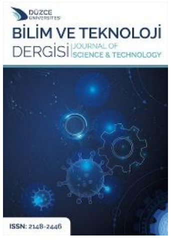

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Research paper

Air Quality Forecasting in Urban Environments: A Deep Learning Approach

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ABSTRACT

Air pollution has become an important research topic due to its environmental and human health effects. Today, rapid industrialization and urbanization is one of the major factors in the emission of harmful gases, leading to deteriorating air quality. In this study, air quality problems are discussed, and the adverse effects and consequences of pollutants including sulfur dioxide (SO2), nitrogen dioxide (NO2), carbon monoxide (CO), and particulate matter (PM2.5 and PM10) on human health are assessed. In this study, air quality data from Beşiktaş, Istanbul, has been analyzed by using deep learning models based on Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) to predict air pollutant levels and values. The performance of these models is evaluated using metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The study's findings reveal that the presented GRU model provides superior forecast accuracy for pollutants like CO and NO2, while the CNN model performs better for SO2 and O3 forecasts. This study highlights the importance of using advanced deep-learning techniques for air pollution management. It shows the potential of predictive models to contribute to the policy-making process for sustainable development.

Keywords: *Air Quality Forecasting, Deep Learning Models, Urban Environments, Pollution Forecasting*

I. INTRODUCTION

Air pollution is becoming an increasingly important research topic as a severe problem globally. Industrialization and urbanization are emerging as essential factors in the deterioration of air quality. These factors cause harmful gases to be emitted into the atmosphere and seriously affect human health. This damage affects not only humans but also nature. Air pollution and the consequent bad air quality refer to the destruction of the natural composition of the atmosphere. It is a multidimensional environmental problem where physical, chemical, and biological factors affect this natural composition. Fundamental reasons such as industrialization and urbanization and the common use of fossil fuels, especially in developing countries, are among the main factors that cause air quality deterioration and air pollution (Wu et al., 2023).

Air quality problems have negative impacts not only on humanity but also on biodiversity and ecosystems (Zeinalnezhad et al., 2020). Harmful gases in the atmosphere can disrupt the ecosystem balance due to damage to plant productivity and biological life. For example, gases such as nitrogen oxides, ozone, and sulfur dioxide negatively affect the photosynthesis process in plants and can also cause toxic factors. This, in turn, inhibits the growth of plants (Nakhjiri & Kakroodi, 2024).

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Globally, air quality has severe implications for human health. According to the World Health Organization (WHO), nearly 90% of the world's population lives in regions with bad air quality. This results in approximately 7 million premature deaths each year (Yang et al., 2024). According to another European Environment Agency (EEA) study, 307 thousand premature deaths have occurred in Europe in recent years due to bad air quality (Samad et al., 2023). Harmful gases in the atmosphere, such as carbon monoxide (CO) and PM2.5, can cause significant health problems in the respiratory and cardiovascular systems. Long-term exposure to such conditions can cause various chronic health problems, such as asthma and bronchitis (Shakya et al., 2023; Wen et al., 2019). In metropolitan cities where traffic density is intense and industrial activities are common, air quality is poorer, which poses a severe threat to the living population.

Air quality can also cause significant economic costs for the region. Deterioration of air quality can affect health expenditures, cleaning costs, and related labor losses (Jia et al., 2024). Table 1 shows the causes of harmful gases in the atmosphere and their effects on human health (Nakhjiri & Kakroodi, 2024). Developing effective policies and measures to prevent such consequences that directly affect health is becoming necessary.

Table 1. Gases in the atmosphere that affect air quality and their health effects

Gas	**Description**	**Health Problems**
Sulfur Dioxide ($SO2$)	Fossil is a colorless and pungent gas produced by the combustion of fossil fuels such as coal, industrial plants and motor vehicles that use such fuels.	Excessive exposure to SO2 in urban areas can cause respiratory diseases, lung disorders, eye and throat irritation.
Tropospheric Ozone (O3)	Ozone gas is formed by the chemical reaction of nitrogen oxides (NOx) under sunlight. Its concentration increases as a result of traffic and industrial activities.	It causes respiratory diseases including reduced lung function, inflammation of the throat and asthma. It also reduces life expectancy and affects the nervous and reproductive systems.
Nitrogen Dioxide (NO2)	NO2 is a harmful gas produced by the combustion of fossil fuels in industrial centers and industrial power plants.	It causes respiratory diseases and heart diseases.
Carbon Monoxide (CO)	CO is formed as a result of the use of fossil fuels in coal stoves and vehicle fuels.	It causes lung diseases, visual impairment and reduces life expectancy.

