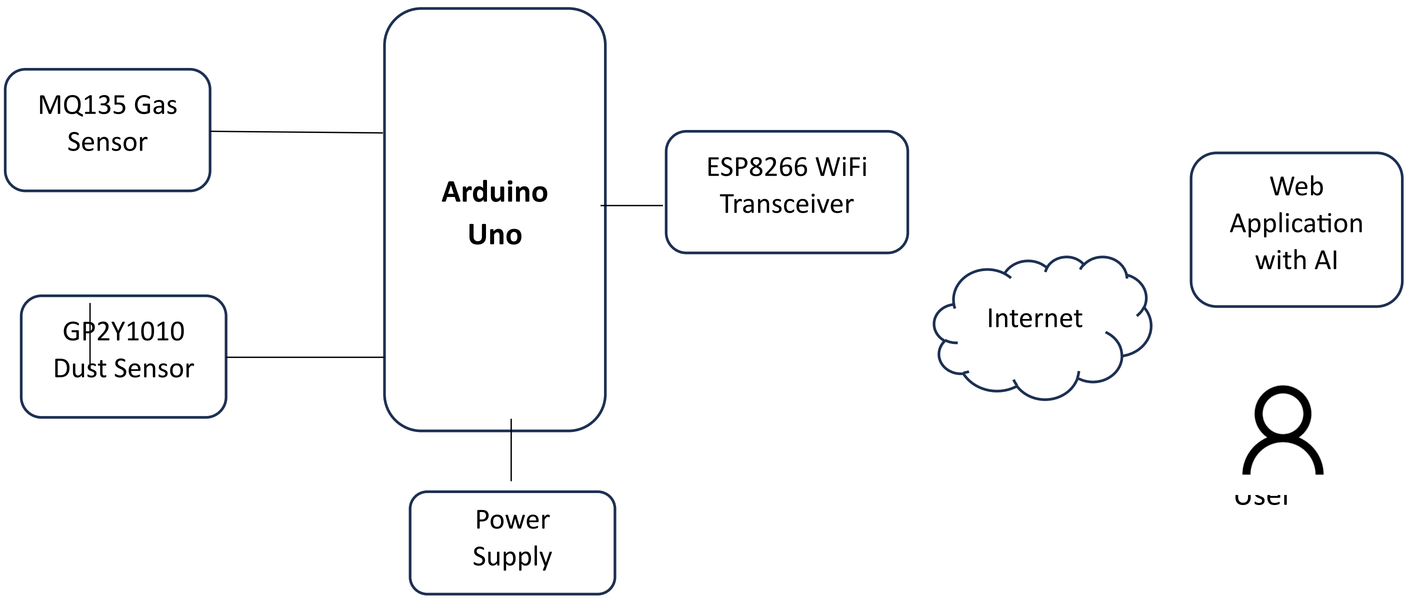

Figure 1. Block diagram of the proposed system

A prototype of the developed device is shown in Figure 2. The prototype is placed near the front of the classroom board. The readings are taken between 9.00 am and 5.00 pm. The information is gathered over the course of 25 days.

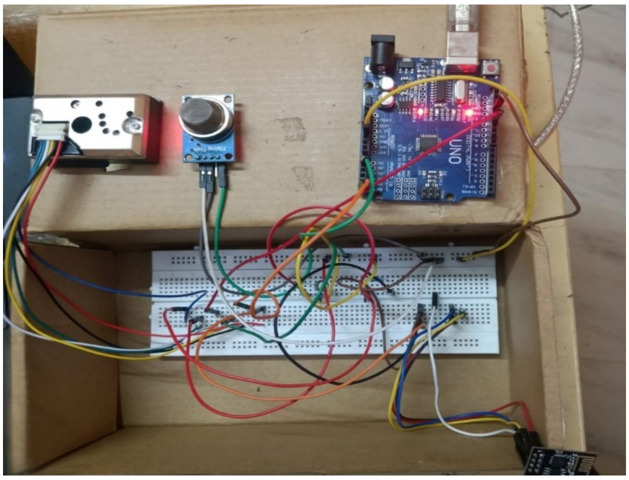

Figure 2. Hardware prototype of the proposed system

The Figure 2 shows the prototype of the proposed classroom air quality monitoring and prediction system.

