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Original scientific paper

Hyb_LSTM+KCNN: Hybrid Long Short Term Memory with Kernel Convolution Neural Networks Based Time Series Forecasting for Air Quality Index Detection

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Abstract: Clean air is essential for maintaining a healthy lifestyle, yet poor air quality remains a major contributor to numerous respiratory ailments. Air pollutants such as PM2.5, NOx, COx, and SOx significantly impact human health, emphasizing the need for accurate forecasting models. However, predicting air quality is challenging due to the dynamic interplay of various factors, including meteorological conditions, vehicular emissions, and industrial discharges. This study proposes a novel hybrid forecasting model, Hyb_LSTM+KCNN, which combines Long Short-Term Memory (LSTM) networks and Kernel Convolutional Neural Networks (KCNN) for time-series prediction of the Air Quality Index (AQI). The LSTM component captures temporal dependencies in air quality data, enabling effective modeling of sequential patterns over time. Meanwhile, the KCNN module enhances feature extraction by leveraging convolutional kernels to identify local data patterns. By integrating these complementary strengths, the hybrid architecture provides a more robust and accurate AQI forecasting model.The proposed model was evaluated on comprehensive datasets, incorporating various pollutant levels and meteorological parameters. Experimental results demonstrated that the Hyb_LSTM+KCNN model consistently outperforms traditional forecasting techniques, achieving higher prediction accuracy and generalization capabilities. The model effectively captures correlations between pollutants and environmental factors, leading to precise AQI forecasts even under dynamic and complex conditions. This study presents a promising solution for air quality prediction, with practical implications for environmental monitoring and public health management. Future research will explore further optimization of the model for real-time applications and investigate its performance when integrating additional data sources, such as satellite and hyperspectral imagery.

Keywords: air quality; convolution neural networks; forcasting; long short term memory; time series model

1 INTRODUCTION

Air pollution significantly harms the ecosystem, exacerbating global warming, facilitating airborne infectious infections, causing chronic health issues, and increasing cancer incidence rates as pollution levels rise [1, 2]. The World Health Organization has indicated that air pollution is responsible for around 7 million premature deaths per year [3]. The Indian Express reports that air pollution caused 6.67 million deaths globally in 2019, with India contributing 1.67 million fatalities, the most of any nation. The AQI is an essential metric for evaluating the level of air pollution. Dependable and precise AQI forecasting is crucial for comprehending prospective health hazards, informing regulatory choices, and fostering cleaner, healthier settings. The U.S. Environmental Protection Agency (USEPA) states that the AQI may be easily calculated when pollutant concentrations are available [4]. Nonetheless, the monitoring platform's susceptibility to missing or abnormal data may result in inconsistencies and mistakes in AQI calculation.

In light of the aforementioned constraints, some studies [5] recommend using a data-driven methodology to improve the precision and dependability of AQI forecasting. This approach's usefulness is in using diverse data sources and attributes instead of just depending on established pollutant concentrations to compute the AQI value [6]. Data-driven methodologies overcome data deficiencies, enhance predictability, and efficiently provide relevant AQI estimates, especially in instances of missing or abnormal data. Data-driven approaches for AQI tasks often include univariate and multivariate models. Univariate approaches concentrate on the analysis of each time series in isolation, without using insights from the dataset. The primary methodologies are autoregressive integrated moving average (ARIMA) and exponential smoothing (ETS) [7], with an emphasis on constructing an AQI prediction model with ARIMA. Multivariate approaches see AQI forecasting as a cohesive system and are inherently compatible with deep neural network (DNN) models because of their capacity to handle high-dimensional data inputs [8].