In recent years, various models have been developed in air quality forecasting. Thanks to these models it is an essential resource for developing appropriate strategies by predicting the spatial and temporal distribution of gas or different factors that cause this problem (Zhang et al., 2024). Machine learning and deep learning techniques provide successful forecasting rates in predicting air quality values, and accordingly, they contribute to producing strategic solutions. In literature, as an illustration, Long Short-Term Memory (LSTM) models have successfully resolved dependencies in time series (Drewil & Al-Bahadili, 2022). Similar artificial intelligence techniques make it possible to analyze and model the complex structure of air pollutants (Nakhjiri & Kakroodi, 2024). Thus, such forecasting models are critical for strategic measures and effective policies to achieve sustainable development goals (Drewil & Al-Bahadili, 2022; Jia et al., 2024; Wang et al., 2020; Zhang et al., 2024). They also play an essential role in guiding decision-makers and mitigating the negative impacts of air pollution.

A. Literature Review

According to the literature research, there are studies of different disciplines, including statistics, computer, and environmental units in air quality forecasting. Traditional air quality forecasting methods are mainly modeled based on atmospheric dynamics and chemical processes. However, their performance could be better in capturing complex and nonlinear time series patterns. Deep learning models have been observed to produce more accurate results in predicting such nonlinear patterns. Due to their multi-layered architecture, it is possible to recognize the structures representing the data related to air quality values more straightforwardly (Liu et al., 2019). Zhang et al. (2024) demonstrated improved results in learning long-term dependencies in PM10 and PM2.5 forecasting with an LSTM-based architecture presented as MTMC-NLSTM (Zhang et al., 2024). As traditional forecasting methods, techniques based on atmospheric and chemical processes have been used. These methods combine air quality values and meteorological data to create quantitative models. Such models as Community Multiscale Air Quality (CMAQ) and Nested Air Quality Prediction Modeling System (NAQPMS) are simulation systems based on this structure. Other statistical methods that utilize linear dependences and mostly linear correlations of atmospheric data, such as Autoregressive Integrated Moving Average (ARIMA) and Multivariable Linear Regression (MLR), are also among the statistical methods (Zhang et al., 2024).

Yand et al., air pollution forecasting, health effects, and economic situation have been evaluated together (Yang et al., 2023). In the study, the seasonality of time series data has been addressed by presenting a model with gray forecasting model and combined with other techniques. A 92% successful result has been obtained. According to the findings, it is concluded that PM 2.5 concentration for Beijing is expected to decrease in 2023-2025. In Wu et al. study, 95.2% accuracy performance has been achieved with CEEMDAN-PE-GWO-VMD-MIF-BiLSTM-AT hybrid models and deep learning model for PM2.5 forecasting in Beijing, Wuhan, Urumqi cities (Wu et al., 2023). In another study, five machine learning methods have been used to predict PM2.5, PM10, and NO2 concentrations in Stuttgart, and it has been shown that close monitoring stations are significant. According to the findings, it has been concluded that virtual monitoring stations can work with 89% accuracy. In their study, Ding et al. achieved high performance using a combined model for air quality forecasting based on four major pollutant data series in Hefei (Ding et al., 2022). In another study, the Land Use Regression (LUR) model has been used to predict PM2.5 in Delhi and achieved high accuracy (Morley & Gulliver, 2018). It has been found that the model provides higher accuracy and stability in PM2.5 forecasting compared to other methods. According to research studies, MSE, RMSE, MAE, and R2 metrics have been used to evaluate the results of the proposed model. These metrics are mostly preferred for the performance of the model and error rates in forecasting. Low MSE, RMSE, and high R2 values indicate that the model provides high performance and explains the effect of independent variables on dependent variables in a well-explained way (Cabaneros et al., 2019). The strengths and weaknesses of literature are summarized conclusively, and it is seen that traditional methods are inadequate in modelling non-linear systems. Deep learning models such as CNN, LSTM and GRU provide a more effective structure in terms of high accuracy and ability to recognize long-term dependencies. Contrary to the approaches in the literature, the proposed methods are able to analyze complex data relationships more successfully and are expected to provide more reliable and faster results in air quality forecasting.

