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Multi-Pollutant Air Quality Prediction Using a ResNet-Based Regression Model: Evaluation Using Abuja and Beijing Air-Quality Datasets

USMAN MUSA BABA[1], SAEED MUSA YARIMA[2], FATIMA UMAR ZAMBUK[3], MOHAMMED ABDULHAMID BABI[4]

[1,2,3,4]*Center for Embedded Artificial Intelligence and Smart Energy Systems, Faculty of Engineering and Engineering Technology, Abubakar Tafawa Balewa University, Gubi Campus, Bauchi, Nigeria.*

Abstract- Prediction of air quality is fundamental to the study of pollution dynamics as well as the implementation of monitoring strategies. In this paper, the construction and performance of a One-dimensional Residual Neural Network (1D ResNet) based multi-output regression model that predicts multiple air pollutants using historical air quality data are reported. Two multi-site datasets with distinct spatial and temporal characteristics have been used to assess the performance of the model, namely, Abuja, Nigeria, and Beijing, China. For the Abuja case study, the model predicted the concentrations of PM1, PM10, and PM2.5 with a location aware and station balanced model approach, while the Beijing case study predicted the levels of PM2.5, PM10, and SO2. Both case studies independent test sets for final evaluation. The Abuja model achieved an overall R^2 of 0.6774, with pollutant-specific R2 values of 0.6721, 0.6885, and 0.6715 for PM1, PM10, and PM2.5, respectively. For Beijing, R2 values of 0.8939, 0.8567, and 0.7117 were achieved for PM2.5, PM10, and SO2, respectively. It is evident from the results that the level of prediction success depends on the type of pollutants, the location of the monitoring stations, and the data situation, where there was a decrease in the prediction success levels during extreme pollution levels. This paper proves the ability of the proposed ResNet-based regression framework to learn temporal relations between multi-pollutants air quality prediction.

Index Terms— Air Quality Prediction, Deep Learning, Multi-Pollutant Prediction, ResNet, Time-Series Regression.

I. INTRODUCTION

The problem of air pollution is still topical due to the impact of air pollutants on the well-being of people and the environment. In particular, high exposure of people to air pollutants leads to cardiovascular and respiratory diseases, chronic obstructive pulmonary disease, lung cancer and even death (Wang et al., 2025). In addition to human health hazards, atmospheric pollution leads to the occurrence of acid rain, environmental degradation, pollution of soil and water resources, and reduces agricultural production. (Ramadan et al., 2024). Moreover, according to the World Health Organization, there is wide exposure of people to air pollution beyond recommended air-quality guidelines that require an efficient approach to air-quality monitoring and prediction (Naveed et al., 2025). The World Health Organization has also reported widespread human exposure to air pollution above recommended air-quality guidelines, emphasizing the need for effective monitoring and prediction approaches (Bekkar et al., 2021). Efficient air quality management implies not only the monitoring of pollution levels but also the identification of trends and prediction of future changes in the concentrations of pollutants. Unfortunately, air-quality prediction is difficult due to the complex nonlinear relations between atmospheric pollutants, meteorological parameters and time-dependent factors. Air-quality data itself are time series with temporal dependencies and periodicity that should be properly captured by prediction models (Bekkar et al., 2021). Therefore, conventional monitoring may not be enough to obtain predictive information necessary for proper assessment and decisions.

In recent times, there have been advancements in AI and ML that enable researchers to analyze sophisticated environmental data and detect complex relationships that cannot be easily detected using traditional methods. Through machine learning algorithms, it is possible to process large air-quality datasets, detect patterns, model environmental influences, and make predictions about air quality monitoring (Chadalavada et al., 2025). In addition, machine learning, when coupled with the use of environmental monitoring systems, can help in establishing early warning systems regarding pollution risks (Karmoude et al., 2025).

Through deep learning methods, these techniques get extended and become capable of learning complex and hierarchical representations from large datasets. Therefore, in cases where there are nonlinear relationships between pollutant concentrations, environmental parameters, and temporal patterns, deep learning can be used for air-quality prediction (Krishna et al., 2024). Within the category of deep learning models, Residual Neural Network (ResNet) represents an architecture where residual connections allow for efficient information flow through deep networks and also help learn residual mappings. This means that ResNet based models can be utilized on air-quality data containing pollutant concentrations and environmental variables (Krishna et al., 2024). Normalization or standardization of data can help mitigate any issues arising out of scale differences between features (Suri et al., 2023). Even though much progress has been made in the field of AI-based air quality prediction, it still suffers from some limitations because of the existence of the non-linear and temporal relationship between pollutants and environmental variables. Hence, it becomes necessary to investigate the possibility of employing deep learning techniques which would be able to learn about the temporal relationship between the pollutants and environment and predict the pollution levels based on historical air quality data. In this research, we develop and test a regression model based on the ResNet architecture that would predict multi-pollutant air quality based on historical air quality data. The effectiveness of this model would be investigated in terms of regression accuracy by calculating such metrics as MAE, MSE, RMSE, R2 and prediction bias. Therefore, the goal of this paper is to design and test the effectiveness of ResNet-based regression model in predicting multi-pollutant air quality through historical air quality data. This research paves the way to assess the efficiency of residual-learning methods in air quality prediction as well as constructing the pollutant prediction module for further air quality assessment.

II. RELATED WORK

As a result of their capability of modeling relationships between various features in multi-dimensional environmental data (Suri et al., 2023). developed an Artificial Neural Network (ANN) model and a Gaussian Process Regression (GPR) model for air quality prediction and obtained correlations of 0.9611 and 0.9843, respectively. They showed that data-driven methods have the potential for air quality prediction, yet the results from ANN may vary greatly depending on network structure and amount of training data (Karmoude et al., 2025). used Random Forest Regression (RFR) and Long Short-Term Memory (LSTM) models based on meteorological factors such as temperature and humidity for predicting PM2.5 concentrations. RFR obtained the performance up to 90%, proving the usefulness of taking account of meteorological information when developing pollutant prediction models. Ensembles of XGBoost, CatBoost, LightGBM, and Random Forest have also proved the potential of combining machine learning algorithms for air quality prediction (Prediction, 2025). Deep learning algorithms have also been used to take temporal dependency into account in air quality observations. A hybrid one-dimensional Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) architecture was developed for hourly PM2.5 prediction, combining convolutional feature extraction with temporal modelling (Prediction, 2021). The model demonstrated improved predictive performance based on RMSE and MAE and was subsequently optimized for execution on Raspberry Pi edge devices.

Residual Neural Networks provide another approach for modelling complex air-quality relationships. ResNet employs shortcut or skip connections that facilitate information and gradient propagation through deep networks (Patil et al., 2025). Residual blocks incorporating convolutional layers, batch normalization, activation functions, and shortcut connections can help address the vanishing-gradient problem while enabling complex feature extraction from pollutant and environmental data (Krishna et al., 2024).

