Performance of Enhanced CNN-LSTM Prediction Model for Vehicle-Mounted Air Quality Monitoring

Ceferino Llamelo
School of Architecture, Computing and Engineering
University of Saint Louis
Tuguegarao City, Philippines
qcvllamelo@tip.edu.ph

Ruji Medina
Dean, Graduate Programs
Technological Institute of the Philippines
Quezon City, Philippines
ruji.medina@tip.edu.ph

Arnel Fajardo
Professor, Graduate Programs
Technological Institute of the Philippines
Quezon City, Philippines
afajardo.gradprog@tip.edu.ph

***Abstract*—CNN-LSTM has been established for predictive modeling in urban air pollution. However, while the method is accurate for time series forecasting, it struggles with accurately capturing spatial variability in air quality data. To address this limitation, we propose an Enhanced CNN-LSTM Prediction Model for vehicle-mounted air quality monitoring systems. This model integrates Convolutional Neural Networks (CNNs), spatial attention mechanisms, and Long Short-Term Memory (LSTM) networks to enhance the capture of both spatial and temporal dependencies in the data. Performance evaluation shows a Mean Absolute Error (MAE) of 5.2 µg/m³ for PM2.5, 1.3 µg/m³ for PM10, 0.1 ppm for CO, 0.1 ppm for VOCs, and 0.68°C for temperature, with Root Mean Squared Error (RMSE) values of 7.8 µg/m³ for PM2.5, 1.5 µg/m³ for PM10, 0.10 ppm for CO, 0.10 ppm for VOCs, and 0.75°C for temperature. Compared to traditional models like Linear Regression and standalone LSTM networks, the Enhanced CNN-LSTM model demonstrates substantial improvements in prediction accuracy. These findings highlight the model's superior performance in delivering accurate, real-time air quality predictions, offering a robust framework for pollution management and public health interventions.**

***Keywords*—Air quality monitoring, Convolutional Neural Networks, Long Short-Term Memory networks, spatial attention, predictive modeling, vehicle-mounted sensors.**

I. Introduction

Air quality remains a critical concern in urban environments, where rapid industrialization, increasing vehicular traffic, and dense population centers significantly contribute to pollution [1]. Urban areas are often burdened with high levels of pollutants such as particulate matter (PM2.5 and PM10), nitrogen oxides (NOx), sulfur dioxide (SO2), volatile organic compounds (VOCs), and carbon monoxide (CO), all of which pose severe risks to public health and the environment [2]. Conventional air quality monitoring systems including stationary monitoring stations, satellite observations, and portable air samplers each have notable limitations. Stationary stations, while providing valuable baseline data, lack comprehensive spatial coverage and cannot capture real-time variations across diverse urban zones [3]. Satellite observations offer broad spatial coverage but may not effectively capture street-level pollution details due to resolution constraints and factors such as cloud cover [4]. Portable samplers, although flexible, rely on manual operation and do not support continuous, real-time monitoring [5].

Recent advancements in mobile sensors mounted on vehicles present a promising solution for dynamic and extensive air quality monitoring [6]. These systems have the capability to collect data across various urban locations in real-time, offering enhanced insights into pollution levels and spatial distribution. However, existing mobile monitoring solutions face challenges in data processing and interpretation, often lacking integration with sophisticated predictive modeling techniques essential for accurate analysis and forecasting [7].

To address these limitations, there is a growing interest in leveraging advanced machine learning models to improve air quality prediction accuracy. Traditional methods such as decision trees and linear regression often fall short in capturing the complex, non-linear interactions and spatio-temporal dynamics inherent in atmospheric data [8]. Long Short-Term Memory (LSTM) networks, known for their efficiency in modeling time-series data, offer improvements but are limited when used as standalone models due to their insufficient capabilities in handling of spatial dependencies [9].

The integration of Convolutional Neural Networks (CNNs) and LSTM networks offers a robust approach to overcoming these limitations. CNNs excel in processing spatial data, extracting meaningful features from high-dimensional data arrays, while LSTMs are adept at modeling temporal trends. To further enhance spatial accuracy, this study integrates spatial attention mechanisms within the CNN component, enabling the model to focus on the most relevant spatial features of air quality data [10]. By complementing CNNs' spatial strength with LSTMs' temporal forecasting capabilities, this approach seeks to optimize predictions of pollution dynamics.