Recently, advancements in computational algorithms have enabled the use of deep learning models to assess and predict nonlinear correlations among data variables. Similarly, deep learning models have markedly enhanced data analysis performance by yielding very dependable findings [9]. Furthermore, deep learning methodologies, including deep neural networks (DNNs) and long short-term memory (LSTM) models, have been used for diverse applications in meteorology, hydrology, precipitation, and drought studies, particularly for forecasting [10]. Furthermore, in recent decades, several researchers have examined and forecasted air pollutant concentrations to mitigate the detrimental effects of air pollution and improve predictive accuracy [11]. In the majority of prior researches, data from all stations within the study region were regarded and used as independent variables. However, utilizing all the surrounding station data distorts outcomes since extraneous data are utilized for model learning. Given this, this work's contributions are as follows:

- Kernal Convolution Neural Network extracts spatial correlations from meteorological parameters, while LSTM captures long-term dependencies.
- Adaptive kernel-based convolution helps to dynamically adjust receptive fields for different meteorological factors. It can optimize kernel sizes based on pollutant distributions and atmospheric conditions.

The structure of this study is: Section 2 describes the literature review. The proposed technique is provided in Section 3. The performance and outcome analysis with comparative research is covered in Section 4. Sections 5 concludes the work and future work.

2 LITERATURE SURVEY

Recent research emphasizes sophisticated learning algorithms for air quality assessment and air pollution forecasting. The following approaches are provided. In [12] the Multi-Granularity Spatiotemporal Fusion Transformer is proposed, which consists of the dynamic fusion block, the spatiotemporal attention block, and the residual de-redundant block. The residual de-redundant block eliminates information redundancy across data granularities and protects the model from unnecessary data. In [13], a novel model for daily AQI prediction, VMD-CSA-CNN-LSTM, was introduced using convolutional neural networks (CNN) and long short-term memory (LSTM) networks, the chameleon swarm algorithm (CSA) for hyperparameter optimization, and a variational mode decomposition approach. It achieved an *RMSE* of 2.25, *MAPE* of 0.02, adjusted *R*-squared of 98.91%, and training efficiency of 95. The CNN, LSTM, and BiGRU networks are combined in CLSTM-BiGRU [14]. The [15] technique forecasts seasonal air quality using regularized combinational LSTM. In [16], CNN-LSTM was introduced. Data attributes were first derived using CNN's successful feature extraction. Sequential feature vectors were sent to the LSTM network. The LSTM layer predicted air quality values using changing patterns. CNN-LSTM *MAE* and *RMSE* decreased by 3.17% and 5.46%. In [17] presented is CNN-ILSTM, a CNN-based AQI prediction model. ILSTM removes the output gate, improves the input and forget gates, and adds a Conversion Information Module (CIM) to reduce learning supersaturation. CNN-ILSTM has an *MAE* of 8.4134, an MSE of 202.1923, an R^2 of 0.9601, and a training time of 85.3 seconds.

The models explained above for air quality prediction, while innovative, have several limitations. These include challenges in effectively reducing data redundancy without losing critical patterns, increased model complexity that hampers real-time deployment, and the difficulty of optimizing hyperparameters for better accuracy and efficiency. Additionally, models like REG-CLSTM struggle with generalizing across seasonal variations, and many LSTM-based models are prone to overfitting, limiting their robustness. Furthermore, while improvements in training efficiency, as seen in CNN-ILSTM, have been made, there is still room to reduce computational costs without sacrificing prediction performance. Addressing these issues is key for enhancing the accuracy and practicality of air quality prediction models using Hyb_LSTM+KCNN, which can effectively extract high-level features from raw data, reducing redundancy. The kernel approach allows for more flexible and efficient feature extraction compared to traditional CNNs, as it can better capture the spatial-temporal dependencies in air quality data.

3 STUDY AREA AN DATA COLLECTION

The selected location for the study is the city of Gorakhpur. It is situated in the state of Uttar Pradesh, India, on the bank of the Rapti River. From a geographic perspective, Gorakhpur is situated about approximately 26.76 °N and 83.37 °E. The research region has a specific landscape and encompasses an urban area of approximately 3483.8 km^2. The city has become especially vulnerable to air pollution because of its high population, and the rapid industrial development of the area only makes things worse. Vehicle emissions, burning of agricultural waste, and other sources that lead to abnormally high concentrations of PM_{10}, NO_2, CO_2, SO_2 are the main causes of air pollution in the city. The CPCB monitoring station is located on Deoria Road in Singhariya, Kunraghat, Gorakhpur. The monitoring is done continuously for one hour, with different sample frequencies for gaseous pollutants and particulate matter. Air pollution is monitored biweekly. Regularity allows systematic and frequent citywide air quality evaluations. The 4 hourly and 8 hourly monitoring of gaseous pollutants detects short-term changes in pollutant levels, including daytime fluctuations.

