# An AI-Enabled Edge-IoT Framework for Real-Time Air Quality Forecasting and Microclimate Zoning in Urban Smart Environments

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**Abstract**
The fast-rising urbanization and industrialization rates associated with urban agglomeration studies during recent decades have resulted in a considerable reduction in air quality in urban zones, specifically in cities such as Rajasthan, with profound impacts on public health, environment, and urban liveability. Taking into account all the aforesaid concerns and associated complexities, this research study presents an innovative AI-powered Edge IoT system with real-time air quality forecast models and microclimate zones for effective smart urban infrastructure embedding. The proposed system includes a hybrid Long Short-Term Memory-Convolutional Neural Network architecture for efficient and precise forecast models concerning critical air quality components such as PM2.5 & PM10. The system is developed with comprehensive historical datasets ranging from 2019 to 2024 pertaining to air quality and corresponding meteorological factors compiled from Central Pollution Control Board and Open NASA API. Performance analysis with prevalent parameters illustrates its potent predictive aptitude with $R^2$ value 0.88, low values for both RMSE & MAE, with a target MAPE value of 9.8% with high efficacy and reliability. The forecasted values for air quality constituents are applied for simulating real-time response actions with virtual IoT sensing systems developed with Autodesk Tinkercad. Additionally, the framework is capable of micro-climate zoning by employing unsupervised machine learning algorithms such as k-means clustering algorithms to identify pollutant and meteorological patterns. This is done to enable the creation of hyper-local zones for pollutant emissions as well as environmental predictions.

**Keywords:** Air Quality Forecasting, LSTM-CNN, IoT, Microclimate Zoning, PM2.5, PM10, Rajasthan, Smart Cities, Environmental Monitoring

## 1. Introduction

Urbanization and industrialization have brought considerable changes in the environmental conditions in both developed and developing countries. Among the most hazardous issues arising from these conditions, air pollution stands as a major concern. This not only affects the health conditions of people but also affects the environment, nature, and sustainability. According to the World Health Organization, being frequently exposed to both PM2.5 and PM10 is associated with severe health problems such as respiratory, cardiovascular, and neurosurgical issues, among others [33]. In regions with dense population, air pollution in India, for instance, is mainly caused by major emissions from vehicle traffic, industries, and use of fuel in residential sectors. This calls for monitoring and analysis of air quality in real time and space to enable public health and policy formulation. Currently, air quality monitoring involves a


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centralized system, meaning they are not densely distributed and fail to respond dynamically to the ever-changing conditions of the environment [5].

Effective forecasting related to pollution level is essential for ensuring that measures can be taken by citizens and authorities alike to prevent them. The inclusion of Internet of Things (IoT) technologies in air quality assessment systems allows for information to be gathered from different zones of urban settings, thus providing improved resolution and awareness [34]. Additionally, with the aid of intelligence tools such as AI, IoT systems can provide near-real-time information related to forecasts and notifications for different zones. The combination of IoT and AI has brought technological innovativeness to a new dawn in the field of environmental monitoring systems. The IoT device with a sensor can gather information related to different dimensions of a particular environment—particulate matter, temperature, humidity, and wind speed. However, sophisticated algorithms related to AI, specifically methods such as Long Short-Term Memory and Convolutional Neural Network algorithms, prove effective in understanding different dimensions and complexities related to this information, leading to future levels related to pollutants being effectively assessed [38,39].

The rationale for conducting this research is based on the requirement for a comprehensive, economical, and intelligent solution that can provide, in real time, air-quality forecasting and warning messages in an urban area. In fact, although air-quality forecasting based on AI techniques and air-quality monitoring using IoT networks have been investigated separately in previous studies, less work has been seen focusing on an overall Edge-IoT solution that encompasses both aspects. Further, there is variability in air quality across an urban area because of climatic differences. Hence, zoning based on microclimates, via clustering, is necessary for increasing accuracy in local air-quality forecasting [6].

Paper Organization

The rest of the paper is outlined as follows:

- Section 2 entails a thoroughly considered examination of existing literature regarding AI and IoT implementations within air quality observation systems.
- The system architecture and the proposed microclimate zoning approach and model for the forecast system are explained. These methods and concepts can be understood by reading Section 3.
- Section 4 presents and interprets the results.
- Section 5 presents a summary of this study and Future Work.