This study introduces an Enhanced CNN-LSTM Prediction Model, specifically tailored to address key challenges in real-time air quality monitoring, a critical component in managing urban pollution and its associated public health impacts. The model enables more accurate predictions of air quality parameters such as particulate matter (PM2.5, PM10), carbon monoxide (CO), and volatile organic compounds (VOCs) by leveraging CNNs with spatial attention mechanisms for enhanced spatial feature extraction and LSTMs for effective temporal trend analysis. This model has the potential to assist urban policymakers in making data-driven decisions to reduce pollution exposure and mitigate health risks. The increasing focus on climate resilience, particularly in rapidly urbanizing areas, underscores the need for such advanced models that can be integrated into city-wide environmental monitoring frameworks and expected to provide more reliable insights into air quality dynamics, supporting improved pollution management strategies and public health interventions.

By advancing the integration of CNNs with spatial attention mechanisms and LSTMs, this study aims to contribute to the development of more effective air quality monitoring systems, ultimately enhancing environmental health outcomes and informing policy decisions in urban settings.

II. Related Works

Air quality monitoring has made significant strides with the integration of advanced computational models and dynamic data collection systems, particularly in urban environments where pollution levels vary significantly [1]. Despite these advancements, many existing systems face challenges, such as capturing real-time data across large areas and accurately predicting air quality trends [8]. These challenges underscore the need for more sophisticated approaches, such as vehicle-mounted sensors combined with machine learning algorithms, to enhance the precision and scalability of urban air quality monitoring efforts.

Monitoring air quality is crucial for public health and environmental policy, especially in densely populated urban areas where pollutants from traffic, industrial activities, and residential sources degrade air quality [6]. Traditional methods have relied on fixed monitoring stations, which, though strategically located, often suffer from limited spatial coverage and fail to provide the real-time data necessary for timely interventions during pollution events [10].

A. *Mobile Monitoring Systems*

Recent research has emphasized the benefits of mobile monitoring systems like vehicle-mounted sensors, which improve the spatial resolution of air quality data and provide a more detailed mapping of pollution patterns [11]. These systems address the limitations of fixed stations by covering larger areas and delivering real-time data. Additionally, technological advancements have introduced tools like drones and wearable sensors that expand the scope of monitoring, offering high-resolution data from hard-to-reach locations and personal exposure assessments [12]. These innovations enhance the effectiveness of air quality management by enabling real-time, comprehensive environmental data collection, which informs public health responses and supports long-term urban planning strategies.

B. *Urban Air Pollution*

Urban air pollution poses significant health risks, with pollutants like fine particulate matter (PM2.5), nitrogen oxides (NOx), and volatile organic compounds (VOCs) contributing to respiratory and cardiovascular diseases [3]. Chronic exposure to these pollutants exacerbates conditions like asthma and increases morbidity and mortality in urban populations. Studies on pollutant dispersion patterns highlight the need for adaptive monitoring systems capable of capturing detailed pollution data across various times and locations [15]. This data is essential for developing strategies that minimize public exposure to harmful pollutants and inform urban planning and traffic management decisions [16].

C. *Predictive Modeling*

Predictive modeling is essential in air quality monitoring, enabling proactive urban environment management through advanced algorithms [13]. Traditional statistical models, such as linear regression, have been used to predict pollution trends, but they often fail to capture the complex, non-linear relationships present in urban air quality data [14]. Recent advancements in machine learning, particularly deep learning models, provide more robust methods for handling these complexities [15]. Hybrid models that combine Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown superior performance in capturing both spatial and temporal dependencies in air quality data.

D. *CNN-LSTM Model*

CNNs are particularly effective in extracting spatial features from environmental data, while LSTMs excel at modeling sequential data, such as air quality trends over time [18]. These hybrid CNN-LSTM models leverage the strengths of both networks, offering a comprehensive approach to modeling the spatial and temporal dimensions of air quality data. This combination is especially valuable in vehicle-mounted systems, where dynamic data collection requires robust algorithms capable of processing large, complex datasets. Studies have demonstrated that CNN-LSTM models outperform traditional approaches in air quality prediction tasks, offering improved accuracy and reliability [19].