i. Arduino UNO

The Arduino UNO (Badamasi, 2014) is a device that collects and processes sensor data. There are six analog pins and fourteen digital pins on the device. The Arduino UNO is a low cost microcontroller that uses the ATmega328 and operates on 8-bit data. The sensor data is wirelessly transmitted to the webserver via the ESP8266 transceiver (Rosli et al., 2018).

ii. Air Quality Sensor (MQ135)

When the target polluting gas is present, the sensor's conductivity increases proportionally to the gas concentration. Ammonia, sulphur, and benzene, as well as smoke and other hazardous gases, are detected by the MQ135 gas sensor (MQ135 datasheet, 2023). It is a low-cost sensor that can detect a wide range of hazardous gases and has a wide range of applications.

iii. Dust Sensor (GP2Y1014AU0F)

The dust sensor GP2Y1010AU0F (Dust sensor datasheet, 2023) works based on optical sensing. GP2Y1010AU0F is very good at detecting very small particles. The dust sensor uses very little power ranging from 11mA to 20mA and can be powered directly from the Arduino board. The output of the sensor is an analog voltage proportional to the observed dust density.

3.3. Data pre-processing

The pre-processing procedures aid in decreasing the noise in the data, which ultimately speeds up processing and improves generalization ability. To obtain the values between two successive sample points, we employed interpolation (Davis, 1975). The system is smoothed out to default.

3.4. Hierarchical clustering analysis

The Algorithm 1 represents the working of hierarchical clustering algorithm. The algorithm begins with a dataset of n data points. A dissimilarity matrix D is computed, measuring the dissimilarity between each pair of data points using the euclidean distance (Liang et al., 2012). Initially, each data point is assigned to an individual cluster. The algorithm iteratively merges the two closest clusters based on the dissimilarity matrix. The linkage criterion determines how the distance between clusters is calculated, with options such as single linkage, complete linkage, or average linkage. The dissimilarity matrix is updated by recalculating the dissimilarities between the new cluster and the remaining clusters. Merged clusters are removed from the list. The algorithm continues until only one cluster remains, representing the complete hierarchy. The output is a dendrogram, a visual representation of the clustering process. The dendrogram displays the hierarchy of clusters and the order in which they were merged. The height at which clusters are merged indicates the dissimilarity or distance at which the merge occurred.

Algorithm 1. Hierarchical clustering analysis

Step 1: Start with a dataset consisting of n data points.

Step 2:

Compute the dissimilarity matrix D, where D[i,j] represents the dissimilarity between data point i and data point j. The dissimilarity measure used in this case is the Euclidean distance.

Euclidean Distance:

$$D[i, j] = \sqrt{\sum_{k=1}^{p} \left(x[i,\ k] - x[j,\ k]\right)^{2}}$$

for k = 1 to p, where x[i, k] and x[j, k] are the values of the k^{th} feature of data points i and j, respectively.

Step 3:

Assign each data point to an individual cluster: C[i] = {i}, where C[i] is the cluster containing data point i.

Step 4:

While the number of clusters is greater than 1:

a. Find the two closest clusters, C_i and C_j, based on the dissimilarity matrix D.

- Single Linkage: $D(C_i, C_j) = min(D[i, j])$ for all i in C_i and j in C_j
- Complete Linkage: $D(C_i, C_j) = max(D[i, j])$ for all i in C_i and j in C_j
- Average Linkage: $D(C_i, C_j) = average(D[i, j])$ for all i in C_i and j in C_j

b. Merge the two closest clusters C_i and C_j into a new cluster C_{new}:

$$C_{new} = C_i \cup C_j$$

c. Update the dissimilarity matrix D by recalculating the dissimilarities between C_{new} and the remaining clusters.