In this study, deep learning techniques have been used to predict air quality parameters, including NO2, NO, O3, CO, SO2, PM10 and PM2.5 in the highly populated Beşiktaş region of Istanbul, and multiple models have been presented. The performance of the models is compared with standard metrics like R2, MSE, RMSE, and MAE, which are also used as standards in other studies. This study makes an analytical contribution to the deep learning-based approaches in literature by focusing on air quality prediction in urban environments. Particularly for a highly populated metropolis like Istanbul, the unique aspects of the study are the prediction of multi-pollutant levels (CO, NO2, O3, PM10, SO2) using different deep learning models, including CNN, LSTM, and GRU, and a comprehensive comparison of their performance. The results contribute to identifying the model appropriate for specific pollutants and improve the accuracy of prediction for air pollution management and effective policy making.

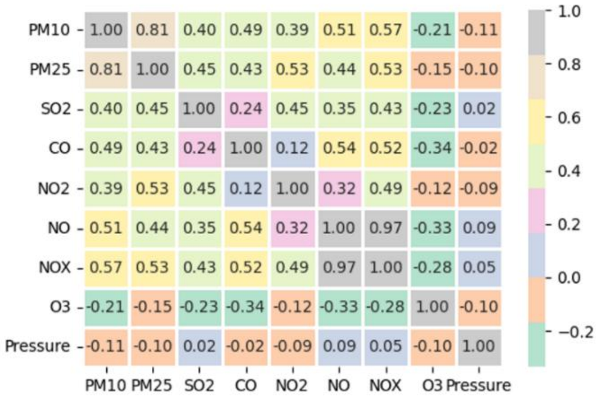
II. MATERIALS AND METHODS

A. Exploratory Data Analysis (EDA)

Beşiktaş is one of the leading provinces of Istanbul, which is dense in terms of industrial factories, traffic, economic activities, and population. This density also causes environmental problems such as air pollution, which also negatively affects human health. In this study, 1823 air quality values, including particulate matter (PM10), sulfur dioxide (SO2), ozone (O3), nitrogen dioxide (NO2), carbon monoxide (CO), and pressure values from the Istanbul Air Quality Monitoring Center between 2018-2023 have been used.

	count	mean	std	min	max
PM10	1826.0	32.42	14.58	4.3	98.5
PM25	1826.0	20.45	9.94	2.9	67.4
SO2	1826.0	3.54	2.61	0.5	26.0
CO	1826.0	514.74	183.6	78.5	1364.8
NO2	1826.0	50.41	20.17	9.0	129.3
NO	1826.0	55.49	47.03	0.3	310.9
NOX	1826.0	135.81	83.39	0.5	516.6
O3	1826.0	22.1	18.06	1.1	167.2
Pressure	1826.0	1016.61	6.47	995.4	1040.3

a



b

Figure 1. (a) Descriptive Statistics Data (b) Descriptive Data Correlation Heat Map

Figure 1 (a) shows the descriptive statistical data of the collected data, which includes statistical values of mean, standard deviation, minimum and maximum values of air pollutant values for Beşiktaş region. Figure 1 (b) shows the correlation heat map for the variables. Correlation coefficients range between -1 and 1, where 1 indicates positive correlation, -1 indicates negative correlation, and values close to 0 indicate no correlation between variables. In general, according to the correlation table, it can be concluded that air pollutants are positively correlated and arise from sources related to similar environmental problems. O3 has a negative correlation, which can be explained by the fact that this substance also occurs as a result of chemical reactions, unlike environmental conditions. The correlation coefficients presented in Figure 1 (b) have been calculated to understand the relationships between air pollutants from an observational perspective. No statistical significance tests have been applied for these coefficients. Correlation values have been used only to assess general trends and the direction of the relationships. The missing data in the dataset has been filled with the linear interpolation method in Formula 1 (Noor et al., 2015).

