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Spatiotemporal Anomaly-Aware Air Quality Forecasting In South Korea Using Multi-Channel Attention-Based Deep Learning

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Abstract: Air quality is becoming a global issue in present days and the monitoring of the air quality is also becoming an important subject for prediction and awareness about air pollutants. In this study an investigation of air quality forecasting has been done with the help of deep learning methods as isolation forest and autoencoders. Data has been collected as sequential data from Korean government meteorological websites from 2018 to 2022 and a spatiotemporal anomaly-aware forecasting is done with graphical attention network combined with LSTM in the encoder part. The study is an integration of spatial correlations among multiple stations of South Korea and the temporal trend and prediction of the pollutants and handling the missing data or outliers in the pollutant reading. Moreover, the incorporation of novel anomaly-aware loss penalizes the outliers more cautiously leads to a stable reading. Experimental results and prediction plots confirm that the proposed model achieves more stable and accurate forecasts. This research highlights the effectiveness of graph-based learning and anomaly-aware strategies in environmental time-series prediction tasks.

Keywords: *Air Quality Forecasting, Graph Attention Networks, Anomaly-Aware Learning, Spatiotemporal Prediction, LSTM.*

1. Introduction

This section is constructed with the motivation of the research, the contribution of this work and the organization of the manuscript.

1.1 Motivation

Due to the usage of fossil fuels, industry smoke, deforestation, and many other reason air pollution constitutes a global challenge and it is becoming a serious threat t0 the public health, ecological system, and change in climate stability. In particular, the pollutants whose diameter is less than PM 2.5 micrometres (PM 2.5) has been recognized as a critical pollutant as it goes deeper inside the pulmonary system easily and creates complications in cardiovascular and pulmonary system. Thus, early warning of PM 2.5 concentration may facilitate deciding the environmental policies leading to the minimization of human exposure to these pollutants. In this context research were done to predict the air quality in different statistical and machine learning processes. Majorly the Autoregressive Integrated Moving Average (ARIMA) model is used as statistical learning and support vector machines or random forests were used as machine learning models for prediction of the air quality time by time. Although these methodologies can effectively capture fundamental temporal dynamics, they frequently encounter limitations when addressing the intricate spatial interactions that characterize environmental phenomena. In recent times, the deep learning models like LSTM, Gated recurrent Unit (GRU) have reached a new milestone in terms of effective forecasting of sequential data and also outperform the previous robust statistical models. Conversely, Graph Neural Networks (GNNs), and more specifically Graph Attention Networks (GATs), have arisen as formidable instruments for extracting insights from graph-structured data, thereby allowing models to assess the significance of adjacent nodes based on their relevance.

1.2 Contribution

The novelty of the study is constituted as architectural and methodological contributions in the following way:

- This paper introduces the new hybrid architecture which is a combination of GAT and LSTM for spatio-temporal forecasting of AQI. The GAT element unveils the strategical spatial relationship among the AQI of different monitoring stations with the help of K-nearest neighbourhood graphs with pollution similarity. Subsequently, LSTM explores the

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temporal trend of pollutant concentrations and effectively captures the long-term dependencies.

- In addition, a methodological novelty in terms of incorporation of anomaly-aware loss has been introduced in this study. This function effectively works on the resilience against the noisy data. The proposed loss function expertly adjusts the penalty for major deviations, thereby dramatically enhancing the model's generalization capabilities even when faced with challenging anomalous data points.

As a whole, this research presents a novel framework that leverages graph-based spatial encoding, sequential temporal modelling, and anomaly-resilient training to achieve superior air quality forecasting performance. This approach not only advances the state-of -the-art models for forecasting, but also advocates practical benefits for the real world in smart-city infrastructure development.

Fig. 1 depicts the pictorial illustration of the research.