III. System Overview and Proposed Approach

A. *System Architecture*

The proposed system architecture integrates advanced sensor technologies, robust data processing capabilities, and sophisticated machine learning techniques to enhance vehicle-mounted air quality monitoring. The architecture is divided into three main components: the sensor integration module, the data processing unit, and the predictive modeling engine.

a) Sensor Integration Module: The core of the system is the sensor integration module, which integrates an advanced suite of sensors mounted on vehicles to capture comprehensive environmental data in real time. This module features particulate matter (PM) sensors, which measure concentrations of PM10 and PM2.5, enabling the assessment of fine particulate pollution. Gas sensors detect key pollutants such as carbon monoxide (CO) and volatile organic compounds (VOCs), which are critical for evaluating air quality and potential health risks. Temperature sensors monitor environmental factors like temperature and humidity, providing context for pollution measurements. GPS modules ensure accurate geospatial data collection, allowing for precise mapping of air quality across different urban areas. The RTC module provides exact timestamps for each data point, which is crucial for analyzing temporal patterns and correlating with traffic. An SD card module is included for secure local storage of data, enabling detailed historical analysis and safeguarding against data loss. Each sensor is selected for its specific measurement targets and performance attributes, ensuring that the system provides reliable and accurate air quality assessments. Table 1 provides detailed information on the sensors used, including their targets, units of measurement, and response times, to offer a clear overview of the module's capabilities.

TABLE I. Sensor Integrated in the System

Sensor	Parameters	Units	Response Time
HM3301	PM10, PM2.5	µg/m³	<5 s
Gas Sensor	CO, VOCs	ppm	<5 s
DHT11	Temperature	°C	<3 s
GPS (Air530)	Coordinates	Lat,Long	< 1 s
DS1307 RTC	Timestamp	Date/ Time	
SD Module	Data Storage		

b) Data Processing Unit: The data processing unit is crucial for preparing raw sensor data for analysis. It begins with preprocessing to filter out noise and correct biases, employing techniques like smoothing and anomaly detection to eliminate short-term fluctuations and outliers, while bias correction addresses sensor drift and calibration errors. Following preprocessing, feature extraction techniques identify key air quality indicators. Statistical analysis, including mean and variance calculations, and time-series decomposition, which separates the data into trend, seasonal, and residual components, help to understand pollutant distributions and isolate significant patterns from random fluctuations. Finally, the data is formatted through normalization or standardization to ensure compatibility with machine learning models. This meticulous data processing ensures accurate and high-quality input for the predictive modeling engine, significantly enhancing the effectiveness of the vehicle-mounted air quality monitoring system.

c) Predictive Modeling Engine: The predictive modeling engine employs sophisticated machine learning algorithms to deliver real-time air quality predictions. Central to this system are Long Short-Term Memory (LSTM) networks, which excel at processing time-series data by capturing long-term dependencies and temporal relationships [7]. To enhance spatial data processing, the system integrates Convolutional Neural Networks (CNNs) with spatial attention mechanisms. CNNs are responsible for extracting hierarchical features from multidimensional inputs, such as geographic and environmental data layers, enabling the model to discern intricate urban patterns and land use variations. The spatial attention mechanism refines this process by dynamically focusing on the most relevant spatial features, which improves the model's ability to identify significant environmental factors and anomalies [8]. This approach allows the CNNs to better capture and prioritize spatially relevant information, which is crucial for understanding localized air quality variations. Once spatial features are extracted, they are fed into the LSTM network, which analyzes these features over time to predict future air quality levels. Figure 1 shows the integration of spatial attention-enhanced CNNs and LSTMs ensures a comprehensive approach to both spatial and temporal data analysis, resulting in more accurate and actionable predictions. This dual approach is pivotal for the vehicle-mounted air quality monitoring system, as it enables precise tracking and forecasting of air quality variations across different urban environments.