More specifically, (Cheng et al., 2022) developed a stacked ResNet-LSTM and Correlation Alignment (CORAL) model for multi-site PM2.5 prediction. Their framework combined ResNet-based feature extraction with LSTM-based temporal modelling, model stacking, and CORAL. The basic ResNet-LSTM achieved an average RMSE of 44.886 µg/m3, MAE of 25.946 µg/m3, and R2 of 0.760, while the stacked model improved performance to an RMSE of 40.679 µg/m3, MAE of 23.746 µg/m3, and R2 of 0.804 (Cheng et al., 2022). This study demonstrates that ResNet has already been successfully applied to air-quality prediction, particularly when integrated with other temporal-learning techniques.

2.1 Research Gap

The reviewed studies demonstrate considerable progress in air-quality prediction using ANN, GPR, Random Forest, LSTM, CNN-LSTM, ensemble learning, and ResNet-based architectures. However, many of the reviewed approaches concentrate on individual pollutants, particularly PM2.5, while some deep-learning approaches employ combinations of several architectures. Hence, further research into a simplified ResNet regression model able to predict multiple pollutant concentrations through modeling of multivariate air quality data is still warranted. This research fills this gap by performing modeling and multi-output regression analysis for temporal multi-pollutants via a residual network model.

III. METHODOLOGY

3.1 Research Design

The proposed research used a simulation-based approach for developing and evaluating a ResNet-based multi-pollutant air-quality prediction model. Simulation allowed systematic data preprocessing, feature extraction, model training, validation, and independent evaluation while excluding the influence of any hardware factors in assessing the model's predictive performance. The methodology thus aimed at investigating the ability of residual learning to capture nonlinear and temporal dependencies inherent in the multivariate air quality datasets. The ability of residual learning networks to be suitable for air quality prediction has been proven due to the presence of skip connections that allow information and gradients flow within deep networks (Cheng et al., 2022). The methodology clearly specifies a simulation-based nature of the research and allows distinguishing algorithm evaluation from any hardware factors. The prediction methodology involved a sequential process of data collection, data preprocessing, feature extraction, data normalization, temporal sequences generation, ResNet-based prediction model training, pollutant prediction, and independent evaluation.

3.2 Air-Quality Datasets

Historical air-quality data and associated environmental measurements were used for the experimental study. Pollutants concentration levels served as the prediction targets, with meteorology and time features serving as the explanatory variables for modeling the variability of atmospheric pollution. Historic pollutants' behavior and meteorology variables were taken into account concurrently, because environmental conditions affect the formation, transport, transformation and dispersion (Zhang & Li, 2023). Two datasets were used for the experimental analysis: the Abuja air quality dataset and the Beijing Multi-Site Air Quality dataset. The Abuja dataset consisted of monitoring data gathered from various locations under relatively unequal data availability conditions, whereas the Beijing dataset offered a much larger and continuous multi-site air quality database. By using two different datasets, it became possible to evaluate the performance of the ResNet framework under various monitoring data conditions. Target pollutants were chosen depending on the pollutants presented in each dataset. Thus, it was necessary to evaluate the model performance for each target pollutant separately and not assume identical target set across the two datasets.

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Table 1: Summary of the Abuja and Beijing Air-Quality Datasets

Dataset Characteristic	Abuja Air-Quality Dataset	Beijing Multi-Site Air Quality Dataset
Study location	Abuja, Nigeria	Beijing, China
Monitoring locations/stations	4 locations: 3581, 3599, 3613, 3619	12 stations: Aotizhongxin, Changping, Dingling, Dongsi, Guanyuan, Gucheng, Huairou, Nongzhanguan, Shunyi, Tiantan, Wanliu, Wanshouxigong
Observation period	November 2022 – December 2023	March 2013 – February 2017
Temporal resolution	Hourly after aggregation/preparation	Hourly
Original number of observations	873,519 raw records	420,768 observations (35,064 per station × 12 stations)
Pollutant measurements available/used	PM1, PM2.5, PM10	PM2.5, PM10, SO_2, NO_2, CO, O_3
Meteorological variables	Temperature, relative humidity	Temperature, dew point, pressure, rainfall, wind direction, wind speed
Spatial information	Location ID	Station
Temporal/engineered inputs	Temporal features, lagged pollutant values, rolling statistics and selected predictors	Temporal features, historical pollutant and meteorological variables, and selected predictors
Target pollutants for ResNet model	PM1, PM10, PM2.5	PM2.5, PM10, SO_2
Dataset characteristic	Low-cost multi-location monitoring data with unequal representation across locations	Larger, more continuous multi-station monitoring dataset
Role in the study	Evaluation of location-aware and station-balanced ResNet prediction	Evaluation of ResNet prediction using a larger multi-station dataset

3.3 Data Preprocessing and Feature Engineering

Environmental measurements were preprocessed in a systematic way prior to the model training. Preprocessing steps included missing values' treatment, outliers' handling, duplicate entries' removal, temporal feature extraction, feature selection, normalization and temporal modeling data preparation. These actions were aimed at improving the data quality and ensuring preprocessing of inputs for the ResNet regression included the following. For missing values, the solution depended on whether the problem was related to the gap in observations, while detection of statistical outliers involved the use of Interquartile Range (IQR). Duplicates were excluded in order to avoid the overrepresentation of repeated observations in training. For inclusion of information regarding time, derived time features (hour, day, month, weekend) were calculated based on the timestamp data. Moreover, for including information about the history, lagged pollutant measurements as well as rolling features were created. Assessment of features and their selection was done based on analysis of the Pearson correlation and Mutual Information (MI), which made it possible to analyze both linear and non-linear relations between candidate features and pollutants. As the values of environmental variables were measured in different scales, Min-Max normalization to the range [0, 1] was used. (Gu et al., 2026):

$$x' = \frac{(x - x\_min)}{(x_{max} - x_{min})} \tag{1}$$

where: x is the original feature value, x_{min} the minimum value of the feature observed in the training set, $x_{max}$is the maximum value of the feature observed in the training set; x′ is the normalized value lying in

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[0, 1]. Normalization parameters (x_{min}, x_{max}) are computed exclusively on the training partition and subsequently applied to the validation and test partitions to avoid data leakage. The processed observations were subsequently organized as temporal sequences before being supplied to the one-dimensional ResNet regression network.