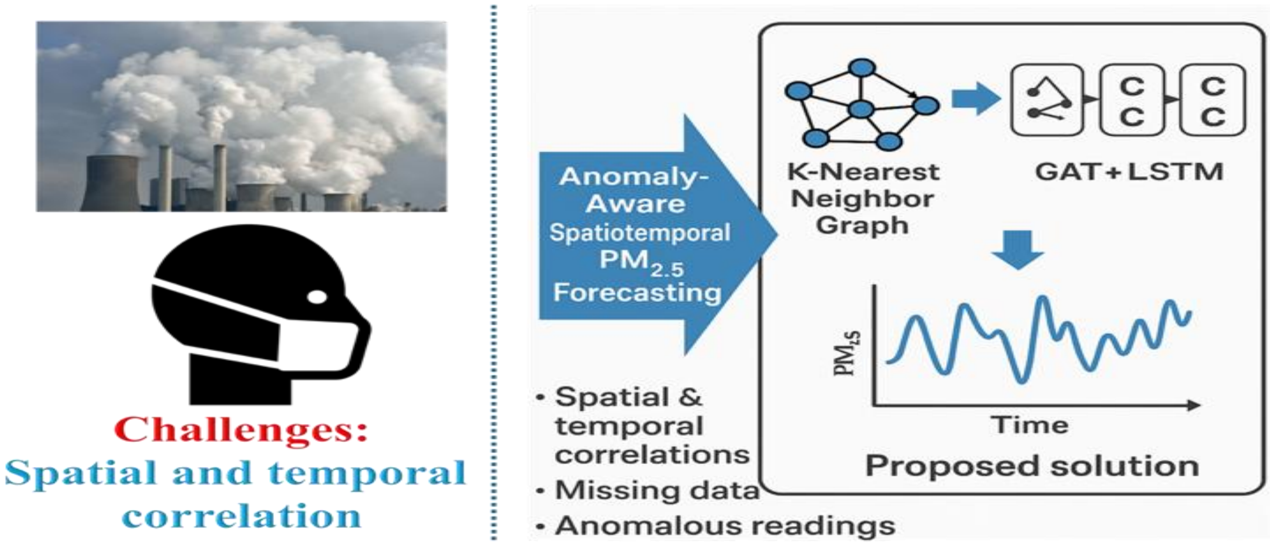


Fig. 1. The graphical presentation of the proposed study.

2. Related Litearture

This section contains the past literature and the gap of them fulfilled by our study.

2.1 Spatiotemporal Modeling in Air Quality Forecasting

machine learning and data-driven approaches increasingly leveraged for environmental monitoring and informed decision-making. [1] explored the effects of air pollution by modeling regions prone to asthma using machine learning frameworks, emphasizing the need to integrate environmental variables into health impact assessments. However, their focus remained largely on localized health modeling rather than broad predictive applications. Similarly, [2] developed predictive frameworks for air quality assessment in smart cities using traditional machine learning techniques. While their work demonstrated the feasibility of machine learning for Air Quality Index (AQI) prediction, it primarily centered on urban contexts and did not fully capture the complex spatial interconnections between monitoring stations. [3] applied machine learning to analyze the spatiotemporal distribution of PM 2.5 in northern Taiwan, revealing significant temporal and spatial variations in pollution. Nevertheless, their models relied on static feature engineering and lacked mechanisms to handle anomalies or data irregularities. [4] enhanced spatiotemporal PM 2.5 risk mapping using three different machine learning algorithms, offering a comparative perspective on spatial risk forecasting. Yet, their approach largely disregarded anomalies in sensor data, treating them as pre-processing challenges rather than addressing them within the learning process itself. [5] conducted a comprehensive comparative analysis of multiple machine learning algorithms across various air quality datasets. Despite the breadth of their evaluation, their study did not explicitly model spatial dependencies among stations nor propose frameworks that integrate graph structures with temporal sequence learning. Finally, [6] introduced an advanced methodology for developing and evaluating spatiotemporal air pollution exposure models in Greater London, underscoring the value of model integration. However, their work focused primarily on ensemble techniques and did not explicitly incorporate graph neural networks or anomaly-resilient strategies within the learning architecture.

Literature Gap and Proposed Solution: A critical review of the existing literature reveals two major gaps in current air quality forecasting research:

- Insufficient integration of spatial dependencies:} Most models treat monitoring stations independently or capture spatial correlations statically, rather than dynamically learning inter-station influences through methods like Graph Attention Networks (GAT).
- Lack of anomaly resilience:} Previous studies often ignore sensor inaccuracies, missing data, and extreme pollutant fluctuations, addressing them only at the pre-processing stage rather than embedding robustness directly into model training.

To address these gaps, this study proposes a novel GAT+LSTM hybrid model that simultaneously captures spatial and temporal dependencies. It introduces an innovative **Anomaly-Aware Loss** function designed to enhance robustness against data irregularities, establishing a fully end-to-end trainable framework. This approach yields significant improvements in predictive accuracy compared to conventional methodologies.