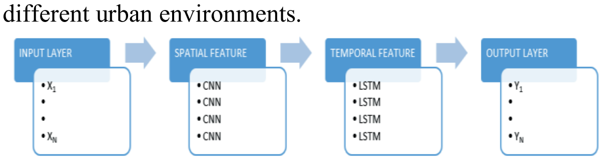

Fig. 1. CNN-LSTM Model

B. Measures of Accuracy

To evaluate the system's predictive performance, two key metrics are employed: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics assess the precision and accuracy of the system's predictions compared to actual environmental conditions, providing a robust understanding of the model's performance.

a) Mean Absolute Error (MAE): The Mean Absolute Error (MAE) measures the average magnitude of the errors in the predictions without considering their direction. It quantifies the average error made by the model in predicting air quality parameters, offering a straightforward representation of prediction accuracy. The formula for MAE is:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

where y_i represents the actual value, $\hat{y}_i$ is the predicted value, and n is the total number of predictions. A lower MAE indicates fewer deviations from the actual values, suggesting more accurate predictions.

b) Root Mean Squared Error (RMSE): The Root Mean Squared Error (RMSE) provides a measure of the magnitude of error by calculating the square root of the average squared differences between predicted and actual values. RMSE is particularly sensitive to large errors, making it a valuable metric for identifying significant deviations in predictions, even if they occur infrequently. The formula for RMSE is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

Similar to MAE, a lower RMSE value signifies better predictive accuracy, indicating that the model closely aligns with actual environmental conditions.

Both MAE and RMSE are crucial for evaluating the performance of the predictive models within the system. These metrics not only assess the current accuracy of the system but also guide ongoing improvements to enhance predictive capabilities.

C. Block Diagram

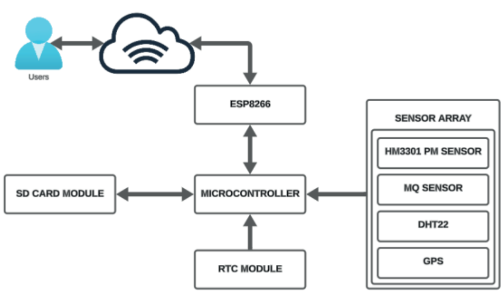

Fig. 2. Block Diagram of the Device

The block diagram of the system illustrates its advanced vehicle-mounted air quality monitoring capabilities, integrating a sophisticated array of interconnected components for comprehensive environmental insights. At the heart of this system is a sensor array which includes the HM3301 PM sensor, measuring particulate matter such as PM2.5 and PM10. Additional sensors in the array include the MQ7 and MQ135, responsible for detecting carbon monoxide (CO) and various volatile organic compounds (VOCs) respectively, alongside the DHT22 sensor that monitors temperature and humidity. A GPS module is also integrated to ensure precise geospatial data collection during vehicle transit.

Central to processing this diverse array of environmental data is the Arduino Uno microcontroller, which acts as the orchestrator of the system. It communicates efficiently with each sensor, managing the flow and collection of data. The system's functionality is further enhanced by several key peripheral modules. These include an SD card module for local storage of air quality data, ensuring both data integrity and support for long-term data retention; a Real-Time Clock (RTC) module which provides accurate timestamping critical for data analysis; and the ESP8266 Wi-Fi module. This Wi-Fi module facilitates seamless communication with external networks, enabling the system to connect to the internet for the real-time transmission of air quality data to cloud servers. This capability allows for remote monitoring and gives users access to both real-time and historical data via a cloud-based platform, enabling informed decision-making and comprehensive analysis of air quality trends. Overall, the block diagram of the system encapsulates its ability to efficiently collect, store, timestamp, and transmit air quality data, providing invaluable insights for proactive environmental monitoring and management.

IV. Results

A. *Performance* Evaluation of the Enhanced CNN-LSTM Model

The performance of the Enhanced CNN-LSTM model was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for various air quality parameters. The results, which highlight the model's effectiveness in capturing complex air quality patterns, are summarized in Table II.