3.1 Data Pre-Processing

Data from monitoring stations includes observed values $\{x_t\}$ at certain intervals *t*. Each hour, time series data is collected. After data imputation, we normalize all observations in [0, 1] using the following procedure.

$$X_t = \frac{x_t - \min(x_t)}{\max(x_t) - \min(x_t)} \tag{1}$$

The additive model breaks the time series into trend, seasonality, and irregular components (the cyclic component is not included in this research).

$$X_t = trend_t + cyclic_t + seasonal_t + irregular_t \tag{2}$$

where the trend component $trend_t$ at time t displays the series' long-term evolution, which may be linear or non-linear. The seasonal component $seasonal_t$ represents seasonal variation-related fluctuations at time *t*. The $irregular_t$ component (also known as "noise") at time *t* has stochastic and unexpected effects. Time series may exhibit cyclic $cyclic_t$, signifying irregular or recurring changes.

3.2 Proposed Hyb_LSTM+KCNN Architecture

The integration of LSTM and KCNN in a hybrid architecture offers complementary advantages. LSTM focuses on learning temporal sequences and trends, ensuring that long-term dependencies in air quality data are effectively modeled. Simultaneously, KCNN strengthens feature extraction by emphasizing localized patterns within the input data. This fusion of sequential and spatial feature learning improves the overall predictive performance, leading to a more accurate and reliable air quality forecasting model. The model has two layers: the input layer and the LSTM recurrent layer. The output layer connects to the cell's input, output, and forget gates. Z is the input, and Z_i is the input gate control signal. Z_f is the forget gate control signal, Z_o is the output gate control signal, and $f(x)$ is generally the Sigmod function.

$$f(x)=\frac{1}{1+\mathrm{e}^{-x}} \tag{3}$$

This function indicates door opening degree and has a value range of [0, 1]. Both $g(x)$ and $h(x)$ activate. After passing the activation function, *Z* passes the Sigmod function to obtain $f(Z_i)$ and multiplies it to get $g(Z)f(Z_i)$. The hidden layer neuron's input x_t and output h_{t-1} are multiplied by multiple weight vectors to form the hidden layer's input at time *t*. The activation function obtains the three gates' control signals Z_f, Z_i, Z_o and the input value *Z*. Following is the formula:

$$Z_f=\omega_f\cdot[h_{t-1},x_t]+b_f \tag{4}$$

$$Z_t=\omega_t\cdot[h_{t-1},x_t]+b_t \tag{5}$$

$$Z_o=\omega_o\cdot[h_{t-1},x_t]+b_o \tag{6}$$

$$Z=\omega_x\cdot[h_{t-1},x_t]+b_x \tag{7}$$

where Biases of varied connection weights include b_f, b_i, b_o, b_x. The memory unit's *c* is updated after LSTM operation.