$$y = y1 + \frac{(y2 - y1)}{(x2 - x1)} \times (x - x1) \tag{1}$$

According to formula;

$(x1, y1)$ and $(x2, y2)$: Two known data points

x: x coordinate of the missing value

y: The y-coordinate of the missing value (estimated value)

B. Proposed Deep Learning Models for Air Pollution Forecasting

Deep learning-based air pollution forecasting models have been created for each model with CO, NO2, O3, PM10, and SO2 values, active gases, and substances in air pollution forecasting as separate forecast values for each model. The following three deep learning models have been used in the study, and their forecast performances have been compared.

Convolutional Neural Network (CNN) Model: CNN, one of the deep learning models, is primarily preferred in image processing problems, but it can also produce effective results in time series forecasting. Time series data is treated as a two-dimensional structure, just like image data, and the same technique is applied as in image data. Convolutional layers are used to extract patterns and structures in time series data. In time series data, one-dimensional layers are used to extract features and detect trends by sliding filters across sequential data series. This deep learning method can be preferred for short-term forecasting or noise data sets (Bouvrie, 2006; Gu et al., 2018; Sharma et al., 2018).

Long Short-Term Memory (LSTM) Model: LSTM is a Recurrent Neural Network (RNN) architecture type. It is a common technique for time series problems. The LSTM architecture is widely used for time series problems because of its ability to understand long-term dependencies and produce effective results. According to the model structure, the components are the input, forget, and output gates. This structure makes it capable of storing important information for a long time and forgetting unnecessary information (Graves, 2012; Hochreiter & Schmidhuber, 1997; Van Houdt et al., 2020). Thus, effective forecasting results can be obtained for time series with complex and long-term dependencies.

GRU (Gated Recurrent Unit) Model: GRU is a type of RNN like LSTM architecture. The GRU architecture is more straightforward than the LSTM, with fewer gate mechanisms. Its structure includes update and reset gates, thus offering the advantage of faster computation compared to LSTM (Shen et al., 2018; Wang et al., 2019; Zhao et al., 2017). This technique, which produces effective results in time series, is used in problems where computational cost is essential and in forecasting problems with short-term dependencies.

The hyperparameter values and architectures of the CNN, LSTM, and GRU-based deep learning models proposed in this study, such as the number of layers, number of units in layers, and dropout rate, are shown in Figure 2.