## 2. Literature Review

Air quality and microclimate dynamics have evolved as some of the most important areas of concern in sustainable cities, and in relation to smart cities as well. For a synthesis of past research and to understand areas where more research is required on air quality and microclimate dynamics, related areas include air quality monitoring, forecast approaches, deep learning approaches to predict time-series data, IoT-based sensing for environmental parameters, and microclimate zonation for regions and cities. The Internet of Things (IoT) has found its way as a new paradigm in environmental sensing and monitoring, and acquiring data on parameters in real time using been a few studies on the development of an inexpensive IoT-based sensor network for pollution analysis [38]. For instance, Karar et.al. proposed an Arduino Uno-based wireless air quality analysis system that uses an MQ135 gas sensor for urban pollution analysis. Though this system is based on real-time analysis, it lacks predictability features [32]. This, in turn, leads to the requirement of integrating AI models that can trend and forecast the level of pollutants. Additionally, the role of the IoT node in most systems is that of a passive data point instead of edge computing [17].

Air quality forecasting entails the use of historical concentration and weather data to make future forecasts. Most of the earlier works used statistical methods such as ARIMA (AutoRegressive Integrated Moving Average) modeling for air quality forecasting, in addition to other techniques including Holt Winters and simple exponential smoothing methods [30, 35]. While these models are interpretable, they struggle with non-linear patterns and fail to adapt to dynamic urban environments [29]. To overcome these limitations, machine learning algorithms like Random Forest, Support Vector Regression (SVR) [21], and Gradient Boosted Trees (e.g., XGBoost, LightGBM) [27] have been adopted. These models capture non-linearity better and are scalable. However, they often require extensive feature engineering and are limited in modeling temporal dependencies unless lag features are explicitly introduced [16].

Deep learning techniques, particularly Recurrent Neural Networks which have revolutionized time series prediction tasks [31]. Long Short-Term Memory (LSTM) networks address the vanishing gradient problem of standard RNNs and are highly effective for modeling long-term temporal dependencies [2]. Several researchers have shown that LSTM models outperform traditional ML models in air quality prediction [28]. CNNs, though originally designed for image data, have been adapted to time series by treating multivariate temporal sequences as pseudo-images [8]. CNNs can extract local temporal patterns using convolutional filters, which improves performance when combined with LSTM in a hybrid architecture. Recent works have shown the efficiency of LSTM-CNN combinations for air quality forecasting with better values of RMSE and MAE than traditional models. In spite of their accuracy, most air quality models are processed centrally without being combined with edge computing or IoT circuits for real-time notifications, which is the target of this work. Microclimate zoning is the partitioning of urban areas into regions characterized by similarities within their environment [36]. Cities usually show heterogeneity between air qualities contained within them due to geographical, use, traffic density, as well as industrial activities [19]. Methods such as K-means clustering [22], DBSCAN [4], as well as hierarchical clustering algorithms [7] have been used for dividing cities or geographic areas into microclimate regions. It has been shown that air quality zoning enables better analysis results as well as accuracy within localized predictions [39]. In addition, very few studies have conducted air quality zoning within deep learning-based prediction models, especially with real-time air quality sensing by IoT devices [20].

Edge Computing pushes AI model interpretation closer to data sources, reducing expectancy and improving responsiveness [24]. In environmental systems, deploying lightweight AI models (e.g., TensorFlow Lite or ONNX) on edge devices like Raspberry Pi or ESP32 enables real-time decision-making [37]. Research by Aljumaily et al. (2023) demonstrates using edge-deployed AI models to trigger alerts for forest fire detection based on sensor data [1]. Few studies, however, simulate or demonstrate this integration using academic tools like Tinkercad [23]. This paper bridges this gap by simulating a real-world IoT circuit in Tinkercad, integrate it with a Python based LSTM-CNN Model and proposing a conceptually deployable framework.

The review highlights the following research gaps:

- Lack of integration between real-time IoT sensor simulation and predictive deep learning models.
- Minimal use of hybrid LSTM-CNN architectures tailored to air quality

- Limited simulation-based demonstrations combining AI, IoT, and edge computing within a single workflow.