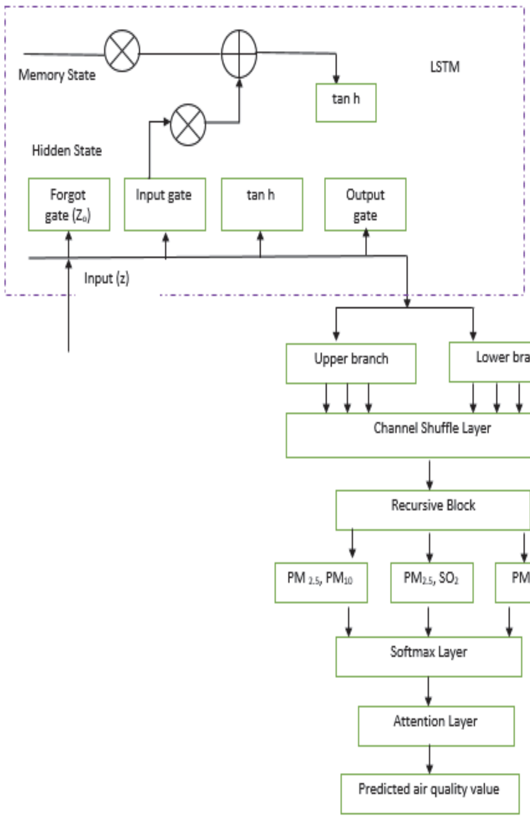

Figure 1 Flow diagram

The output from the buried layer neurons is given by Eq. (8):

$$\begin{aligned}c' &= g\left(w_x\times[h_{t-1},x_t]+b_x\right)f\left(w_t\times[h_{t-1},x_t]+b_t\right)+\\&+cf\left(w_f\times[h_{t-1},x_t]+b_f\right)\end{aligned} \tag{8}$$

where KCNN uses c' to extract local patterns in the data based on projected temporal relationships. The original time series is equally split into two channels to decrease network parameters. The top branch extracts features with a strong receptive field, whereas the bottom branch preserves semantic characteristics by using three 3 × 3 × 3 convolution layers to expand the field. Next, channel shuffling ensures information exchange across branches. A recursive block is shown below:

$$Z=shuffle(concat\left(\begin{matrix}split\left(x,\dfrac{C}{2}\right)conv_{3\times3\times3}\\ \left(conv_{3\times3\times3}\left(split\left(x,\dfrac{C}{2}\right)\right)\right)\end{matrix}\right) \tag{9}$$

where *x* is the input time series. The *split* toggles split operations based on parameter $\dfrac{C}{2}$, which divides series equally per channel. The second step uses the softmax function to normalize the similarity score from the first stage, resulting in the weight coefficient φ_t of each unit vector (Eq. (10)). In the third step, Eq. (11) shows that the attention mechanism weighted sums the vector produced by each LSTM unit and the weight coefficient to acquire the final attention values c_t of each variable:

$$\varphi_t^f=\frac{\exp\left(S_t^f\right)}{\sum_{f=1}^{n}\exp\left(S_t^f\right)} \tag{10}$$

$$c_t=\sum_{f=1}^{n}\varphi_t^f h_t^f \tag{11}$$

where *j* represents the variable serial number, *t* the current instant, and s_t the similarity score of $PM_{2.5}$ concentration to other variables.

4 RESULT AND DISCUSSION

We trained this model using an 8GB Nvidia Geforce 2080 GPU. The experiment tested 5% or 10% of the data for validation and testing, while the rest was used for training. For Gorakhpur air quality monitoring locations, data usage in validation and testing dropped from 10% to 5%. This experiment utilized a PC with an Intel Core i3 CPU and 8 GB of RAM. This categorization and improvement scenario uses Python 3.9.7.

4.1 Performance Metrics

The efficacy of the proposed method is assessed using four indicators. The metrics are mean square error (*MSE*), mean absolute error (*MAE*), and root mean square error (*RMSE*). The expressions are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y'_t - y_t)^2} \tag{12}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y'_t - y_t)^2 \tag{13}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(y'_t - y_t)^2\right| \tag{14}$$

where N is the dataset's total sample count, y_t and y' represent the real and average true values, and y'' represents the model's anticipated concentration. A lower *RMSE*, *MSE*, and *MAE* suggests a better model prediction. Air quality metrics ($PM_{2.5}$, PM_{10}, NO_2, SO_2, CO) and meteorological factors (temperature, humidity, wind speed, atmospheric pressure) affect pollution levels. Tab. 1 lists all contaminants' national limits.