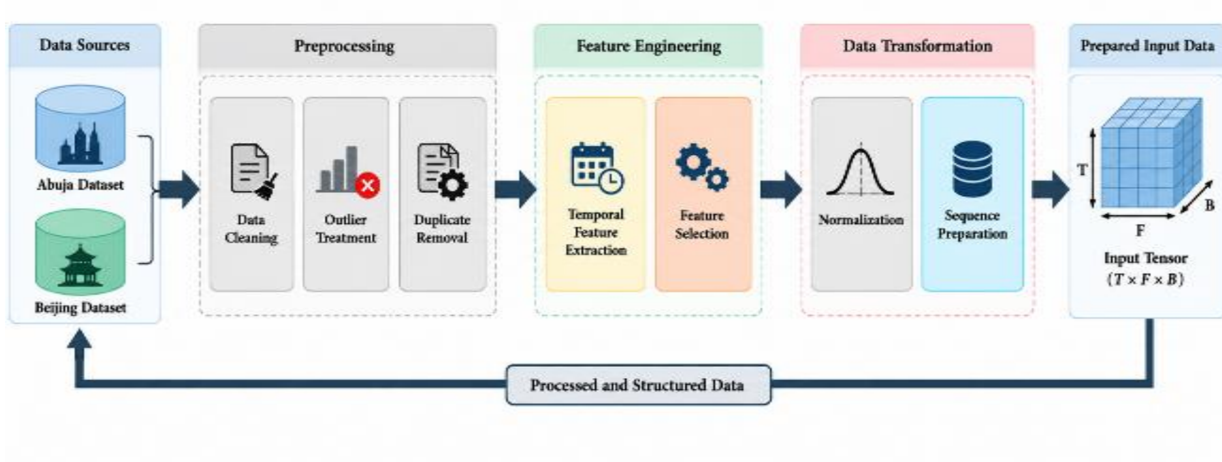

Figure 1: Data preprocessing and temporal feature-engineering workflow used for multi-pollutant prediction

3.4 Proposed ResNet-Based Multi-Output Regression Model

The central component of the proposed prediction framework is a one-dimensional Residual Neural Network (1D-ResNet) adapted for multivariate time-series regression. The architecture was designed to learn nonlinear and temporal representations from historical pollutant, meteorological, and engineered features and simultaneously generate continuous pollutant-concentration predictions. Residual learning reformulates the problem so that stacked layers learn a residual function f(x)=H(x)-x rather than the underlying mapping H(x) directly. The original mapping is then recovered by:

$$y = f(x) + x \tag{2}$$

where: x is the input feature vector (or feature map) to the residual block, F(x) is the residual mapping realized by a sequence of convolutional (or dense) layers, batch normalization, and activation functions, y is the output of the residual block, the addition "+" denotes element-wise (identity) addition, also called a skip connection or shortcut connection. When the optimal mapping is close to an identity function, the residual F(x) is driven toward zero, which is easier to learn than a full identity. More generally, the skip connection provides an unimpeded gradient pathway:

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial y} \cdot \left(\frac{\partial \boldsymbol{F}}{\partial x} + 1\right) \tag{3}$$

The "+1" term guarantees that the gradient cannot vanish even if ∂F/∂x approaches zero, this method converges towards zero, hence overcoming the vanishing gradient problem and allowing deep nets to be learned stably. Recent literature concerning the prediction of air quality states that the use of residual connections significantly improves the accuracy of multi-step pollutant predictions compared to baseline convolutions and recurrent networks.(Chen et al., 2023). In case of temporal air quality data, the use of one-dimensional convolutional operation in each residual layer helps extract temporal features. The residual layer consists of Conv1D operation, batch normalization, ReLU activation, a Conv1D operation followed by batch normalization and element-wise summing of the output with the shortcut. If the size of input and output are not equal, then the projection shortcut is used to make them compatible. These residual layers are then processed using the final regression layers to get continuous predictions of different pollutants at the same time. Hence, instead of having a separate architecture for predicting different pollutants, the use of the multi-output framework allows shared representation in the network to be used for predicting different pollutants.

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3.4.1 Proposed Model Architecture

The architecture of the suggested model is illustrated in Figure 2 below. It shows the flow from the temporal data input all the way to the regression output via the Conv1D feature extraction process and the residual blocks. The use of the shortcut connections is apparent, emphasizing the difference between the residual and standard convolutional regression architectures.

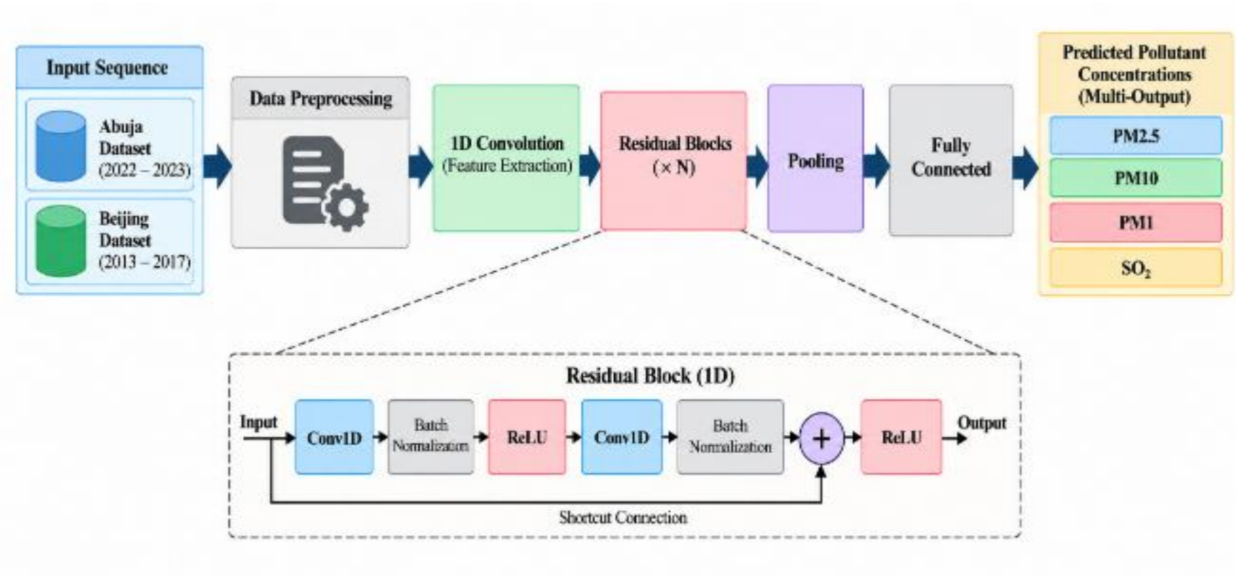

Figure 2: ResNet-based multi-output regression architecture

Table 2: Configuration and hyperparameters of the proposed ResNet-based regression model.