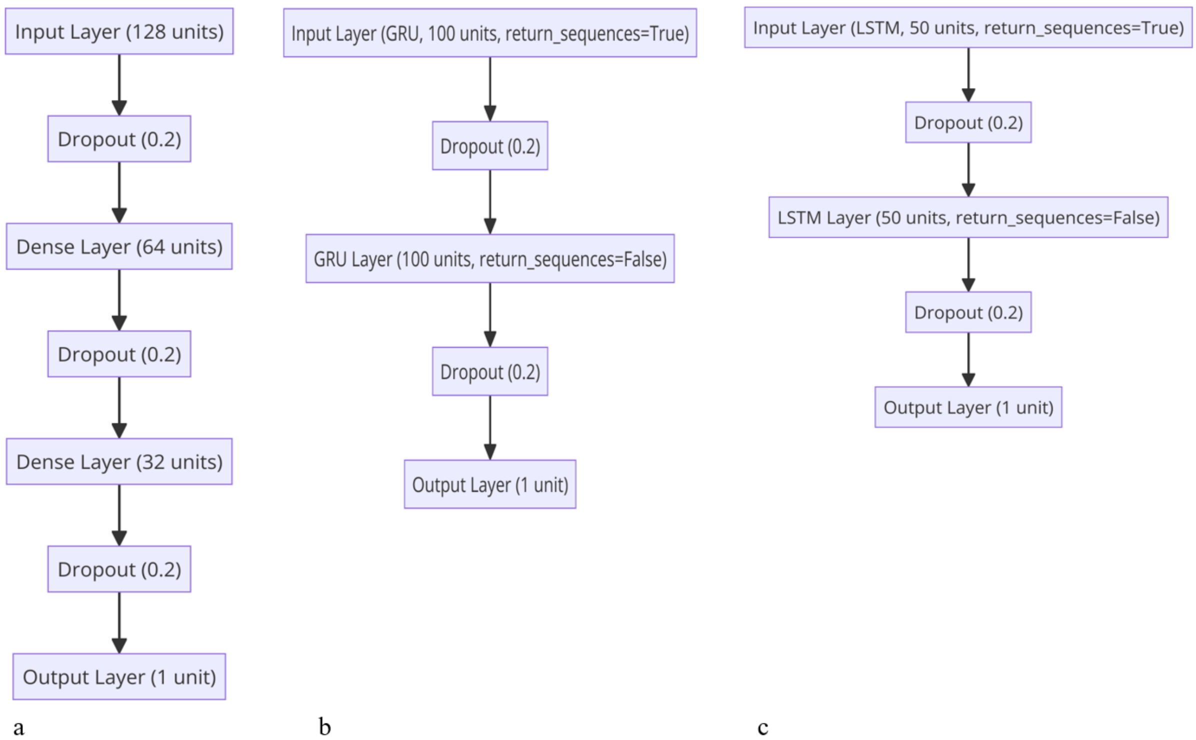


Figure 2. (a) CNN Model (b) GRU Model (c) LSTM Model

In this study, carbon monoxide (CO), nitrogen dioxide (NO2), ozone (O3), particulate matter (PM10) and sulfur dioxide (SO2) are selected as dependent variables (response variables) in deep learning models for predicting air pollutant levels. Each response variable has been modeled using explanatory variables (explanatory variables) environmental factors including concentration values of other pollutants and atmospheric pressure. Table 2 shows the explanatory variables used for each response variable. This approach allows for a multidimensional analysis of air pollution sources and atmospheric dynamics.

Table 2. Response and explanation variables for modeling

Response variables	**Explanatory variables**
CO	PM_{10}, PM_{25}, SO_2, NO_2, NO, NO_X, O_3, Pressure
NO_2	PM_{10}, PM_{25}, SO_2, CO, NO, NO_X, O_3, Pressure
O_3	PM_{10}, PM_{25}, SO_2, CO, NO_2, NO, NO_X, Pressure
PM_{10}	PM_{25}, SO_2, CO, NO_2, NO, NO_X, O_3, Pressure
SO_2	PM_{10}, PM_{25}, CO, NO_2, NO, NO_X, O_3, Pressure

Z-Score normalization (Patro & Sahu, 2015; Singh & Singh, 2020) has been performed to standardize the data distribution before the model and turn it into a meaningful and easily interpretable structure. As a result of this method, the data set values have been normalized with a mean of 0 and a standard deviation of 1. This method is used as shown in Formula 2.

$$zi = \frac{xi - \mu}{\sigma} \tag{2}$$

xi: Original data point

μ: Dataset average

σ: Standard deviation value

zi: Refers to the standardized data point.

III. RESULTS AND DISCUSSIONS

The forecast performances of the deep learning models CNN, LSTM, and GRU for each air pollutant have been compared. Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) (Lahmiri, 2016) metrics in Table 3 have been used to evaluate the forecast performance of the models.