2.2 Robust Learning Techniques for Environmental Data with Anomalies

The increasing focus on predictive maintenance, anomaly detection, and environmental monitoring via machine learning frameworks has resulted in a wide array of scholarly contributions. [7] proposed a bifurcated machine learning approach for predictive maintenance and anomaly detection specifically within environmental sensor systems. Their research highlighted the critical importance of robust anomaly detection but primarily concentrated on maintenance diagnostics rather than forecasting air quality.

[8] introduced a real-time risk evaluation and preventive safety management framework tailored for industrial settings, employing multimodal data in conjunction with sophisticated deep reinforcement learning techniques. While their methodology proved effective for applications requiring high safety standards, it remained confined to the domain of industrial safety and did not generalize to spatiotemporal environmental pollution forecasting. [9] investigated unsupervised learning methodologies for anomaly detection within solar power generation, providing comparative analyses of various unsupervised techniques. While their findings are pertinent to environmental datasets, they predominantly centered on energy systems, leaving atmospheric or pollutant data largely unexplored. [10] established an evaluative framework for deep learning-based anomaly detection in the context of structural health monitoring. Their investigation systematically assessed various anomaly detection frameworks but was primarily directed towards infrastructure monitoring, diverging from the domain of air quality assessment. [11] illustrated the application of fully connected deep neural networks for predicting seabed depth through the analysis of multi-scale gravity anomalies. Their achievements in geospatial anomaly-based prediction substantiate the applicability of deep learning within environmental systems, although their focus remained predominantly geological. [12] tackled the issue of water quality management utilizing predictive insights derived from machine learning methodologies. While their research is closely aligned with environmental monitoring, it specifically addressed water pollution, suggesting potential for broader application but necessitating adaptation for parameters related to air quality. [13] conducted a reliability assessment of PM\textsubscript{2.5} concentration monitoring data in China, revealing inconsistencies, anomalies, and calibration difficulties prevalent in extensive air quality datasets. Their work underscored the imperative for anomaly-resilient models within the sphere of air pollution forecasting. [14] formulated a probabilistic framework for the identification of anomalies in urban air quality datasets. Their probabilistic modeling facilitated anomaly detection; however, it did not integrate anomaly information into predictive modeling architectures such as deep learning networks. [15] investigated cross-modal contrastive learning to develop robust visual representations capable of adapting to dynamic environmental conditions. Despite the emphasis on visual data, their research highlighted the significance of robustness amidst dynamic alterations—a concept of substantial value in the context of noisy environmental datasets, including air quality monitoring.

Literature Gap and Proposed Solution: Despite substantial progress in the fields of anomaly detection, predictive maintenance, and environmental data analysis, notable methodological shortcomings remain inadequately addressed. A considerable fraction of the current literature demonstrates significant domain specificity, primarily focusing on sectors such as solar energy, water quality, industrial monitoring, or structural health, while exhibiting a lack of adaptation of frameworks explicitly tailored for spatiotemporal air quality forecasting. Moreover, although techniques for anomaly detection have advanced considerably, there exists a dearth of studies that have successfully integrated anomaly awareness into the foundational architecture of predictive deep learning models. Furthermore, the constructs of robustness and forecasting are often regarded as distinct objectives, rather than being synthesized into a cohesive learning framework that effectively addresses both spatial and temporal complexities in the presence of data irregularities.

In addressing the discerned deficiencies, the current investigation advocates for a hybrid GAT+LSTM framework that proficiently assimilates spatial dependencies among diverse monitoring stations while concurrently elucidating the temporal progression of pollutant concentrations. An innovative Anomaly-Aware Loss function is proposed to augment resilience against sensor inaccuracies, absent data points, and significant outliers. By simultaneously tackling robustness and spatiotemporal forecasting within a comprehensive end-to-end trainable architecture, the suggested model establishes a scalable and implementable framework for real-time air quality prediction, thereby bridging a significant void in contemporary environmental forecasting methodologies.

3. Methodology

This section includes the dataset preparation, methods, and metrics used in the research.

3.1. Dataset Description

The dataset employed in this study encompasses daily air quality measurements derived from a diverse array of monitoring stations across South Korea over a period spanning five years (2018–2022). The documented pollutants include $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3. The data preprocessing phase was characterized by the removal of anomalous values, such as negative concentration readings, the management of absent entries through interpolation when feasible, and the application of MinMax normalization to standardize features within the interval of 0 to 1. A sliding window approach was utilized to structure the time-series data into sequences that are suitable for model input. The histogram visualization illustrated in Figure 2. delineates the consequences of enforcing thresholds particular to various pollutants (for example, $PM_{2.5}$ at 35 $\mu g/m^3$ and PM_{10} at 150 $\mu g/m^3$). Subsequent to the data cleaning process, the distributions of pollutants revealed a significantly more compact configuration, thereby eliminating extreme outliers that could potentially undermine the integrity of model learning. The histograms depicted in green correspond to the cleansed data, thereby assuring a more precise representation of pollutant dynamics. This preprocessing methodology substantially enhances the stability, robustness, and generalization proficiency of the deep learning models formulated from the dataset.