This research contributes by:

- Developing a hybrid deep learning model for pollutant forecasting using historical meteorological and pollution data.
- Simulating a real-time IoT circuit using Tinkercad to reflect data acquisition and alerting.
- Introducing microclimate zoning using unsupervised learning to segment urban regions.
- Conceptualizing and partially implementing an AI-IoT-edge integration model with potential for smart city deployment.

## 3. System Architecture and Methodology

The proposed AI-enabled edge-IoT is a light-weight framework system combines machine learning and embedded system design to real-time air pollution forecasting and microclimate zoning using air pollutant and meteorological data as shown in Figure 1. The framework consists of the 5 components as shown in figure:

1. **Data Acquisition Layer:** Historical air pollutant and meteorological data from four cities (Jaipur, Kota, Bhiwadi, Udaipur) from 2019 to 2024.
2. **Microclimate Zoning Layer:** Clustering-based segmentation of cities into similar environmental zones.
3. **Forecasting Layer:** LSTM-CNN deep learning model for predicting PM2.5 and PM10 levels.
4. **IoT Sensing and Alerting Layer:** Arduino-based simulation in Tinkercad for real-time data collection and alert generation.
5. **Integration Layer:** Data interface between Python-based AI models and the IoT circuit via serial or hypothetical network communication

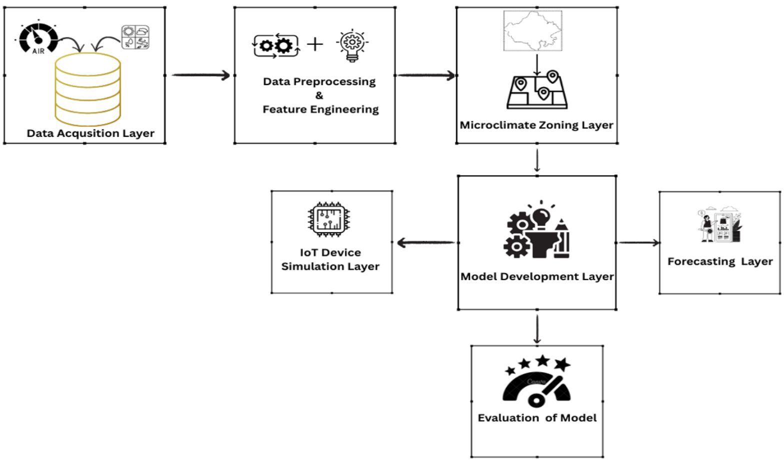


**Fig. 1.** System Architecture

The methodology comprises of 7 key phases:

## 3.1. Data Acquisition:

To build a competent and representative data pool for air quality prediction and microclimate zoning, data was collected from a number of credible sources. Concentrations of major air pollutants are provided by the Central Pollution Control Board (CPCB), and high-resolution atmospheric and radiation data is collected from global reanalysis datasets like NASA POWER. The paper focuses on four carefully selected major cities in Rajasthan: Jaipur, Kota, Udaipur, and Bhiwadi. All these cities have been chosen not just for their heavy industrialization, fast pace of urbanization, and recognized air quality, but also due to their different geographical environments in and around the Aravalli ranges.

Rajasthan is located in northwestern India and contains both arid and semi-arid climatic zones, with significant topographic variation because of the presence of the Aravalli hills [26]. The Aravalli Range is one of the oldest mountain systems in the world and extends diagonally from northeast to southwest within the state. It leads to large variability in wind flow, rainfall distribution, and localized micro-climates within different cities. It also acts as a natural barrier that can affect pollutant transport and meteorology and hence forms an important geographical feature in the development of air quality modeling [22]. Jaipur, the capital city, lies on the eastern extent of Aravalli hills and is highly urbanized with increasing vehicular and industrial emissions [10]. Kota, located in the southeastern part of the state along the Chambal River, has rich industrial hubs and a high population density, which causes localized air pollution episodes [13]. Udaipur, nestled in southern Aravalli hills, presents contrasting hill topography with typical atmospheric circulation because of the surrounding topography [14]. Bhiwadi is an industrially rich city in northeastern Rajasthan and forms part of the NCR and is highly polluted due to proximity to Delhi and heavy manufacturing [15]. For this purpose, there are two broad types of variables included in the dataset: air pollutants, which are represented in table 1, and meteorological variables. The air pollutants include PM2.5, PM10, NO, $NO_2$, NOx, CO, $SO_2$, $NH_3$, and ozone key parameters of air quality. Then there are meteorological variables that include temperature, humidity, wind speed, wind direction, solar radiation, rainfall, and evapotranspiration. After combining all this data, there would be over 8,500 daily observations for each of the cities, which would be a total of over 34,000 observations.