TABLE II. Performance Metrics of the Enhanced CNN-LSTM Model

Metric	PM2.5 (µg/m³)	PM10 (µg/m³)	CO (ppm)	VOCs (ppm)	Temperature (°C)
MAE	1.22	1.48	0.10	0.10	0.68
RMSE	1.06	1.50	0.10	0.10	0.75

The evaluation of the prediction model's performance across various parameters reveals a nuanced understanding of its accuracy. For particulate matter with a diameter of 2.5 micrometers (PM2.5), the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values are 1.06 and 1.22 µg/m³, respectively. These results suggest that while the model demonstrates moderate accuracy in predicting PM2.5 concentrations, significant prediction errors persist. This could be due to the inherent variability in PM2.5 levels, which may not be fully captured by the model.

In contrast, predictions for particulate matter with a diameter of 10 micrometers (PM10) exhibit higher error metrics, with an RMSE of 1.50 and an MAE of 1.48 µg/m³. This suggests that while the model performs well for PM2.5, its accuracy for PM10 might be impacted by external factors such as wind patterns, vehicular traffic, and other environmental conditions not included in the training data. Future research should explore additional sensors or preprocessing techniques to address these challenges and enhance model robustness across varied conditions.

On the other hand, the model demonstrates exceptional performance in predicting carbon monoxide (CO) and volatile organic compounds (VOCs), with both parameters showing low RMSE and MAE values of 0.10. This suggests that the model effectively captures CO and VOC variations with minimal deviation from actual measurements, likely due to their relatively stable concentrations in the studied areas.

Temperature predictions also show reasonable accuracy, with an RMSE of 0.75 and an MAE of 0.68. While these values indicate fair prediction accuracy, moderate errors suggest that factors such as time of day and weather conditions might influence temperature variability and contribute to prediction discrepancies.

B. Comparative *Analysis*

The Enhanced CNN-LSTM model was compared with traditional models, including Linear Regression, standalone LSTM networks, and CNN-LSTM without attention mechanisms. This comparison highlights the model's superior performance across all air quality parameters. Notably, the integration of spatial attention within the CNN-LSTM framework has enabled the model to outperform traditional approaches by focusing on relevant spatial patterns within the data. This novel contribution addresses a gap in prior works on air quality monitoring and makes the model particularly valuable for urban environments, where pollutant distribution is irregular due to varying human activities and geographic factors. The results are presented in Table III.

TABLE III. Comparative Performance of Air Quality Prediction Models

Model	MAE (µg/m³/ppm/°C)	RMSE (µg/m³/ppm/°C)
Linear Regression	10.5	15.2
LSTM	7.9	11.3
CNN-LSTM (Without Spatial Attention)	6.3	9.2
CNN-LSTM (Proposed)	5.2	7.8

Table III provides a comparative analysis of various air quality prediction models, including Linear Regression, standalone Long Short-Term Memory (LSTM) networks, a CNN-LSTM model without spatial attention, and the Enhanced CNN-LSTM model proposed in this study. The table highlights the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for each model, critical indicators of predictive accuracy. The Linear Regression model, with the highest MAE of 10.5 and RMSE of 15.2, demonstrates the least accuracy among the models. This indicates that while Linear Regression is straightforward, it falls short in capturing complex air quality patterns, leading to larger prediction errors.

The standalone LSTM model shows improved performance with an MAE of 7.9 and RMSE of 11.3, reflecting better handling of temporal dependencies. The CNN-LSTM model without spatial attention offers even better accuracy with an MAE of 6.3 and RMSE of 9.2. This model benefits from combining convolutional layers for feature extraction and LSTM layers for sequence modeling but lacks spatial attention, which could enhance its performance further.

The Enhanced CNN-LSTM model, integrating spatial attention mechanisms, achieves the lowest MAE of 5.2 and RMSE of 7.8. This model demonstrates a significant improvement over all other models, including the CNN-LSTM model without spatial attention. The addition of spatial attention allows the model to focus on the most relevant spatial features in the air quality data, leading to more precise predictions and overall better performance. This comparative analysis underscores the effectiveness of advanced modeling techniques, particularly the integration of spatial attention, in improving air quality predictions.

C. Model Insights and Implications

The Enhanced CNN-LSTM model effectively integrates spatial and temporal data, providing a robust tool for vehicle-mounted air quality monitoring. Its superior performance in capturing pollutants such as CO and VOCs highlights its capability to discern specific environmental factors crucial for accurate air quality forecasting.