- Single Linkage: $D[C_{new}, C_k] = min(D[i, j])$ for all i in C_{new} and j in C_k
- Complete Linkage: $D[C_{new}, C_k] = max(D[i, j])$ for all i in C_{new} and j in C_k
- Average Linkage: $D[C_{new}, C_k] = average(D[i, j])$ for all i in C_{new} and j in C_k

d. Remove clusters C_i and C_j from the list of clusters.

The air quality samples are partitioned into distinct subsets using hierarchical cluster analysis, which is performed with the aim of achieving the objective of indoor air quality monitoring.

- Group 1: Low Pollution

This group consists of indoor spaces with low levels of pollutants such as particulate matter (PM), Air quality index. These spaces have good ventilation systems, effective air filters, and low occupant density. The air quality in this group is considered to be of high quality.

- Group 2: Moderate Pollution

This group consists of indoor spaces with moderate levels of pollutants. The levels of PM and Air quality index may be slightly higher compared to Group 1. These spaces may have average ventilation systems and moderate occupant density. The air quality in this group is considered to be moderate.

- Group 3: High Pollution

This group consists of indoor spaces with high levels of pollutants. The levels of PM and Air quality index are significantly higher compared to Group 1 and Group 2. These spaces may have poor ventilation systems, lack of air filters, or high occupant density. The air quality in this group is considered to be poor.

3.5. Prediction

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They consist of interconnected nodes called neurons, organized in layers. ANNs are capable of learning complex patterns and relationships in data through a training process. Long Short-Term Memory (LSTM) (Karim et al., 2019) is a type of recurrent neural network (RNN) that addresses the vanishing gradient problem, which is common in traditional RNNs. LSTM networks are well-suited for handling time-series data as they can capture long-term dependencies and store information over extended sequences.

To construct an ANN model with LSTM layers for time-series prediction, the following steps are involved (Sagheer & Kotb, 2019):

i. Architecture Design: Determine the number and arrangement of LSTM layers in the network. Each LSTM layer will have a specific number of memory cells or hidden units that can retain information from previous time steps.

ii. Input Preparation: Prepare the input data in a suitable format for the LSTM network. In the case of time-series prediction, the input data should include the historical values of the features (e.g., AQI and dust level) at different time steps.

iii. LSTM Layer Configuration: Configure each LSTM layer by specifying the number of memory cells or hidden units within the layer.

iv. Connection and Data Flow: Connect the LSTM layers sequentially to form the network. The output of one LSTM layer serves as the input to the next layer until the final layer is reached.

v. Training: Train the ANN model with LSTM layers using a suitable optimization algorithm, such as backpropagation. During training, the model learns to adjust the weights and biases of the LSTM cells to minimize the prediction error between the actual and predicted values.

vi. Time-Series Prediction: Once the model is trained, it can be used for time-series prediction. Provide the current and previous values of the features (e.g., AQI and dust level) as input to the LSTM layers, and the model will generate predictions for future time steps.

The equation computes LSTM are as follows:

Input Gate: $i(t) = \sigma(U(i)[h(t\text{-}1), x(t)] + V(i))$ (1)

Forget Gate: $f(t) = \sigma(U(f)[h(t\text{-}1), x(t)] + V(f))$ (2)

Output Gate: $o(t) = \sigma(U(o)[h(t\text{-}1), x(t)] + V(o))$ (3)

Memory Cell: $c(t) = tanh(U(c)[h(t\text{-}1), x(t)] + V(c))$ (4)

Final Cell: $C(t) = f(t)C(t\text{-}1) + i(t)c(t)$ (5)

Hidden Layer: $h(t) = o(t)tanh(c(t))$ (6)

Output Layer: $y(t) = W(y)h(t)$ (7)

where h(t) represents the hidden layer state, x(t) represents the input data (including AQI and dust level), y(t) represents the predicted output, and the variables (U, V, W) represent the model's weights. The biases are denoted by the new variables (V(i), V(f), V(o), V(c)).

4. RESULTS AND DISCUSSION

This section describes the results obtained by our proposed system.