Component / Hyperparameter	Configuration
Input	Temporal input sequences
Convolution type	1D Convolution (Conv1D)
Initial convolution filters	64
Kernel size	3
Stride	1
Residual blocks	Conv1D–BN–ReLU–Conv1D–BN + shortcut
Batch normalization	Applied within residual blocks
Activation function	ReLU
Shortcut connection	Identity/projection connection
Pooling	Global Average Pooling 1D
Dense layer	64 units
Dense activation	ReLU
Dropout rate	0.30
Output activation	Linear
Prediction type	Multi-output regression
Abuja targets	PM1, PM2.5, PM10

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Component / Hyperparameter	Configuration
Beijing targets	PM2.5, PM10, SO_2
Optimizer	Adam
Loss function	Mean Squared Error (MSE)
Performance metrics	MAE, MSE, RMSE, R^2, Bias

3.4.2 Model Training and Validation

The ResNet architecture used for experiments was trained using the Adam optimizer along with the Huber loss function. The use of the Huber loss is helpful to reduce the effect of large errors in predictions while still remaining sensitive to small errors. The dataset used was split temporally into training, validation, and test sets to preserve the order of observation of air quality and avoid leakage of information. Historical observations of the dataset were arranged into 24-hour input sequences to train the models. During the training phase, the performance of models was measured on the validation set while the test set was kept aside for evaluation purposes. In the Beijing case study, the number of trainable parameters in the ResNet was 150,019 and was trained with a batch size of 256. Additionally, a bigger network having 514,947 parameters was used to train the model; however, the smaller network outperformed the validation set and hence was tested on the test set

.

Table 3: Final Model-Training Configuration

Training Parameter	Abuja Dataset	Beijing Dataset
Model architecture	Station-balanced location-aware 1D ResNet	Baseline 1D ResNet
Prediction task	Multi-output regression	Multi-output regression
Input sequence length	24 hours	24 hours
Output dimension	3	3
Target pollutants	PM1, PM10, PM2.5	PM2.5, PM10, SO_2
Training sequences	5,992	293,952
Validation sequences	1,255	62,832
Independent test sequences	1,180	62,832
Station balancing	Station-balanced sample weighting	Balanced across 12 stations
Optimizer	Adam	Adam
Loss function	Huber loss	Huber loss
Model selection	Station-balanced location-aware model	150,019-parameter baseline ResNet

3.5 Location-Aware and Station-Balanced Modelling

The issue of imbalanced distribution of monitoring locations was addressed in the Abuja experiment through the model development. Imbalances in the distribution of the observations' counts could lead to locations having many observations having an excessive effect on the process of optimization. In order to reduce the effects of imbalances in the distribution of locations and allow for location-specific assessment of the generalization, location and station-balanced sampling weights were used. This modification of the methodology is specified in the original work as being done specifically in the Abuja experiment. The Beijing data, which had larger and more continuous observations across several stations, offered a complementary setting to examine the residual learning approach with different data characteristics of monitoring data.

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3.6 Performance Evaluation
Predictive performance on the independent test dataset was assessed after inverse transformation back to the original pollutant concentration scale. Four main regression performance metrics defined in the methodology were used: mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE) and the coefficient of determination (R2).

MAE measures the mean absolute value of the difference between observed and predicted concentrations.:

$$MAE = \frac{1}{n}\sum\{i = 1\}^{\{n\}}|y_i - \hat{y}_i| \quad (4)$$

MSE measures the average squared prediction error:

$$MSE = \frac{1}{n}\sum\_\{i = 1\}^{\{n\}}(y_i - \hat{y}_i)^2 \quad (5)$$

RMSE is equal to the square root of MSE and hence brings back prediction errors into their original units

$$RMSE = \sqrt{\left[\frac{1}{n}\sum\_\{i = 1\}^{\{n\}}(y_i - \hat{y}_i)^2\right]} \quad (6)$$

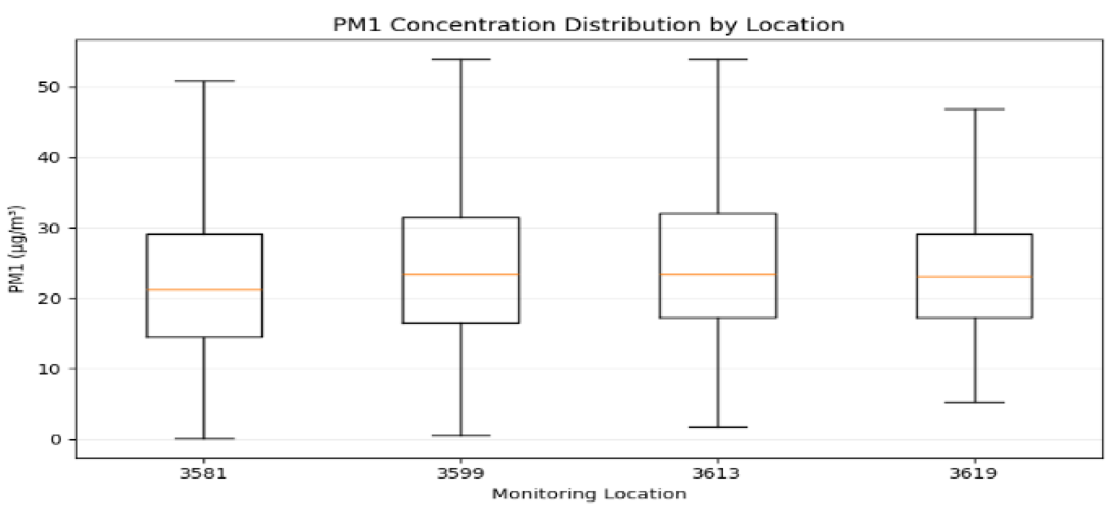
The coefficient of determination was applied in determining the percentage variation of the pollutant concentration that could be attributed to the regression model:

$$R^2 = 1 - \left[\frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}\right] \quad (7)$$

Overall, all four metrics offer complementary information about absolute error, sensitivity to large errors and goodness of fit. The thesis specifies that evaluation is carried out on the independent test dataset after inverse normalization.

IV. FINDINGS

4.1 Abuja Dataset Results
The Abuja experiment used air-quality observations collected from four monitoring locations between November 2022 and December 2023. Following hourly aggregation and preprocessing, the data were examined for spatial and temporal variations before model development. The analysis showed differences in PM1, PM10 and PM2.5 concentrations among the monitoring locations and across the study period.