**Table 1.** Dataset Attributes

| Category | Variables |
|---|---|
| Pollutants | PM2.5, PM10, NO, $NO_2$, $NO_x$, CO, $SO_2$, $O_3$, $NH_3$ |
| Meteorological | Temp (max, min, avg), RH, Wind Speed, Sunshine, Precipitation, Radiation, Pressure, Wind Direction |
| Temporal | Date, Day, Month, Season |
| Location | City, Area, Station |

### 3.2. Data Preprocessing and Feature Engineering:

The dataset begins with air pollutants and weather data recorded on a day-to-day basis. A proper data preprocessing pipeline is applied to prepare the dataset for use in the models. The Date column is converted into proper date-time data, which is then sorted and aggregated on a rolling mean basis, preserving the day-to-day variations and removing noise from the data. Missing data points are imputed with medians, which are helpful in keeping the data stable under the presence of outliers. All numerical columns are then scaled with the Min-Max scaling technique, scaling all data into the 0 and 1 range. Finally, for PM2.5 and PM10 data, a seasonality component is decomposed from the data using an additive seasonality model, which decomposes the data into trend, seasonality, and residuals, also shown in Figure 2. These components are retained in addition to the original data.

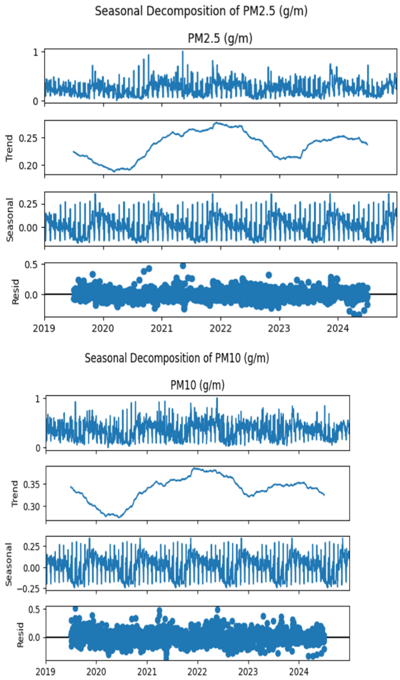


**Fig. 2.** Seasonal Decomposition of PM2.5 and PM10

Engineered features added further richness to the dataset. We calculated 7-day and 30-day window rolling averages for the capture of short- and medium-term trends, respectively, and also lag features of 1, 3, and 7 days were included, embedding historical dependencies, which are crucial for forecasting. Temporal features also include month, day, weekday, and weekend indicators that will reflect in the periodicity and behavioural cycles of air quality. Mutual information regression was also used to check how meteorological variables are associated with PM2.5 and PM10. Feature Correlation As can be seen in Figure 3, features such as pressure_nasa, temp_avg, rel_humidity, et0, windgusts_max, and wind_speed_nasa had a high pairwise connection with pollutant level variation and were retained for model training, balancing interpretability against predictive power.