Table 3. Forecast performance metrics

Metric	Formula
Mean Squared Error (MSE)	$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$
Mean Absolute Error (MAE)	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert y_i - \hat{y}\rvert$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}$
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\lvert y_i - \hat{y}_i\rvert}{y_i}$

Table 4 summarizes the performance metrics for each model separately. According to the table, the performances of deep learning models differ according to the air pollutant variable. The results show that the proposed GRU deep learning model performs better than the proposed LSTM and CNN models. It is shown that the proposed GRU model has better accuracy in predicting NO2 and CO air pollutant values. It is also observed that the proposed CNN model performs better in SO2 and O3 forecasting with a lower error rate than the other models. In CO estimation, the proposed GRU model showed the best forecasting performance with 0.2162 MAPE and 123.1169 RMSE values. Similarly, in NO2 estimation, 0.1474 MAPE and 9.3458 RMSE values were observed, and the forecasting results were better than those of other proposed models. In PM10 forecasting, the proposed GRU and LSTM models showed similar performance values. In SO2 forecasting, the proposed CNN model has a lower error rate than the other models, with 0.4049 MAPE and 1.9221 RMSE metrics.

Table 4. Model performance values

Proposed Deep Learning Model	Air Pollutant Substance	MAPE	R2	MSE	RMSE	MAE
GRU	**CO**	**0.2162**	**0.5300**	**15157.7785**	**123.1169**	**95.3332**
LSTM	CO	0.2192	0.5134	15692.6730	125.2703	96.3916
CNN	CO	0.2248	0.4537	17618.0320	132.7329	100.3945
GRU	**NO2**	**0.1474**	**0.7899**	**87.3452**	**9.3458**	**6.6977**
LSTM	NO2	0.1492	0.7795	91.6659	9.5742	6.7919
CNN	NO2	0.1482	0.7581	100.5414	10.0270	7.1607
GRU	O3	0.8253	0.4202	158.8944	12.6053	9.2265
LSTM	O3	0.7620	0.4390	153.7240	12.3985	8.9654
CNN	**O3**	**0.7201**	**0.4557**	**149.1655**	**12.2133**	**8.7807**
GRU	PM10	0.1748	0.7564	50.2214	7.0867	5.0920
LSTM	**PM10**	**0.1732**	**0.7577**	**49.9549**	**7.0678**	**5.0405**
CNN	PM10	0.1662	0.7370	54.2210	7.3634	5.1377
GRU	SO2	0.4617	0.4865	4.0114	2.0028	1.3216
LSTM	SO2	0.4608	0.5080	3.8433	1.9604	1.2983
CNN	**SO2**	**0.4049**	**0.5271**	**3.6946**	**1.9221**	**1.2481**

According to the analyzed forecast performance metrics, the best models presented for each air pollutant have been determined. These models have been visualized for each air pollutant and the actual and predicted values for each air pollutant. Figure 3.a and Figure 3.b show the graphical demonstration of the proposed GRU model, Figure 4.a. and Figure 4.b. show the actual and forecasting values of the proposed LSTM and CNN models respectively for the selected instances. Forecast levels of pollutants like CO, NO2 and PM10 are of public health importance. It is known that long-term exposure to these pollutants can lead to serious health problems in the respiratory and cardiovascular systems. Consequently, air quality prediction models have a critical role in identifying potential health risks and taking preventive measures.