Table 1 Indication pollutants and its national limits

Pollutant	Observed range	National limit
$PM_{2.5}$ / μg/m^3	50 - 120	60
PM_{10} / μg/m^3	80 - 180	100
NO_2 (ppb)	30 - 80	40
SO_2 (ppb)	20 - 50	50
CO	0.8 -2.5	2

Table 2 Correlation analysis by proposed Hyb_LSTM+KCNN for 7 days

Feature	Days	Correlation analysis
$PM_{2.5}$	7 days	0.89 (strong correlation)
SO_2	7 days	0.79 (moderate correlation)
NO_2	7 days	0.83 (strong correlation)
CO	7 days	0.76 (moderate correlation)

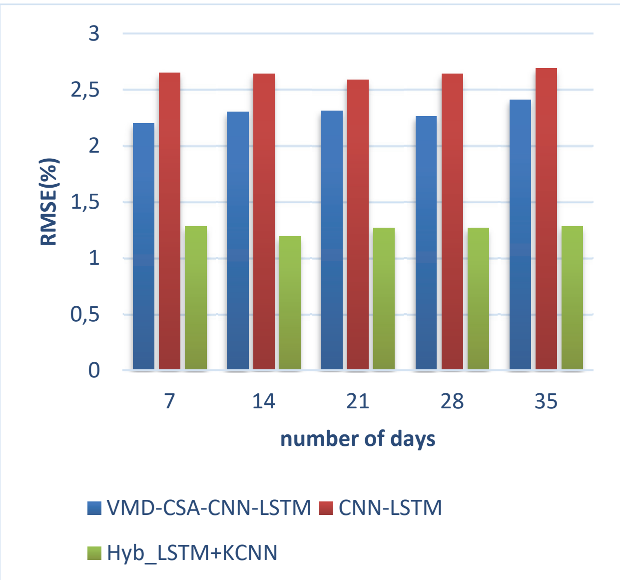

Figure 2 Comparison of *RMSE*

Fig. 2 compares the RMSE of three air quality prediction models such as VMD-CSA-CNN-LSTM, CNN-LSTM, and Hyb_LSTM+KCNN over forecast periods of 7 to 35 days**.** Hyb_LSTM+KCNN consistently achieve the lowest *RMSE*, demonstrating superior accuracy due to LSTM's temporal dependency modeling and KCNN's spatial feature extraction**.** CNN-LSTM shows the highest *RMSE*, indicating weaker predictive capability, while VMD-CSA-CNN-LSTM performs better than CNN-LSTM but remains suboptimal**.** The stable RMSE trend across time suggests model consistency, with Hyb_LSTM+KCNN emerging as the most precise and reliable approach for air quality forecasting.

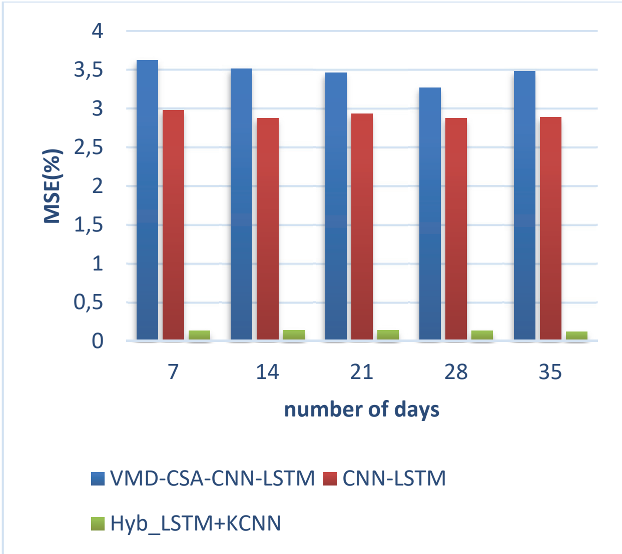

Figure 3 Comparison of *MSE*

Fig. 3 illustrates the performance of *MSE* among the existing methods VMD-CSA-CNN-LSTM, CNN-LSTM, and the proposed technique Hyb_LSTM+KCNN. The existing approaches reach 3.62 and 2.98 at 7 and 35 days, respectively. The proposed Light-AirNet approach attained a *MSE* of 0.13, the lowest value in comparison to other methods. Consequently, the proffered approach demonstrates superior efficacy.