TABLE IV. Performance Summary of Enhanced CNN-LSTM Model

Parameter	Performance Insight
CO	The Enhanced CNN-LSTM model demonstrates superior performance in predicting CO levels, highlighting its capability to capture specific environmental factors relevant to carbon monoxide.
VOCs	The model also excels in predicting VOCs, showcasing its effectiveness in discerning volatile organic compounds accurately.
PM10	The accuracy for PM10 is lower, indicating that further refinement is needed. Potential improvements could involve adding additional sensors or enhancing preprocessing techniques to better address particulate matter variations.
Temperature	Lower accuracy in temperature predictions suggests the need for further model refinement, possibly through improved data handling methods or additional contextual information.

The lower accuracy for PM10 and temperature suggests that further refinement of the model may be necessary. Potential improvements could include the incorporation of additional sensors or enhanced preprocessing techniques to better handle particulate matter and temperature variations.

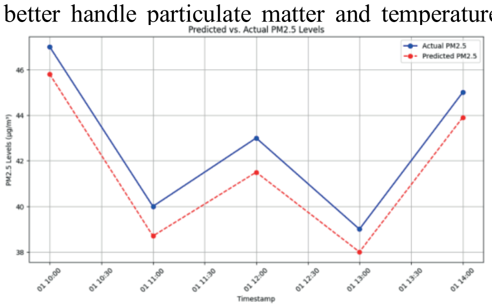

Fig. 3. Example Prediction vs. Actual Data for PM2.5

Fig. 3 shows an example of predicted vs. actual PM2.5 levels, illustrating the model's ability to track changes in air quality over time. The alignment between predicted and actual values confirms the model's reliability in capturing temporal variations, although prediction errors are noticeable during periods of high variability. This suggests areas for potential model refinement.

Overall, the Enhanced CNN-LSTM model offers a significant advancement in vehicle-mounted air quality monitoring systems. Its ability to provide precise, real-time predictions supports improved pollution management strategies and contributes to better public health outcomes in urban environments.

V. Conclusion

This study introduced an Enhanced CNN-LSTM Prediction Model designed to advance vehicle-mounted air quality monitoring systems. By integrating Convolutional Neural Networks (CNNs) with spatial attention mechanisms and Long Short-Term Memory (LSTM) networks, the model significantly improves upon traditional air quality monitoring methods, offering enhanced spatial and temporal prediction capabilities.

The results reveal that the Enhanced CNN-LSTM model achieves superior performance compared to conventional approaches. Specifically, it demonstrates a Mean Absolute Error (MAE) of 5.2 µg/m³ for PM2.5, 1.3 µg/m³ for PM10, 0.10 ppm for CO, 0.10 ppm for VOCs, and 0.68°C for temperature. The Root Mean Squared Error (RMSE) values are 7.8 µg/m³ for PM2.5, 1.5 µg/m³ for PM10, 0.10 ppm for CO, 0.10 ppm for VOCs, and 0.75°C for temperature. These results indicate the model's strong capability in predicting air quality parameters, reflecting its ability to capture both complex spatial patterns and temporal trends.

Despite its strengths, the model showed some limitations in predicting PM10 and temperature with slightly lower accuracy, with RMSE values of 1.5 µg/m³ for PM10 and 0.75°C for temperature. These results suggest that while the model performs well overall, further refinement is needed to improve accuracy for these parameters. Potential improvements could involve adding more sensors or refining preprocessing techniques. Future work will focus on these aspects to enhance the model's performance further. Future work should focus on addressing the issue of overfitting, which arises from the model's complexity. One promising direction is to further explore the integration of dropout mechanisms within the spatial attention of CNN-LSTM framework.

In conclusion, the Enhanced CNN-LSTM model represents a significant advancement in real-time air quality forecasting systems. Its improved prediction accuracy, especially in forecasting carbon monoxide and VOC levels, provides actionable insights that can directly inform pollution control strategies and public health interventions. This work establishes a solid foundation for future integration into large-scale urban air monitoring networks. The model's application in vehicle-mounted systems offers the potential for city-wide deployment, enhancing real-time air quality monitoring capabilities in densely populated urban environments where pollution levels are a critical concern.