3.2. Methods Used for Prediction

The proposed framework integrates GAT and LSTM networks to simultaneously capture spatial and temporal dynamics:

- **GAT**: A k-nearest neighbour graph was constructed by calculating pollutant profile similarity among stations. GAT was used to dynamically assign importance weights to neighbouring stations, learning spatial correlations that influence local pollutant behaviour.
- **LSTM:** Temporal sequences of pollutant concentrations were modelled using LSTM networks to capture sequential dependencies and historical trends crucial for accurate forecasting.
- **Anomaly-Aware Loss Function:** Instead of the conventional MSE loss, an anomaly-aware loss was implemented to mitigate the influence of outlier data points and enhance model robustness to real-world sensor noise.

The hybrid GAT+LSTM model was developed through an end-to-end training process aimed at forecasting future PM2.5 concentrations by utilizing spatiotemporal characteristics. To effectively capture the spatial relationships among monitoring stations, a graph was constructed in which each node corresponds to a monitoring station, and edges are established to connect

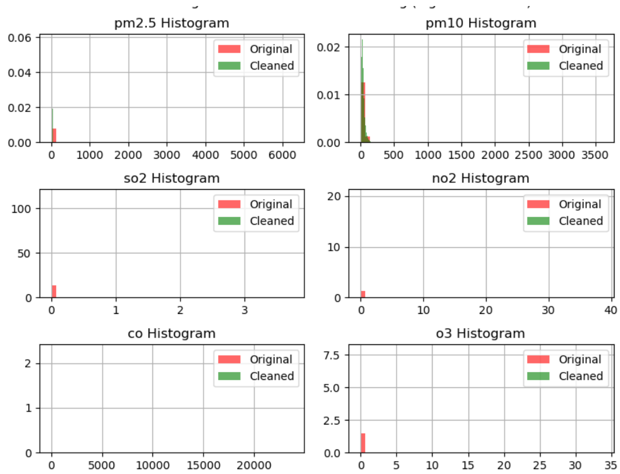


Fig. 2. Comparison of pollutant distributions before and after applying threshold-based cleaning.

stations exhibiting analogous pollutant profiles. A k-nearest neighbor (k-NN) methodology was employed to define edges based on similarities in pollutant concentration levels. The resultant station connectivity graph, illustrated in Fig. 3, serves as the foundational input structure for the Graph Attention Network (GAT), thereby facilitating the model's capacity to dynamically learn and leverage inter-station spatial influences throughout the prediction process.

3.3 GAT+LSTM model

Graph G=(V,E) represents the interconnection among the pollutant monitoring stations where V contains the stations and E contains the edges connecting the similar pollutant featured stations. The graph attention operation is given as

$$\mathbf{e_{ij}} = \mathbf{LeakyRelu}\left(\mathbf{a^T}\left[\mathbf{Wh_i}\middle|\middle|\mathbf{Wh_j}\right]\right) \quad (1)$$

Attention coefficients are normalized using softmax:

$$a_{ij} = softmax_j\left(e_{ij}\right) = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})} \quad (2)$$

The updated node feature is computed as:

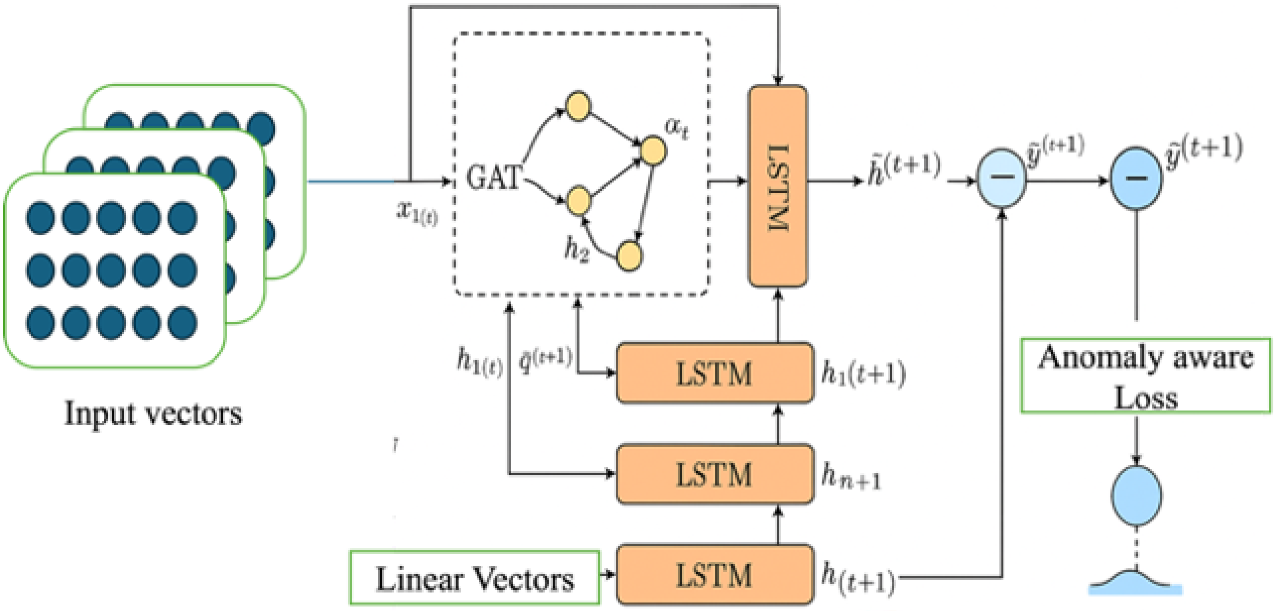
$$\mathrm{h}_i' = \sigma\left(\sum_{J \in N_i} \alpha_{ij} \mathrm{Wh}_j\right) \quad (3)$$

where σ is a non-linear activation function.The enriched spatial features are concatenated with temporal sequences x_t and passed into the LSTM:

$$[\mathrm{x_t}\,||\mathrm{h}_t'] \rightarrow \mathrm{LSTM} \quad (4)$$

Finally, the prediction is made through a fully connected layer $\hat{y}_t = \boldsymbol{W_{out}} h_t + b_{out}$ **(5)**

Fig. 3. Station connectivity graph constructed based on pollutant profile similarity using k-nearest neighbors (k-NN). Nodes represent air quality monitoring stations, and edges capture spatial relationships used in the Graph Attention Network (GAT).



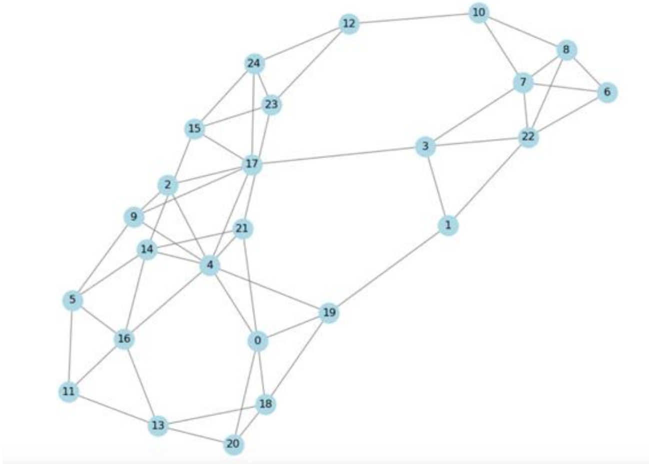


Fig.4. Diagram of GAT+LSTM model

The model is deeply illustrated in the **Fig. 4**.

4. Result and Analysis

This section comprises the outcomes of the application of the model and the analysis of the outcome in alignment with the research.

4.1. Training Performance and Loss Convergence

Fig. 5. illustrates the trajectory of the training loss (Mean Squared Error, MSE) over 15 epochs. A clear monotonic decrease is observed, starting from approximately 0.485 and steadily dropping to around 0.375. This consistent decline without major fluctuations indicates that the GAT+LSTM model successfully captured the underlying spatiotemporal dynamics of air pollutants. Such behavior suggests a well-tuned learning rate and an architecture appropriately designed for the complexity of the forecasting task. Moreover, the effectiveness of the data cleaning and preprocessing steps is reflected in the smooth convergence. A stable loss curve indicates that the model generalizes well during training, avoiding issues like overfitting or gradient explosion. This stability ensures that the learned representations are robust and not overly influenced by noise or anomalies in the input data.