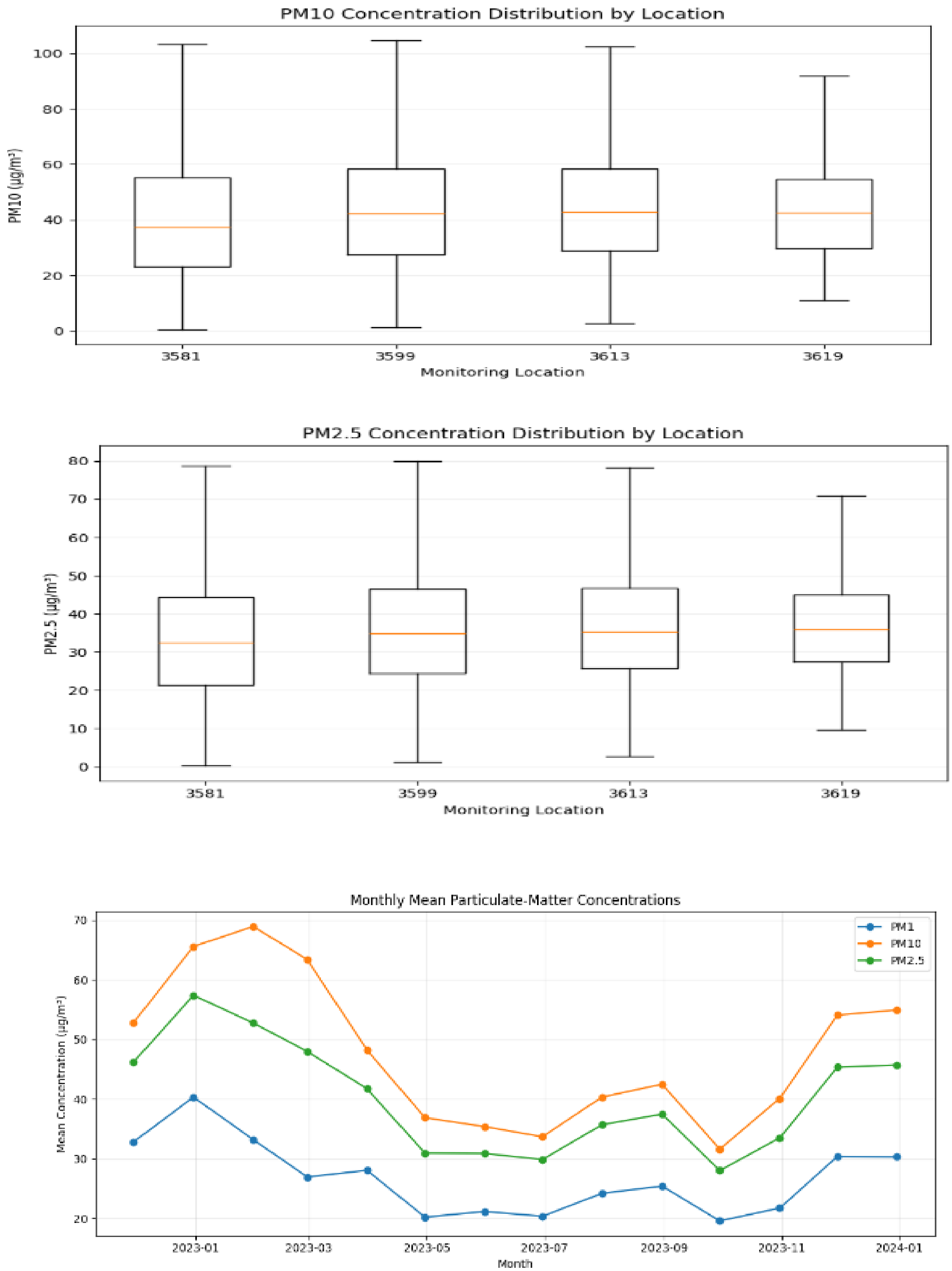


Figure 3: Spatial and temporal characteristics of pollutant concentrations in the Abuja dataset.

Monthly analysis further showed variations in particulate-matter concentrations over the monitoring period, supporting the use of temporal information in the prediction model.

4.2 Abuja Model Performance

After temporal sequence construction, the Abuja data produced 5,992 training, 1,255 validation and 1,180 independent-test sequences. Unequal representation among the four locations motivated the use of location information and station-balanced sample weighting. The final station-balanced location-aware ResNet was trained using 24-hour input sequences, Adam optimization and Huber loss.

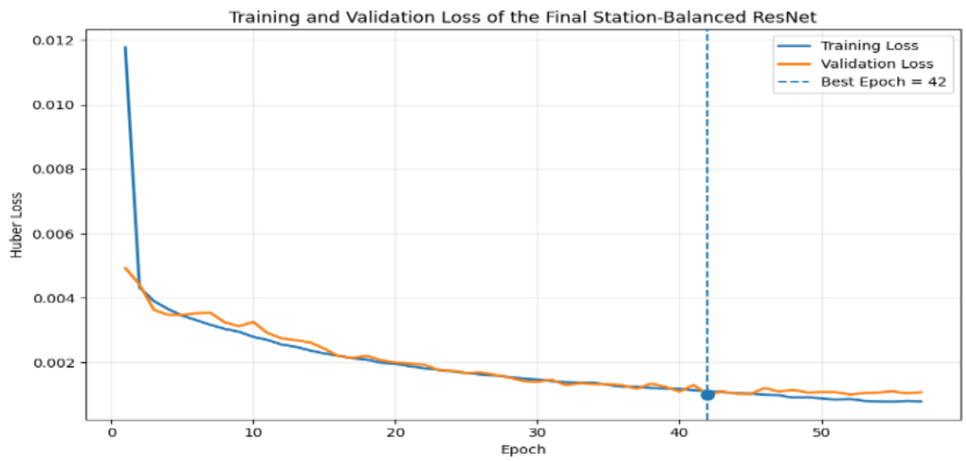


Figure 4: Training and validation loss curve.

The final model achieved an overall independent-test R2 of 0.6774, MAE of 8.6183 µg/m, and RMSE of 14.0454 µg/m³. Pollutant-specific results are presented in Table 4.

Table 4: Independent-test prediction performance using the Abuja dataset

Pollutant	MAE (µg/m^3)	RMSE (µg/m^3)	R^2	Bias (µg/m^3)
PM1	6.1922	9.9560	0.6721	−0.6965
PM10	10.7261	16.5661	0.6885	−4.0260
PM2.5	8.9366	14.7735	0.6715	−1.7247

The observed-versus-predicted plots showed that the model captured the general variation of all three pollutants, although prediction performance differed among monitoring location.