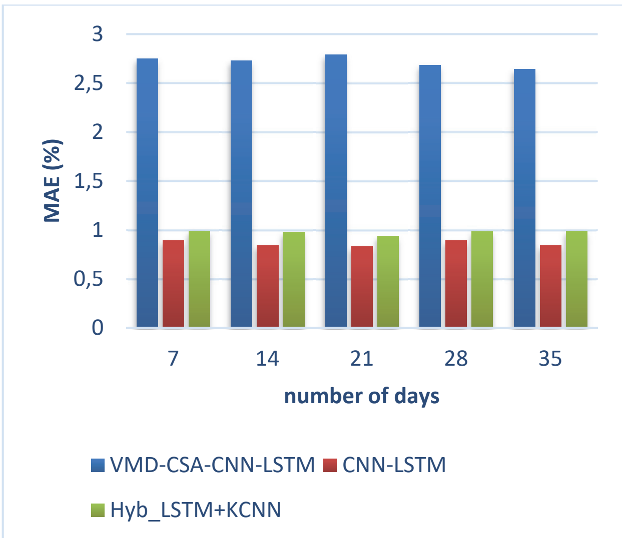

Figure 4 Comparison of *MAE*

From Fig. 4 we can find that VMD-CSA-CNN-LSTM consistently records the highest MAE around 2.7%, indicating weaker predictive accuracy. In contrast,CNN-LSTM maintains a lower MAE around 0.9%, while Hyb_LSTM+KCNN achieves the lowest *MAE* 1.0**,** demonstrating superior performance. The stable *MAE* trends across time suggest model consistency**,** with Hyb_LSTM+KCNN emerging as the most reliable model for air quality forecasting due to its enhanced spatial-temporal feature extraction.

Tab. 3 below presents a comprehensive comparative examination of existing and planned approaches.

Table 3 Overall comparative analysis

Parameter	VMD-CSA-CNN-LSTM[13]	CNN-LSTM [16]	Hyb_LSTM+KCNN [proposed]
RMSE / %	2.25	2.64	1.29
MSE / %	3.62	2.98	0.13
MAE / %	2.75	2.84	0.45
Prediction accuracy / %	0.97	0.89	0.99

5 CONCLUSION

This study successfully implements the Hyb_LSTM+KCNN architecture to address complex data classification challenges effectively. The trial results confirm that the custom pre-trained Inception model, combined with the proposed data preparation methodology, achieves superior accuracy, outperforming state-of-the-art techniques. The first training phase establishes a robust and precise model that performs consistently well even when exposed to challenging conditions, such as noisy and imbalanced datasets. This robustness ensures that the model can make accurate predictions in novel scenarios without requiring additional computational investment, making it suitable for real-time applications where data characteristics may vary significantly. The model's adaptability and resilience offer immense potential for practical deployments in fields such as environmental monitoring, industrial automation, and healthcare analytics. Furthermore, its efficiency in learning from diverse data attributes makes it an attractive solution for dynamic and high-variance data environments. Future work will focus on extending its role in tackling real-world problems effectively.

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6 REFERENCES

[1] Rayapureddy, S. M., Maknickas, A., Matijošius, J., Vainorius, D., & Kilikevičius, A. (2024). Computational study of frequency impact onto the particle parameters and change in acoustic agglomeration time with the number of particles. *Facta Universitatis, Series: Mechanical Engineering*, *22*(4), 741-757. https://doi.org/10.22190/FUME241005050R

[2] Huang, Y. F., Weng, M. W., & Fu, C. J. (2024). A two-stage sustainable production-inventory model with carbon credit demand. *International Journal of Industrial Engineering and Management*, *15*(2), 96-108. https://doi.org/10.24867/IJIEM-2024-2-350