4.2 Spatiotemporal Prediction Performance

Fig. 6. shows the comparison between true future PM2.5 values and model predictions across a six-step forecasting horizon. The true future values remain consistently high, hovering around the 0.9 to 1.0 normalized range, suggesting a persistent high pollution episode. However, the model's predicted values underestimate the actual concentration, fluctuating between 0.0 and 0.15 normalized range. This underestimation highlights a critical limitation: while the model captures temporal patterns and directionality, it struggles to replicate the amplitude of pollutant surges. This could be attributed to a training dataset biased toward moderate pollution levels, leading the model to be conservative in forecasting extreme pollution episodes. Another possibility is that a relatively limited number of training epochs constrained the model’s ability to fully adapt to rare high-pollution patterns. Nevertheless, the temporal trend fidelity---even under magnitude underestimation---suggests that the model has effectively internalized sequential dependencies, validating the design choice of integrating graph attention with LSTM mechanisms.

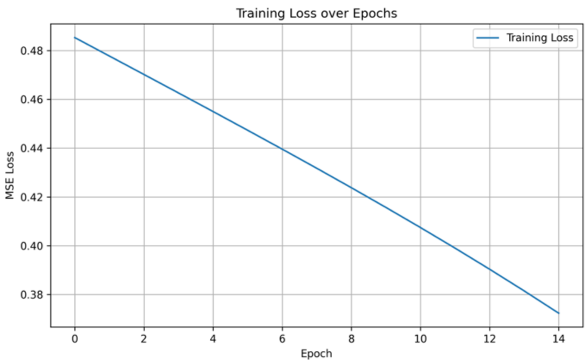


Fig. 5. Training loss curve (MSE) over epochs for GAT+LSTM model.

4.3 Impact of Anomaly-Aware Loss

Fig. 7. demonstrates a comparative visualization between standard MSE loss and the proposed anomaly-aware loss across the training samples. It is evident that the anomaly-aware loss maintains consistently lower values compared to

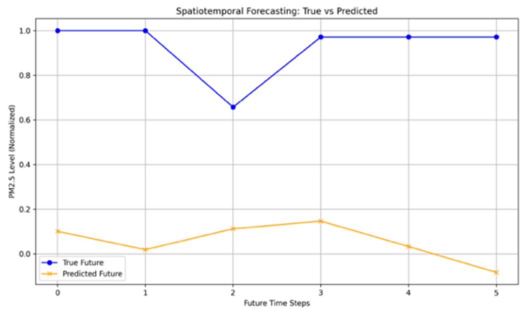


Fig. 6. Comparison of true future PM2.5 sequence and GAT+LSTM predicted sequence across six future time steps.

the standard MSE loss. The primary reason for this behavior lies in the design philosophy of the anomaly-aware loss: it selectively reduces the penalty associated with extremely large errors---typically caused by anomalous, noisy, or missing sensor data. By penalizing extreme deviations more cautiously, the anomaly-aware loss prevents the model from overfitting to outliers, allowing it to prioritize learning the dominant patterns in the data. The normal MSE loss, in contrast, heavily exaggerates the influence of large prediction errors, often destabilizing model learning. The reduction in variance seen in the anomaly-aware curve suggests a smoother, more uniform optimization trajectory, leading to