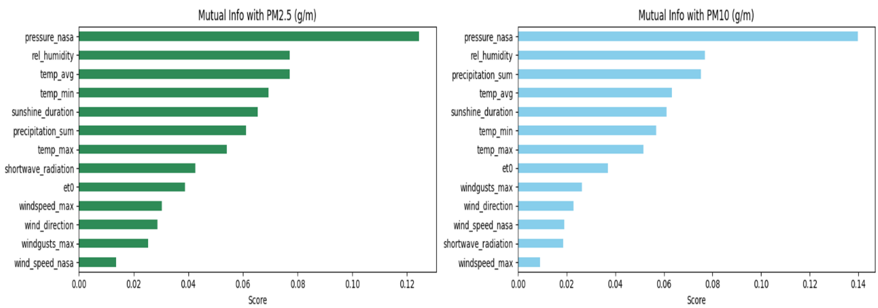


**Fig. 3.** Mutual Information with PM2.5 and PM10

### 3.3. Microclimate Zoning

In order to split the city into different microclimates based on the climatic regions, K-Means clustering was performed on the primary climatic variables that were determined to be relevant by mutual information. The relevant variables were normalized before applying the clustering function. The number of clusters that best described the characteristics of the clusters as well as how they were separated was determined by analyzing the Silhouette Score of the clusters. This resulted in four clusters based on a silhouette score of about 0.51 as seen in Fig.4. These clusters reflected the hidden climatic patterns in the dataset.

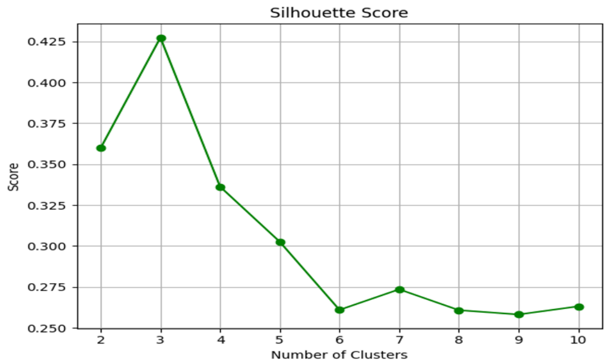


**Fig. 4.** Silhouette Score for each cluster

The results of the clusters were presented on a 2D scatter plot (figure 5). Each point represents a day, colored based on the cluster it belongs to. It is evident from the scatter plot that a negative correlation exists between the atmospheric pressure and the average temperature for all the clusters. For instance, consider the cluster 0, which lies in the lower temperature, higher pressure region, implying a stable, cold environment. However, cluster 3 lies in the higher temperature, lower pressure region, implying a warm and perhaps unstable environment. To understand the correlations among the features in each cluster, a correlation graph was plotted using NetworkX. Edges were created for the variables that are highly correlated (|r|> 0.6). For cluster 0, it is seen that a vehement correlation exists among the variables such as PM2.5, PM10, and meteorological variables like windgusts_max and rel_humidity, implying that the air currents play a pivotal role in the atmospheric constituents' activities in this cluster. The zoning technique used not only identifies spatial predictions, it also enables the use of tailored edge computing systems for IoT predictions in various micro-zones.

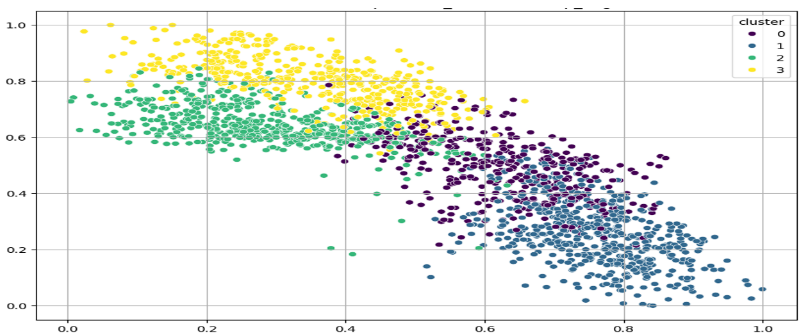


**Fig. 5.** Microclimate Zoning

### 3.4. Model Development

The hybrid model based on LSTM and CNN brings together the time-conscious training capabilities of LSTMs with the spatial pattern recognition capabilities of CNNs. This is very effective in forecasting air pollutant concentration levels using meteorological data.

Input data is treated as multivariate time-series and segmented into five-day sliding windows to analyse the time-series trends on different features. A long-short term memory layer with 64 units is used to process long-term dependencies between the time-series values of pollutant and weather features. Subsequently, a one-dimensional convolutional layer with the filter size set to 64 filters and a kernel size of 2 is applied to analyse the local time-series features. Finally, the features are processed through a dense layer with 32 neurons, followed by the solitary output neuron that predicts PM2.5 or PM10 concentrations.