[3] Abhilash, M., Thakur, A., Gupta, D., & Sreevidya, B. (2018). Time series analysis of air pollution in Bengaluru using ARIMA model. *Ambient communications and computer systems: RACCCS 2017*, 413-426. https://doi.org/10.1007/978-981-10-7386-1_36

[4] Bai, Y., Ni, Y., & Zeng, Q. (2021). Impact of Ambient Air Quality Standards revision on the exposure-response of air pollution in Tianjin, China. *Environmental Research*, *198*, 111269. https://doi.org/10.1016/j.envres.2021.111269

[5] Hindriks, R., Bijma, F., van Dijk, B. W., van der Werf, Y. D., van Someren, E. J., & Van Der Vaart, A. W. (2011). Dynamics underlying spontaneous human alpha oscillations: a data-driven approach. *NeuroImage*, *57*(2), 440-451. https://doi.org/10.1016/j.neuroimage.2011.04.043

[6] Huang, F., Lu, Z., Li, L., Wu, X., Liu, S., & Yang, Y. (2022). Numerical simulation for European and American option of risks in climate change of Three Gorges Reservoir Area. *Journal of Numerical Mathematics*, *30*(1), 23-42. https://doi.org/10.1515/jnma-2020-0081

[7] Galassi, A., Lippi, M., & Torroni, P. (2020). Attention in natural language processing. *IEEE Transactions on Neural Networks and Learning Systems*, *32*(10), 4291-4308. https://doi.org/10.48550/arXiv.1902.02181

[8] Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning models: Literature review. *Water*, *10*, 1536. https://doi.org/10.3390/w10111536

[9] Xingjian, S. H. I., Chen, Z., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2015). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. *Proceedings of the Advances in Neural Information Processing Systems 28 (NIPS 2015)*, 802-810.

[10] Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2018). Rainfall-runoff modelling using long short-term memory (LSTM) networks. *Hydrology and Earth System Sciences*, *22*, 6005-6022. https://doi.org/10.5194/hess-22-6005-2018

[11] Wu, X., Zhou, J., Yu, H., Liu, D., Xie, K., Chen, Y., Hu, J. B., Sun, H. Y., & Xing, F. (2021). The Development of a Hybrid Wavelet-ARIMA-LSTM Model for Precipitation Amounts and Drought Analysis. *Atmosphere*, *12*, 74. https://doi.org/10.3390/atmos12010074

[12] Yu, C., Wang, F., Wang, Y., Shao, Z., Sun, T., Yao, D., & Xu, Y. (2025). MGSFformer: A multi-granularity spatiotemporal fusion transformer for air quality prediction. *Information Fusion*, *113*, 102607. https://doi.org/10.1016/j.inffus.2024.102607

[13] Guo, Z., Jing, X., Ling, Y., Yang, Y., Jing, N., Yuan, R., & Liu, Y. (2024). Optimized air quality management based on air quality index prediction and air pollutants identification in representative cities in China. *Scientific Reports*, *14*(1), 17923.

[14] Ahmed, A. A. M., Jui, S. J. J., Sharma, E., Ahmed, M. H., Raj, N., & Bose, A. (2024). An advanced deep learning predictive model for air quality index forecasting with remote satellite-derived hydro-climatological variables. *Science of the Total Environment*, *906*. https://doi.org/10.1016/j.scitotenv.2023.167234

[15] Sun, X. & Tian, Z. (2024). A novel air quality index prediction model based on variational mode decomposition and SARIMA-GA-TCN. *Process Safety and Environmental Protection*, *184*, 961-992. https://doi.org/10.1016/j.psep.2024.02.010

[16] Zhang, J. & Li, S. (2022). Air quality index forecast in Beijing based on CNN-LSTM multi-model. *Chemosphere*, *308*, 136180. https://doi.org/10.1016/j.chemosphere.2022.136180
[17] Wang, J., Li, X., Jin, L., Li, J., Sun, Q., & Wang, H. (2022). An air quality index prediction model based on CNN-ILSTM. *Scientific Reports*, *12*(1), 8373.

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