Figure 3. Air quality level display on the webpage

The Figure 3 shows the value of air quality measured by MQ135 sensor and dust density is measured by optical dust sensor are displayed on the webpage. In our observation we found the air quality falls in the normal range and dust value ranges from normal to moderate. According to air quality index (AQI Basics, 2023), the moderate AQI value ranges up to 0 – 150 ppm and the moderate Dust density (Cho et al., 2019) ranges up to 0 – 50 µg /m^3. During the days of observation, the values of air quality and dust density were found to be in the normal to satisfactory range. The reason for this is that there is better ventilation in the classroom, better air flow, and more empty space around the classroom.

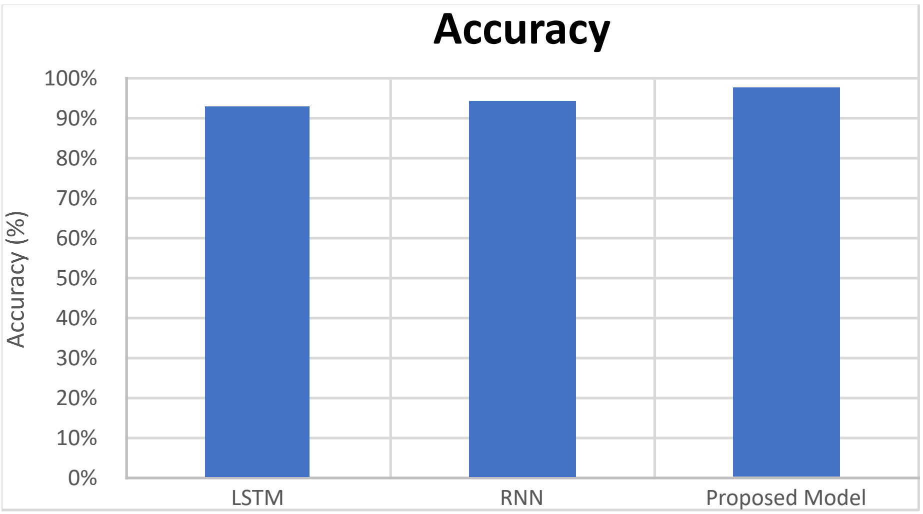

Figure 4. Comparison of accuracy

The accuracy values provided in the Figure 4 reflect the performance of different models in terms of correctly predicting outcomes or classifying data. The models evaluated include LSTM (Long Short-Term Memory), RNN (Recurrent Neural Network) (Medsker & Jain, 2001), and the proposed model. The LSTM model achieved an accuracy of 93%. LSTM is a type of recurrent neural network designed to handle sequence data and mitigate the vanishing gradient problem. The RNN model achieved a slightly higher accuracy of 94.60%. RNNs are neural networks capable of processing sequential data by maintaining information through recurrent connections. This model outperformed the LSTM model, correctly predicting outcomes with an accuracy of 94.60%.The proposed model with the combination of hierarchical cluster and LSTM, attained the highest accuracy of 98.20%. This indicates that the proposed model surpassed both the LSTM and RNN models in terms of accuracy.

Table 2. Performance analysis of proposed model in terms of average MAE/MSE/RMSE

	Average MAE	Average MSE	Average RMSE
Air Quality Index	0.069	0.017	0.130
Dust Density	0.229	0.6327	0.2515

The Table 2 shows the performance analysis of the proposed method on the classification of different pollutants. The proposed model has achieved maximum performance with minimum error.