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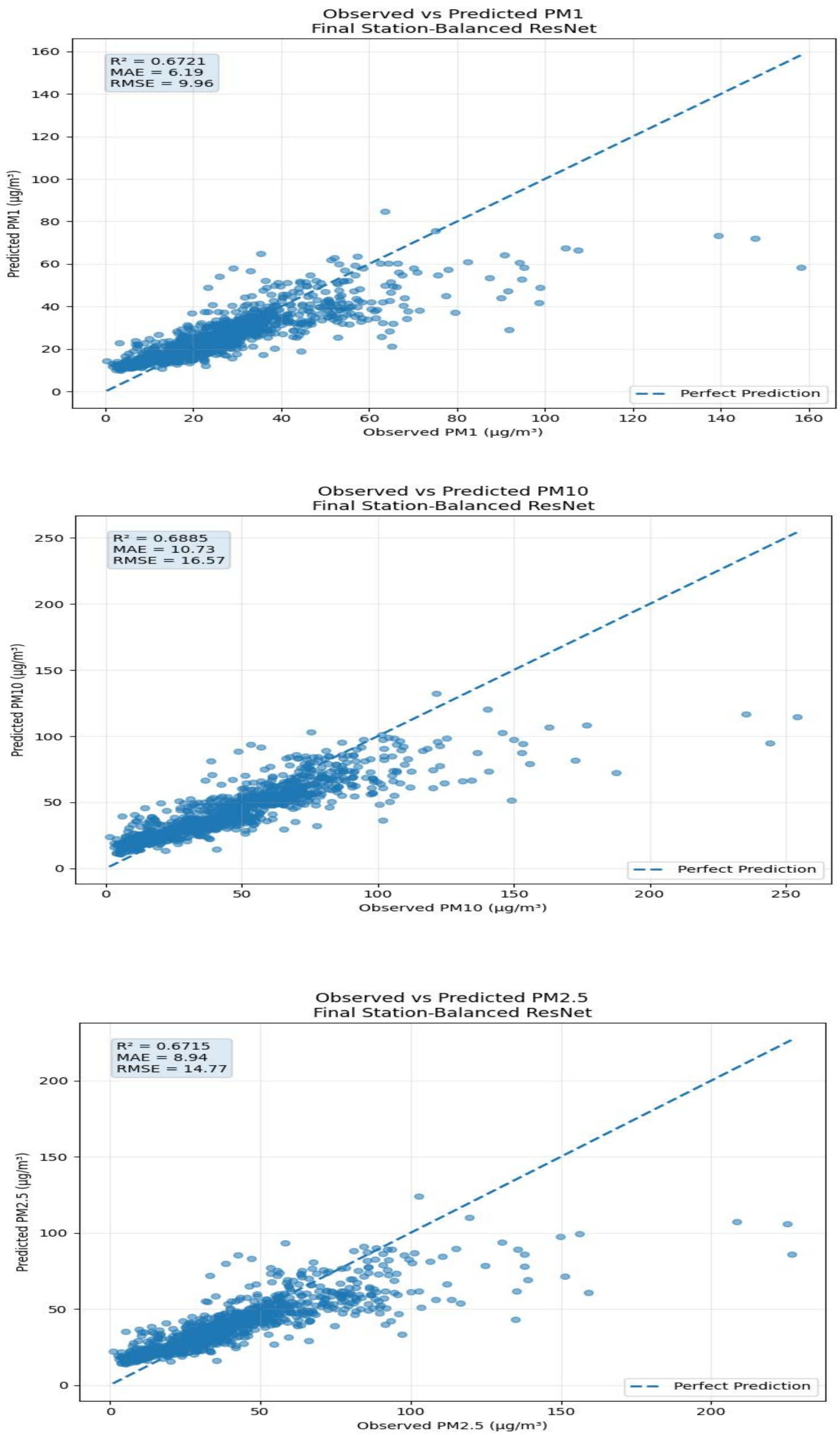

Figure 5: Observed and predicted concentrations of PM1, PM10, and PM2.5 for the Abuja independent test set.

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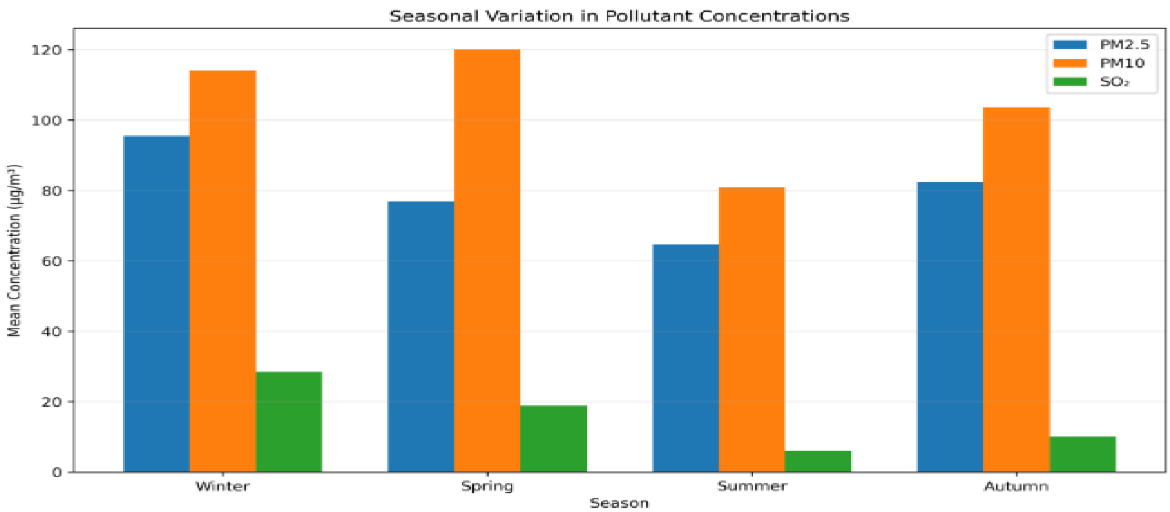
4.3 Beijing Multi-Site Dataset Results

The Beijing dataset contained 420,768 hourly observations from 12 monitoring stations, covering March 2013 to February 2017. Monthly and seasonal analyses showed substantial temporal variation in PM2.5, PM10 and SO2 concentrations



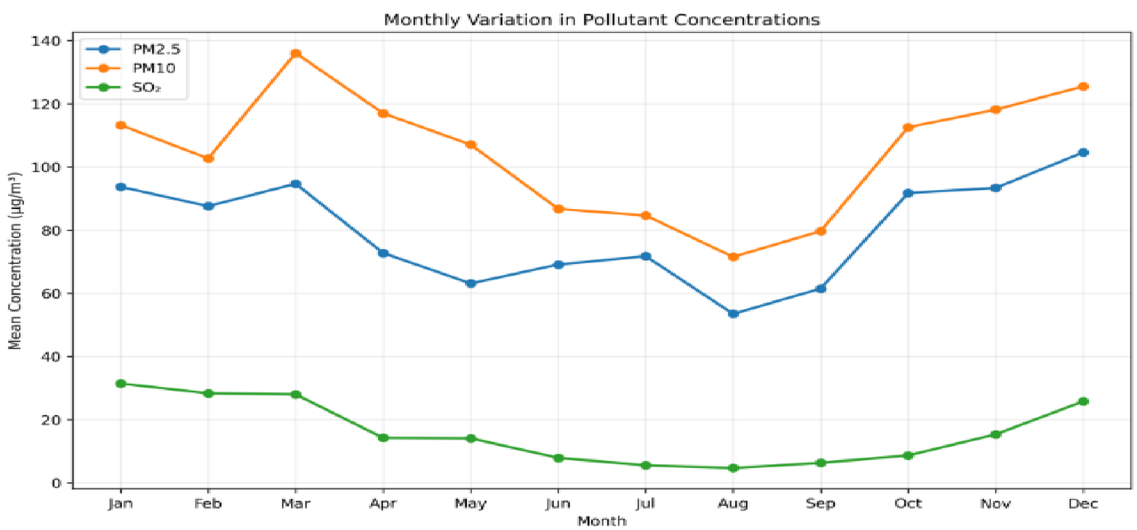


Figure 6: Monthly and seasonal substantial temporal variation in PM2.5, PM10 and SO2 concentrations

The resulting number of predictors used after preprocessing and engineering features is 40. Using 24-hour historical sequences results in 293,952 sequences for training, 62,832 sequences for validation, and 62,832 sequences for testing independently. The selected 1D ResNet has 150,019 parameters. Another model with 514,947 parameters was tried out, but it showed worse validation results.