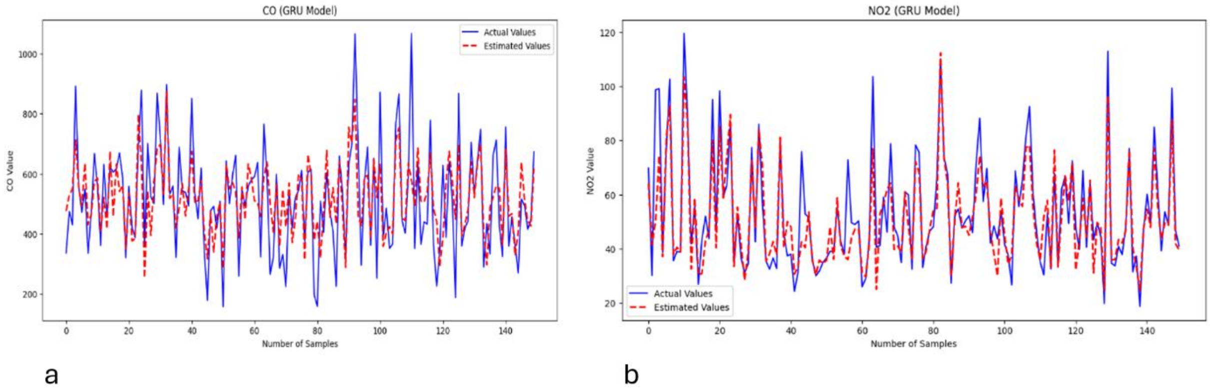


Figure 3. (a) GRU model forecasting for CO (b) Proposed GRU model for NO2

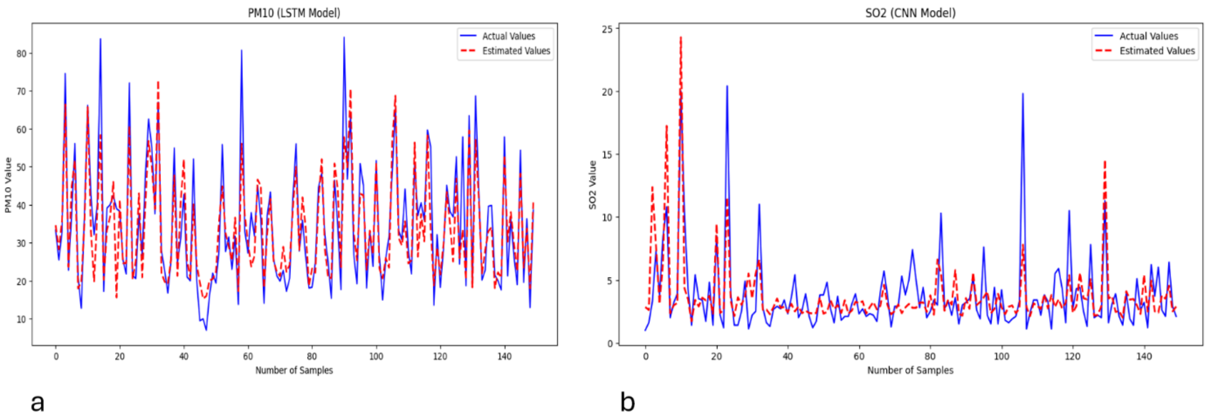


Figure 4. (a) LSTM model forecasting for PM10 (b) CNN model forecasting for SO2

IV. CONCLUSION

Air pollution is a global problem, especially in metropolitan cities of countries, due to the rapid development of industry and technology. This problem, which also existed in the past, has become an even more critical issue for the environment and humanity as a result of rapid developments in the industrial, automotive, and chemical sectors. In this respect, the Internet of Things (IoT), also discussed in this study, makes it possible to analyze pollution levels in real-time with instant and daily measurement data and devices integrated with artificial intelligence. The proposed deep learning models improve the accuracy of air quality forecasting. The predicted air quality data benefits development policies by guiding relevant administrations to make strategic decisions regarding pollution control, traffic regulation, and management of industrial activities. As a result, more effective policies can be developed to protect the environment and public health. This also enables preventive measures to be taken. In recent years, deep learning and machine learning techniques have progressed in this area, and satellite data and ground-based monitoring devices have improved the quality of the data collected. In the future, developing such data collection devices will improve the quality of the data collected and, accordingly, enable the creation of more effective forecasting models. In the study, correlation coefficients are presented in an observational perspective to understand the relationships between air pollutants. Thus, it has not been applied to a significance test. The correlation values are only intended to assess general trends and the direction of the relation. The fact that statistical significance tests have not been supported for a more in-depth examination of these relations is among the limitations of the study. Thus, it is aimed to increase the reliability of the reliability of the obtained findings. In conclusion, this study demonstrates the effective use of deep learning models for air quality forecasting. More effective accuracy results can be targeted in future studies with hybrid deep learning models and larger data sets.

DECLARATIONS

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Ethical Approval and Participant Consent: This study does not involve human or animal participants. All procedures followed scientific and ethical principles, and all referenced studies are appropriately cited.

Plagiarism Statement: This article has been evaluated for plagiarism and no instances of plagiarism were detected.

Availability of Data and Materials: Data sharing is not applicable to this study.

Use of AI Tools: The author/authors declare that no Artificial Intelligence (AI) tools were used in the creation of this article.

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