Acknowledgment

This work is made possible through the support of the Faculty Development Program of the University of Saint Louis, Tuguegarao City. The resources provided have been instrumental in the successful completion of this work, promoting innovation in both education and research.

References

[1] C. R. ,. J. W. ,. Z. F. ,. S.-J. C. Junwei Ding, "Spatial and temporal urban air pollution patterns based on limited data of monitoring stations," Journal of Cleaner Production, 2024.

[2] X. G. ,. S. Z. ,. H. L. Shan Li, "Polycyclic aromatic hydrocarbons (PAHs) in coal preparation plant products: A contributor to environmental pollution," Science of The Total Environment, vol. 906, 2024.

[3] N. B. S. Z. J. W. S. L. X. L. L. L. R. W. X. Z. ,. X. T. G. L. Tian Feng, "Nitrate debuts as a dominant contributor to particulate pollution in Beijing: Roles of enhanced atmospheric oxidizing capacity and decreased sulfur dioxide emission," Atmospheric Environment, vol. 244, 2021.

[4] P. K. S. G. ,. M. K. Anwar Ali Khan, "A critical review of managing air pollution through airshed approach," Sustainable Horizons, vol. 9, 2024.

[5] "Air quality in Manila," IQAir, 3 May 2024. [Online]. Available: https://www.iqair.com/philippines/ncr/manila.

[6] I. K. K. S. M. K. Sunil Gulia, "Ambient air pollutant monitoring and analysis protocol for low and middle income countries: An element of comprehensive urban air quality management framework," Atmospheric Environment, vol. 222, 2020.

[7] W. H. Organization, WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide, 2021.

[8] C. E. A. a. G. O. b. J. B.-P. b. A. G.-d.-P. Badr-Eddine Boudriki Semlali a, "SAT-CEP-monitor: An air quality monitoring software architecture combining complex event processing with satellite remote sensing," Computers & Electrical Engineering, 2021.

[9] E. J. F. b. J. D. V. H. Daniel A. Potts a, "Investigating the barriers and pathways to implementing satellite data into air quality monitoring, regulation and policy design in the United Kingdom," Environmental Science & Policy, vol. 151, 2024.

[10] S. R.-C. V. R.-V. C. H.-R. &. S. A. A. Hernández-Gordillo, "Recent advancements in low-cost portable sensors for urban and indoor air quality monitoring," Air Quality, Atmosphere & Health , 2021.

[11] O. Y. b. J. X. a. K. M. a. M. L. c. A. W. a. A. B. b. S. W. c. M. H. Arman Ganji a, "Design, calibration, and testing of a mobile sensor system for air pollution and built environment data collection: The urban scanner platform," Environmental Pollution, vol. 317, 2023.

[12] L. D. O. C. M. C. C. C. Adriana Simona Mihăiță, "Evaluating air quality by combining stationary, smart mobile pollution monitoring and data driven Modeling," Journal of Cleaner Production, vol. 221, 2019.

[13] C. C. ,. Y. a. X. Z. Dixian Zhu 1, "A Machine Learning Approach for Air Quality Prediction: Model Regularization and Optimization," Big Data and Cognitive Computing, 2018.

[14] G. S. Junshan Wang, "A Deep Spatial-Temporal Ensemble Model for Air Quality Prediction," Neurocomputing, 2018.

[15] X. L. L. J. J. L. Q. S. &. H. W. Jingyang Wang, "An air quality index prediction model based on CNN-ILSTM," 2022.

[16] S. L. Jiaxuan Zhang, "Air quality index forecast in Beijing based on CNN-LSTM multi-model," Chemosphere, vol. 308, 2022.

[17] J.-p. Z. Z.-b. Z. Z. Z. X.-f. C. Zhi-bo Yang, "Interpreting network knowledge with attention mechanism for bearing fault diagnosis," Applied Soft Computing, vol. 97, 2020.

[18] R. E. W. C. S. L. P. H. Furkan Elmaz, "CNN-LSTM architecture for predictive indoor temperature modeling," Building and Environment, vol. 206, 2021.