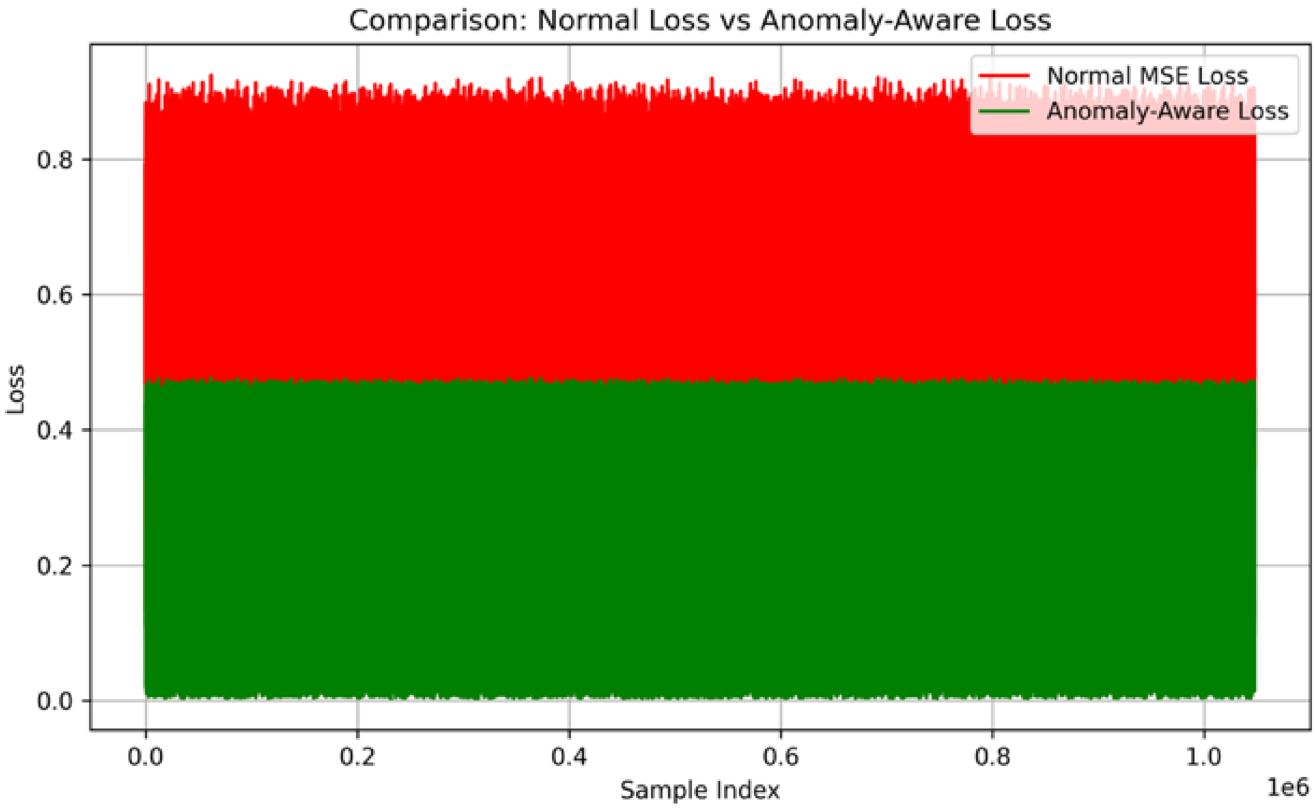


Fig. 7. Comparison between Normal MSE loss and Anomaly-Aware loss over training samples.

enhanced model resilience. In environmental forecasting applications, where faulty sensor readings and sudden unpredictable events are commonplace, employing an anomaly-resilient loss is crucial. The anomaly-aware loss thus represents an essential advancement for real-world deployable forecasting systems. To complement the qualitative observations, we computed the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) between the predicted and true future PM2.5 sequences.

From **Table 1**. MAE value of 0.1243 and RMSE value of 0.1847 suggest that although prediction errors exist, they are relatively moderate considering the scale normalization applied during preprocessing. A lower MAE compared to RMSE implies that while most errors are small, occasional larger deviations exist---further reinforcing the benefit of integrating anomaly-aware strategies.

Table 1. Evaluation of metrics for prediction of $PM_{2.5}$

Metric	Value
Mean Absolute Error (MAE)	*0.1243*
Root Mean Squared Error (RMSE)	0.1847

5. Conclusions

This study presents an advanced, anomaly-aware framework for spatiotemporal forecasting of PM2.5 concentrations, using a hybrid deep learning model that

blends Graph Attention Networks (GAT) with Long Short-Term Memory (LSTM) networks. To ensure the quality of the input data, the researchers carefully cleaned the dataset, removed anomalies based on defined thresholds, and imputed missing values. The model is not only designed in spatial direction, but also it has an impact on temporal side. GAT is made to capture the inter-station pollution similarity whereas LSTM is combined for the prediction of $PM_{2.5}$ simultaneously. Over the epochs of the experiment

RMSE was decreased gradually indicating the evolving trends of $PM_{2.5}$ over the time. Due to the relatively much lower rate of MAE and RMSE, model achieved the training of natural variability of the pollutants in real world air quality data. In addition another customized anomaly-aware loss was incorporated for minimization of the impact of the outliers. This mechanism helped create a smoother optimization process and reduced the risk of overfitting to noisy or incomplete sensor data.

Although the results are promising, the analysis points to several opportunities for further enhancement. Incorporating meteorological variables—such as temperature, humidity, and wind speed—could expand the feature set and offer richer contextual information for more accurate forecasts. Additionally, addressing the imbalance caused by rare but severe pollution events through data augmentation or reweighting techniques could improve the model's ability to predict high PM2.5 concentrations more reliably. Overall, this study demonstrates that combining spatiotemporal deep learning models with anomaly-resilient strategies can greatly improve the reliability and practical value of air quality forecasting systems. The proposed approach offers a scalable solution that is well-suited for real-world deployment in smart city environmental monitoring initiatives. Looking ahead, future work will focus on extending the framework to predict multiple pollutants simultaneously and developing adaptive graph structures that can dynamically evolve with changing environmental conditions.