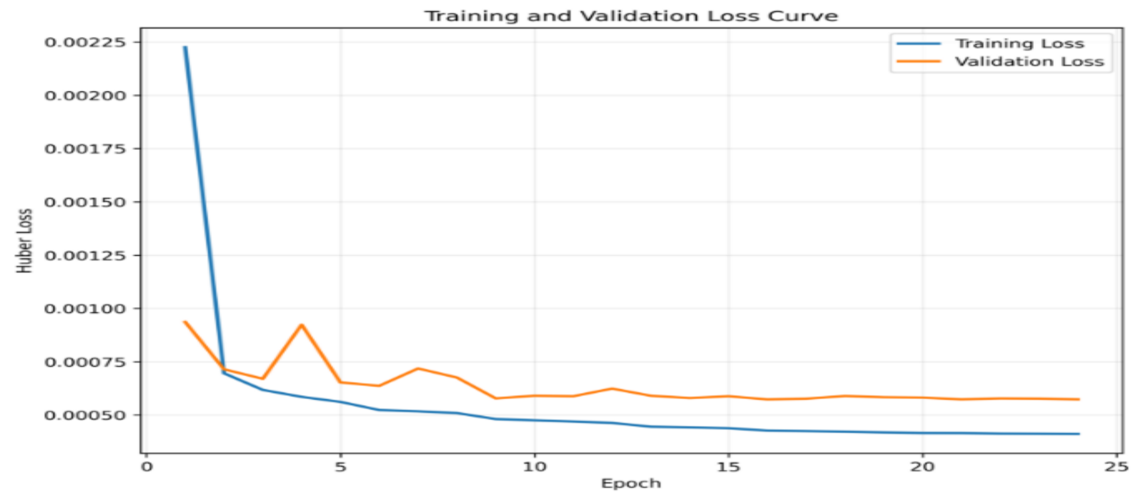
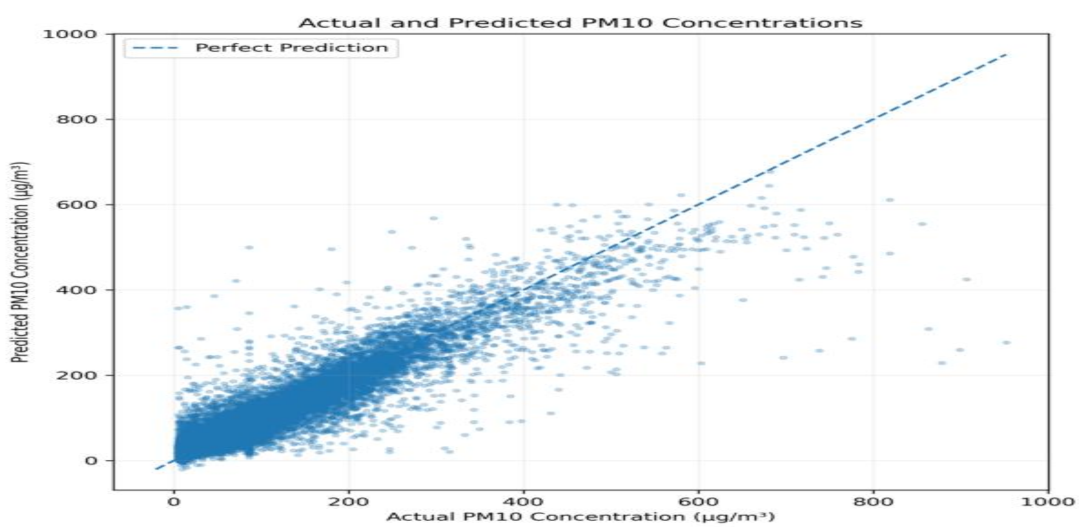


Figure 7: Training and validation loss

Table 5: Independent-Test Performance on the Beijing Dataset

Pollutant	MAE (µg/m³)	RMSE (µg/m³)	R^2	Bias (µg/m³)
PM2.5	16.4245	29.9646	0.8939	−1.7973
PM10	23.0996	38.4741	0.8567	+0.1551
SO_2	4.0096	7.3741	0.7117	−0.1218

It was observed that PM2.5 showed superior prediction ability, followed by PM10 and then SO2. There was high conformity between observed and predicted values, although the size of errors increased with extreme concentrations of pollutants.



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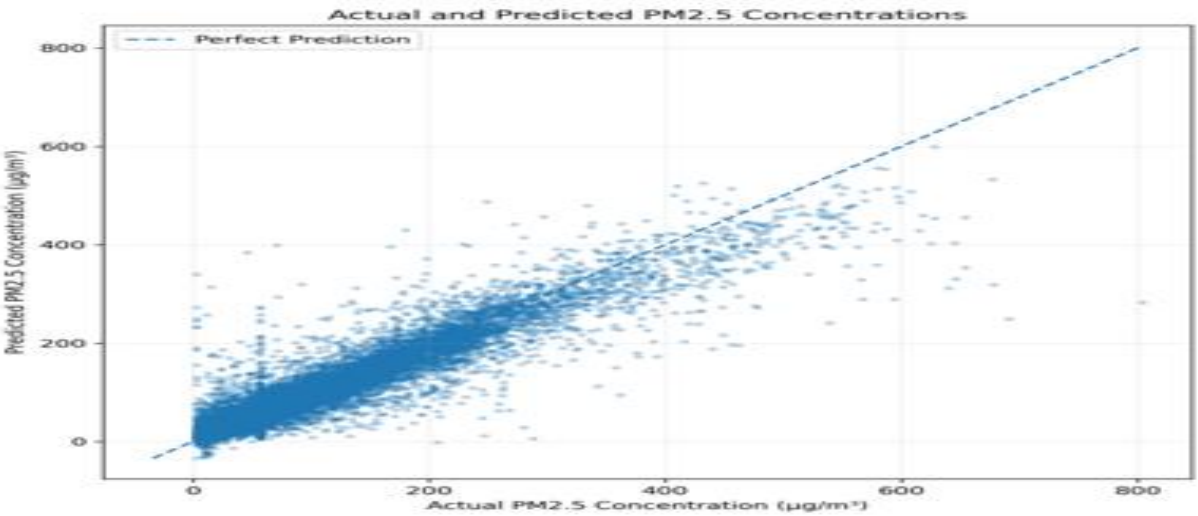