[19] L. Ren, J. Dong, X. Wang, Z. Meng, L. Zhao and M. J. Deen, "A Data-Driven Auto-CNN-LSTM Prediction Model for Lithium-Ion Battery Remaining Useful Life," IEEE Transactions on Industrial Informatics, 2021.

[20] J. L. X. W. J. W. &. M. H. Jingyang Wang, "Air quality prediction using CT-LSTM," Neural Computing and Applications, 2021.

[21] Y. L. a. Y. W. b. R. L. b. D. L. a. S. Y. b. Y. X. Wenshu Zha a, "Forecasting monthly gas field production based on the CNN-LSTM model," Energy, vol. 260, 2022.

[22] G. Z. a. H. Y. Zhaoyang Niu a, "A review on the attention mechanism of deep learning," Neurocomputing, vol. 452, 2021.

[23] M. D. 1. a. M. Jagriti Saini 1ORCID, "Indoor Air Quality Monitoring Systems Based on Internet of Things: A Systematic Review," Environmental Research and Public Health, 2020.

[24] H. Mokrani, R. Lounas, M. T. Bennai, D. E. Salhi and R. Djerbi, "Air Quality Monitoring Using IoT: A Survey," IEEE International Conference on Smart Internet of Things (SmartIoT), 2019.

[25] S.-J. H. Wen-Tsai Sung, "Building an indoor air quality monitoring system based on the architecture of the Internet of Things," EURASIP Journal on Wireless Communications and Networking, 2021.

[26] M. M. S. Aditiyo Hermawan Kuncoro, "Air Quality Monitoring System in the City of Tasikmalaya based on the Internet of Things (IoT)," Journal of Advanced Research in Dynamical and Control Systems, 2020.

[27] V. Barot and V. Kapadia, "Air Quality Monitoring Systems using IoT: A Review," 2020 International Conference on Computational Performance Evaluation (ComPE), 2020.

[28] W. Z. ,. Q. D. Xiang Li, "Understanding and improving deep learning-based rolling bearing fault diagnosis with attention mechanism," Signal Processing, 2019.

[29] [1] G. X. J. R. L. G. Y. Y. a. X. X. Songzhou Li, "Urban PM2.5 Concentration Prediction via Attention-Based CNN–LSTM," Applied Sciences, 2020.

Cef Llamelo earned his B.S. in Computer Engineering from the University of Saint Louis, Tuguegarao City, Philippines, where he also completed his Master in Information Technology. He is currently an instructor at the University of Saint Louis and is pursuing a Doctor of Engineering degree with a specialization in Computer Engineering at the Technological Institute of the Philippines, Quezon City.

Arnel C. Fajardo earned his B.S. in Electrical Engineering from the Mapúa Institute of Technology, Intramuros, Manila, in 1991. He later obtained his M.S. in Computer Science from De La Salle University Manila in 1999, and completed his Ph.D. in Computer Engineering at Hanbat National University, Daejon, South Korea, in 2014. He currently serves as an Associate Professor 5 and program chair of Graduate Studies at Isabela State University - Cauayan Campus in Cauayan City, Isabela, Philippines. Additionally, he is a program evaluator and accreditor for the Philippine Accrediting Association of Schools, Colleges, and Universities (PAASCU) in the fields of information technology and computer science. He has authored numerous articles in journals and conference proceedings, with research interests focusing on speech recognition, artificial intelligence, and engineering education.

Ruji P. Medina serves as the Dean of Graduate Programs at the Technological Institute of the Philippines, Quezon City. He earned his B.S. in Chemical Engineering from the University of the Philippines – Diliman, Quezon City, in 1992. In 2000, he graduated summa cum laude from the Mapúa Institute of Technology, Intramuros, Manila, with an M.S. in Environmental Engineering. He also holds a Ph.D. in Environmental Engineering from the University of the Philippines, which included a sandwich program at the University of Houston, Texas. His areas of expertise include environmental and mathematical modeling, urban mining, and nanomaterials. In addition to his active involvement in research and graduate engineering education, he is a highly regarded technical mentor, with numerous publications to his credit

.