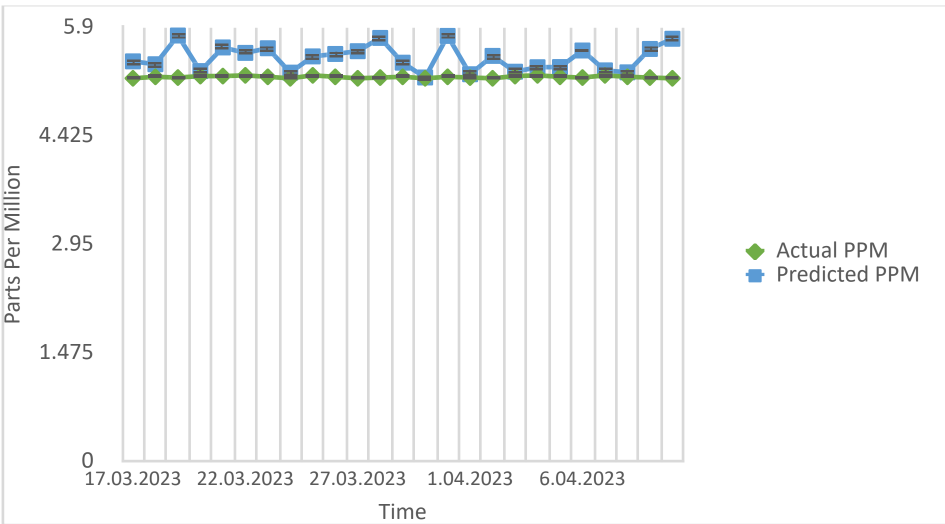

Figure 5. Air quality measurement and prediction

Figure 5 shows the measured and predicted air quality over a specific time period. With an error rate of 0.2 to 0.6, the proposed model is suitable for measuring air quality in a classroom during the day.

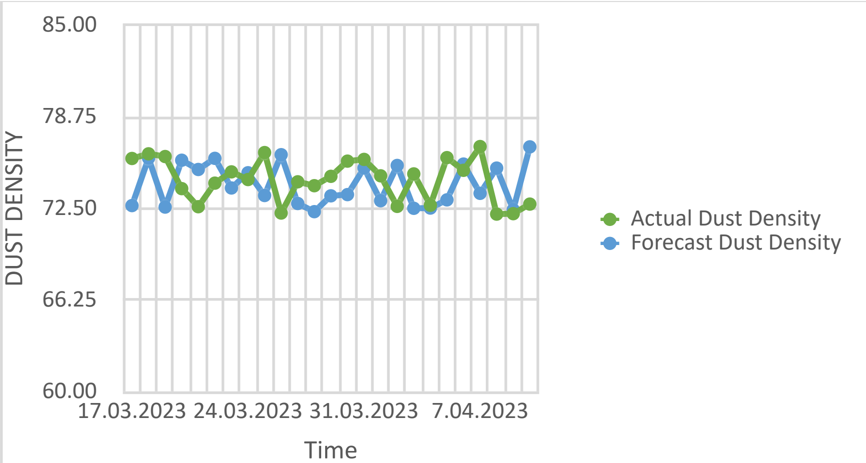

Figure 6. Dust density measurement and prediction

Figure 65 shows the measured and predicted values of dust density over a specific time period. The results show that the error rate ranges from 4 to 10 (µg/m3). During certain hours, the frequency of use of chalk is high, and construction work near the classroom's perimeter causes the dust density prediction to differ from the predicted value.

5. CONCLUSION AND FUTURE WORK

This paper proposed and tested an IoT based system for measuring and forecasting air quality and dust levels in a classroom setting. The prototype was tested in a classroom setting on a small scale. The proposed system's prediction is useful for taking immediate precautionary measures if air quality and dust levels reach dangerous levels. The results show that the machine learning algorithm is appropriate for real-time deployment. As part of future work, we plan to expand the network's size and test the suitability of the proposed algorithm.

Author contribution Conceptualization, A.Pravin Renold (A.P.R.). Data curation, A.Pravin Renold and A.Arockia Abins (A.A.A.). Investigation, Jeevaa Katiravan (J.K.). Methodology, A.Arockia Abins, A.Pravin Renold and Jeevaa Katiravan. Writing—original draft, A.Pravin Renold Writing—review and editing, A.Arockia Abins and Jeevaa Katiravan.

Funding No funding was obtained for this study

Data availability The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations All authors have read, have understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Competing interests The authors declare no competing interests.

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