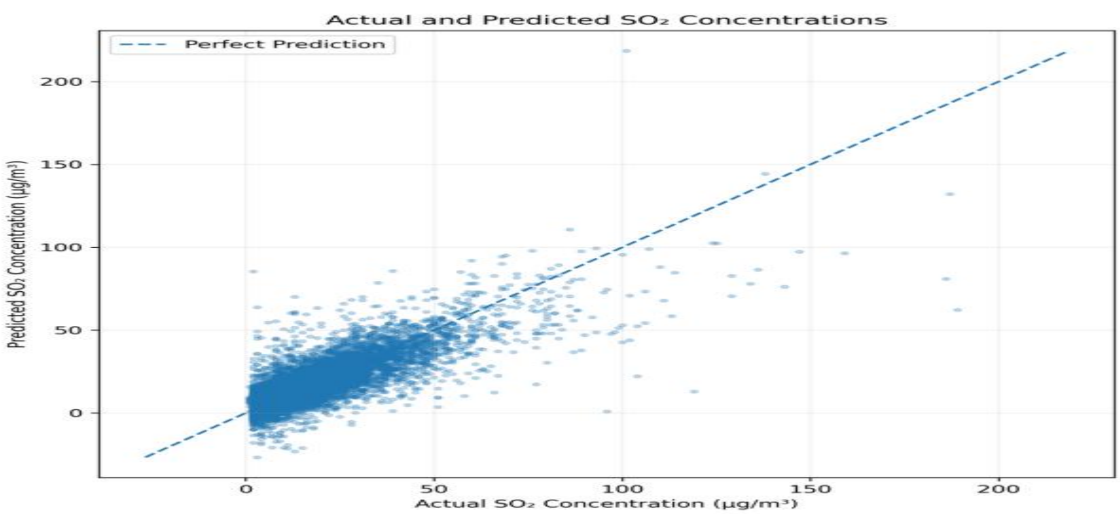

Figure 8: Observed and predicted PM2.5, PM10, and SO_2 concentrations for the Beijing independent test set.

Prediction errors rose with higher pollutant concentrations. MAE reached 102.28 µg/m3 for PM2.5, 126.97 µg/m3 for PM10, and 24.96 µg/m3 for SO2 at the 99th percentile, where negative biases pointed to underpredictions. Similar rises occurred when moving from the 90th to the 99th percentiles in the case of all three pollutants. In conclusion, the model showed better results in normal conditions than in the extreme pollution situation, which means that model optimization needs to focus on capturing infrequent high concentration situations

4.4 Comparative Evaluation

In respect to the pollutants presented in both datasets, the experiment conducted in Beijing showed better results in terms of R2 coefficients. For PM2.5, the coefficient was 0.8939 compared to 0.6715 in Abuja; and for PM10, it was 0.8567 against 0.6885 in Abuja. Such differences can be explained by the features of datasets used.

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Table 6: Comparative Independent-Test Performance of the ResNet Models

Evaluation Metric	PM1 Abuja	PM10 Abuja	PM10 Beijing	PM2.5 Abuja	PM2.5 Beijing	SO_2 Beijing
MAE (µg/m³)	6.1922	10.7261	23.0996	8.9366	16.4245	4.0096
MSE (µg/m³)	99.1221	274.4363	1480.2600	218.2576	897.8767	54.3779
RMSE (µg/m³)	9.9560	16.5661	38.4741	14.7735	29.9646	7.3741
R^2	0.6721	0.6885	0.8567	0.6715	0.8939	0.7117
Bias (µg/m³)	−0.6965	−4.0260	+0.1551	−1.7247	−1.7973	−0.1218

Regarding the two pollutants common to both datasets, the Beijing model gave rise to higher R2 scores. In particular, the R2 score of PM2.5 rose from 0.6715 in Abuja to 0.8939 in Beijing, while the R2 score of PM10 improved from 0.6885 to 0.8567. However, it should be noted that although some of the pollutants' measurements in the Beijing dataset had a higher MAE and RMSE value compared to the corresponding pollutants in the Abuja dataset, absolute error values are not a clear indicator of the performance difference between the two datasets. Since absolute errors depend on the concentration range and distribution of each pollutant and dataset, they should be analyzed together with R2, MAE, RMSE, and bias. Higher R2 values obtained for the Beijing dataset reflect the better time range, larger number of monitoring locations, more representative and balanced station distribution, as well as higher observation continuity of the Beijing dataset. In addition, the Abuja dataset was characterized by fewer monitoring stations, unrepresentative station distribution, discontinuous time range, and differences in the pollution distributions of the training and independent-test datasets.

On the other hand, the Abuja experiment provides an interesting insight into how spatial heterogeneity and unbalanced station distribution affect model generalization and how including location information and using a station-balanced training procedure can help improve performance in such cases.

In conclusion, the results of the two experiments demonstrate that the proposed 1D ResNet architecture can learn temporal representation useful for predicting multiple air pollutants simultaneously. At the same time, the predictive performance is significantly affected by the amount, continuity, spatial representation, and concentration distribution of the monitoring data used. Besides, more complex models do not necessarily generalize better, as shown by the higher validation performance of the Beijing ResNet.

V. CONCLUSION

This research work provides the development and evaluation of one-dimensional ResNet-based multi-output regression model for air quality prediction based on the multi-site datasets in Abuja and Beijing. It shows that spatial heterogeneity and uneven distribution of stations hinder the generalization of the model in Abuja dataset while the inclusion of location information and station-balance sample weighting contributes to better performance. The final Abuja model was able to achieve an independent test R2 score of 0.6774 for the total pollutants and an R2 value of 0.6721 for PM1, 0.6885 for PM10, and 0.6715 for PM2.5. The Beijing results have revealed that there is relatively high performance for the model with R2 values of 0.8939 for PM2.5, 0.8567 for PM10, and 0.7117 for SO2. This suggests that the efficacy of the ResNet architecture depends not only on the architecture but also on the number, continuity, spatial distribution, and the amount of air quality data available. Furthermore, the small Beijing model consisting of 150,019 parameters performed better than the larger model which consisted of 514,947 parameters during validation.

Despite its success in terms of overall accuracy, it was difficult for the prediction to accurately predict at the extreme levels of pollution, and there was always some level of spatial differences in the Abuja case. Some of the improvements to consider for future work include the provision of long continuous monitoring data, accurate prediction of extreme pollution events, attention-based or hybrid architecture, transfer learning, and physical deployment of the embedded system.

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