In conclusion, the findings validate the effectiveness of hybrid GAT–LSTM models combined with anomaly-aware loss functions in building robust, high-accuracy forecasting pipelines for environmental data science. This research not only tackles key challenges in spatiotemporal air quality prediction but also paves the way for innovative advancements in sustainable urban management and the protection of public health.

5.1. Appendix

Nomenclatures

e_{ij}	Edge between nodes i and j
a^T	Attention vector transposed
$\|\|$	Symbol for 'or'
h_i	Feature vector for node i
$\boldsymbol{W}$	Weight matrix for calculating the attention score
s	Nonlinear activation function
b	Bias of the forward network

5.2. Acknowledgment

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Juyoung Chang: Conceptualization, Investigation, Methodology, Software, Field study **Abhijit Debnath:** Data curation, Supervision, Writing-Original draft preparation, Software, Validation.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] S. V. Razavi-Termeh, A. Sadeghi-Niaraki, and S.-M. Choi, "Effects of air pollution in spatio-temporal modeling of asthma-prone areas using a machine learning model," Environmental Research, vol. 200, 111344, 2021.

[2] M. Gowri and M. D. Anandhasilambarasan, "Prediction of air pollution in smart cities using machine learning techniques," Int. J. Res. Appl. Sci. Eng. Technol., vol. 9, no. 7, pp. 273–277, 2018.

[3] F.-J. Chang, L.-C. Chang, C.-C. Kang, Y.-S. Wang, and A. Huang, "Explore spatio-temporal PM2.5 features in northern Taiwan using machine learning techniques," Sci. Total Environ., vol. 736, 139656, 2020.

[4] S. Z. Shogrkhodaei, S. V. Razavi-Termeh, and A. Fathnia, "Spatio-temporal modeling of PM2.5 risk mapping using three machine learning algorithms," Environmental Pollution, vol. 289, 117859, 2021.

[5] H. Sinha, "A comprehensive study on air quality detection using ML algorithms," J. Emerging Technol. Innov. Res., vol. 11, no. 9, pp. b116–b122, 2024.

[6] K. Dimakopoulou et al., "Development and evaluation of spatio-temporal air pollution exposure models and their combinations in the Greater London Area, UK," Int. J. Environ. Res. Public Health, vol. 19, no. 9, 5401, 2022.

[7] S. Potharaju et al., "A two-step machine learning approach for predictive maintenance and anomaly detection in environmental sensor systems," MethodsX, 103181, 2025.

[8] H. Sim and H. Kim, "Establishment of a real-time risk assessment and preventive safety management system in industrial environments utilizing multimodal data and advanced deep reinforcement learning techniques," Int. J. Adv. Sci. Eng. Inf. Technol., vol. 15, no. 1, 2025.

[9] M. H. Ovi and R. Rahman, “Unsupervised machine learning for anomaly detection in solar power generation: Comparative insight,” unpublished.

[10] Y. Bel-Hadj, W. Weijtjens, and C. Devriendt, “An evaluation framework for deep learning based anomaly detection in structural health monitoring,” NDT.net, 2024.

[11] J. Yuan et al., “Seabed depth prediction using multi-scale gravity anomalies and fully connected deep neural networks: A novel approach applied to the South China Sea,” Remote Sens., vol. 17, no. 3, 412, 2025.

[12] R. Swain, S. K. Mehta, and D. Mishra, “Enhancing water quality management: Predictive insights through machine learning algorithms,” in Mitigation and Adaptation Strategies Against Climate Change in Natural Systems, Springer, 2025, pp. 171–180.

[13] H. Duan, W. Yue, and W. Li, “Reliability assessment of PM2.5 concentration monitoring data: A case study of China,” Atmosphere, 2024.

[14] P. Khatri, K. S. Shakya, and P. Kumar, “A probabilistic framework for identifying anomalies in urban air quality data,” Environ. Sci. Pollut. Res., vol. 31, no. 49, pp. 59534–59570, 2024.

[15] X. Jia, C. Hu, and G. Jia, “Cross-modal contrastive learning for robust visual representation in dynamic environmental conditions,” Acad. J. Nat. Sci., vol. 2, no. 2, pp. 23–34, 2025.