A Python-based TensorFlow/Keras framework is used to develop this system. The major parameters used were optimizers=Adam, loss functions MSE (mean squared error function), number of epochs=100, batch size=32, and early stopping with patience=10. Taking into account variations in weather patterns for different regions, we also developed models for each region that were identified through K-means clustering. While training models, we also checked validation loss with early stopping and saving the best models. All these practices assisted our models to capture localized patterns and thus aided in improving our forecasting performance.

### 3.5. IoT Device Simulation

The final, and most critical, part of this study was the simulation of an IoT device. This simulation involves creating a circuit involving an Arduino Uno, along with some necessary modules: a PM sensor, an LCD display, a buzzer, and a potentiometer, all implemented using a breadboard. The circuit will be powered through USB connections, while PM2.5 and PM10 values will be represented on an LCD display of a 16x2 interface. Results will be led out of this LCD through digital pins D2 to D7, along with a contrast-controlled potentiator. The PM sensor will be connected to respective analog or digital ports to detect particulate matter values. The buzzer will sound off whenever critical levels of air pollutants are exceeded. The breadboard allows this circuit to be organized in such a way that there is no obstruction to smooth flow. This prototype design project will enable a real-time CNN-LSTM prediction that will be used to create a functional air quality monitoring system. The completion of this circuit design is represented through figure 8.

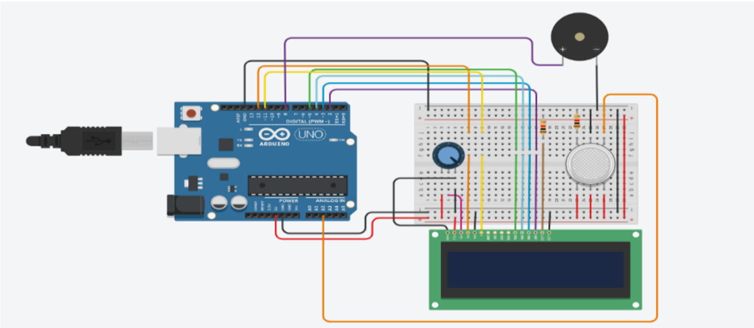


**Fig. 6.** IoT Circuit

After the development of circuit, the model was ported into IoT Device for simulation where the forecasting logic is integrated with a virtual microcontroller setup to mimic real-world deployment.

### 3.6. Forecasting

The Forecasting Layer processes incoming data inputs to generate pollution level predictions in real time. The readings were recorded and saved as an csv file as shown below:

**Table 2.** Forecasted Values

| Date | PM2.5 | PM10 |
|---|---|---|
| **20-06-2025** | 88.07 | 212.11 |
| **20-06-2025** | 129.18 | 155.79 |
| **20-06-2025** | 62.94 | 84.96 |
| **20-06-2025** | 51.68 | 198.59 |
| **21-06-2025** | 114.13 | 173.29 |
| **21-06-2025** | 47.37 | 215.19 |
| **21-06-2025** | 140.73 | 93.97 |
| **21-06-2025** | 65.91 | 89.34 |
| **22-06-2025** | 79.99 | 143.96 |
| **22-06-2025** | 94.67 | 106.6 |
| **22-06-2025** | 115.36 | 82.32 |
| **22-06-2025** | 78.6 | 118.62 |
| **23-06-2025** | 97.45 | 185.63 |
| **23-06-2025** | 67.96 | 142.28 |
| **23-06-2025** | 113.13 | 67.43 |
| **23-06-2025** | 114.87 | 87.28 |
| **24-06-2025** | 52.48 | 211.82 |
| **24-06-2025** | 156.05 | 189.34 |
| **24-06-2025** | 80.03 | 75.63 |
| **24-06-2025** | 123.69 | 130.42 |

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The Hybrid CNN-LSTM Model showed strong alignment between actual and predicted values of PM2.5 and PM10 for the next 5 years as shown in graph below.:

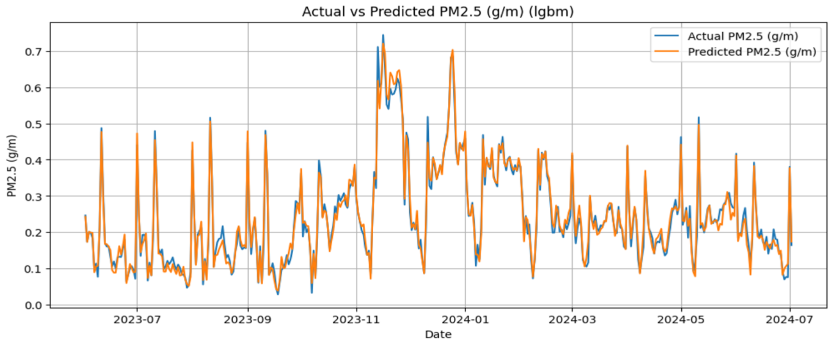


**Fig. 7.** Actual vs Predicted PM2.5

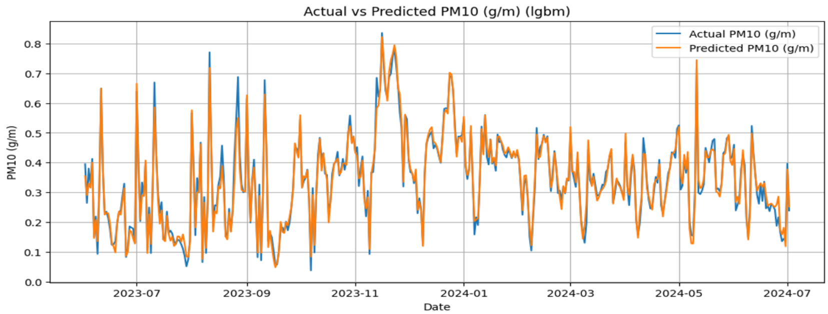


**Fig. 8.** Actual vs Predicted PM10

### 3.7. Model Evaluation

To assess the accuracy level of the new LSTM-CNN model, we chose to apply four different standards for regression evaluation: RMSE, MAE, MAPE, and $R^2$. Taking all these parameters into account will offer a comprehensive insight into accuracy, the impact posed by the outliers, as well as the explained variability in the data for the prediction. This assessment will be conducted for three microclimates that were recognized using K-Means clustering, as shown in Table 3, based on the meteorological and pollution attributes for the different cities.

**Table 2.** Forecasted Values

| Zone | RMSE | MAE | $R^2$ Score | MAPE (%) |
|---|---|---|---|---|
| Zone 0 | 18.35 | 15.52 | 0.86 | 15.52 |
| Zone 1 | 18.45 | 13.02 | 0.88 | 9.8 |
| Zone 2 | 22.61 | 16.83 | 0.84 | 11.5 |
| Zone 3 | 19.77 | 14.21 | 0.85 | 10.2 |

For all zones, the $R^2$ values remained well above 0.80, emphasizing the high explanatory and predictive abilities of the developed models with respect to accurately estimating the level of pollutants in varying environmental conditions. Another factor that helped increase the accuracy of the models was the microclimate zoning of cities through the application of the K-Means clustering method. This helped reduce the variance within the zones and allowed us to create models specific to each microclimate with characteristics differing from one microclimate to the other. For the combined zone, the accuracy of the developed models was outstanding: RMSE 18.45, MAE 13.02, $R^2$ 0.88, and MAPE 9.8%. Additionally, the predictive abilities were consistent for the three microclimates determined through the application of the clustering technique.

## Conclusion

This work proposes an Edge-IoT framework powered by AI that fuses deep learning with embedded systems toward real-time air quality forecasting and microclimate zoning. The work, which is based on a hybrid LSTM-CNN model and simulation of its integration in IoT using Tinkercad software, has presented a modular and scalable approach to predictive environmental monitoring. By incorporating microclimate-based clustering and alert features, the system gains more pronounced spatial detail and practical utility. Results from this study suggest that this method will surely support proactive environmental management, public health protection, and wiser urban planning. The subsequent development of the model involves deployment on actual edge hardware, linking streams of real-time data, and expansion to health risk assessment and multi-city scalability for further impactful results. In summary, this paper lays a good foundation for future advances in intelligent urban air quality systems, driving cities toward more sustainable and data-driven lifestyles.

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