RESEARCH ARTICLE

Urban ecological environment pollution monitoring and governance strategy based on deep learning

Nan Wang*

Faculty of Culture and Tourism, Jiyuan Vocational and Technical College, Jiyuan, Henan, China.

Received: May 30, 2024; **accepted:** August 30, 2024.

Urban ecological pollution has become a significant global concern due to rapid industrialization and urbanization, resulting in increased levels of pollutants such as suspended particulate matter, sulfur dioxide, carbon monoxide, and nitrogen oxides. Traditional pollution monitoring methods are often limited by high costs, inefficiency, and the inability to provide large-scale, real-time data. To address these challenges, this study discussed the strategies of monitoring and controlling urban ecological environment pollution by using deep learning technology and constructed convolution neural networks by combining multi-source data including satellite remote sensing, ground monitoring data, and social media information to achieve efficient environmental pollution monitoring. Data teleprocessing, feature engineering, and model optimization techniques were employed to ensure high-quality model training and accurate performance evaluation. The proposed model demonstrated excellent prediction accuracy and good generalization ability. By constructing convolutional neural networks and integrating multi-source data, the study achieved real-time, accurate pollution monitoring. This study emphasized the crucial role of environmental policy and community feedback in promoting environmental improvement and made recommendations to enhance policy implementation and public participation. In addition, the study evaluated the potential of deep learning in informing environmental policy and community engagement, which could improve policy implementation and public environmental awareness for sustainable urban development.

Keywords: deep learning; urban ecology; environmental pollution; monitoring and management.

***Corresponding author:** Nan Wang, Faculty of Culture and Tourism, Jiyuan Vocational and Technical College, Jiyuan 459000, Henan, China. Email: nan_wang163@hotmail.com.

Introduction

With the rapid development of industrialization and urbanization, urban environmental pollution has become one of the main problems of the world. The deterioration of air quality has had a profound impact on public health and ecosystems. There are many kinds of pollutants in urban ecological environments, including but not limited to suspended particulate matter, sulfur dioxide, carbon monoxide, and nitrogen oxides. Traditional environmental monitoring methods often rely on physical sampling and chemical analysis, which are not only costly, but also inefficient, and difficult to achieve large-scale and real-time environmental quality monitoring. In addition, these methods have limitations in data processing and pollution source tracking, which cannot meet the current needs of urban environmental management. There is an urgent need for advanced technological solutions to enhance the efficiency and accuracy of pollution monitoring and control.

In the field of urban ecology, much in-depth research has been done on the impact of urbanization on ecosystem. Forman *et al*. discussed the differences between urban ecology and natural area ecology and proposed some core principles of urban ecology, which highlighted the unique ecological dynamics of the urban environment [1]. Wu *et al*. sorted out the history of urban ecological research in China, prospected the future development direction, and emphasized the importance of ecological research in the process of urbanization [2]. McPhearson *et al*. committed to promoting the transformation of urban ecology into urban science and believed that urban ecology should pay more attention to the integrity and complexity of urban systems [3]. Shillington and Murnaghan introduced the perspective of urban political ecology into children's geography and discussed how to add attention to children in urban ecological research [4]. In addition, Niemela discussed the intersection of urban planning and ecology and pointed out the important role of biodiversity in urban planning [5], while Cilliers and Siebert compared the practices and challenges of urban ecology from the perspective of Cape Town, South Africa [6]. In terms of theoretical development, Heynen explored urban political ecology and emphasized the importance of this branch in the study of urbanization processes [7]. Pickett and Cadenasso discussed the number of basic principles of urban ecology in their study, which was of guiding significance for understanding and applying the principles of urban ecology [8]. The previous studies constituted a comprehensive perspective on current research in urban ecology, not only providing theoretical richness, but also highlighting the need for research applications in practical urban management and planning.

The purpose of this study was to develop a monitoring and control strategy for urban ecological environment pollution based on deep learning technology. By constructing constitutional neural networks (CNN) and integrating multi-source data such as satellite remote sensing, ground monitoring data, and social media information, the study aimed to achieve real-time, accurate pollution monitoring and enhance data processing, feature engineering, and model optimization techniques to improve prediction accuracy and generalization. Additionally, the study evaluated the potential of deep learning in informing environmental policy and community engagement, aiming to improve policy implementation and public environmental awareness for sustainable urban development. This study would significantly advance the field of environmental science by demonstrating the application of deep learning technologies in urban pollution monitoring and control. The integration of multi-source data and advanced CNN models provided a more accurate and efficient method for real-time pollution monitoring, which was critical for rapid response and effective pollution management. The results of this study would highlight the potential of deep learning to improve environmental policymaking and community engagement, contributing to more informed and sustainable urban development strategies, pave the way for further innovations in environmental monitoring technologies, and underscore the importance of technological advancements in addressing global ecological challenges [9].

Materials and methods

Data acquisition and processing

The data acquisition in this study involved collecting data from satellite remote sensing, environmental indicators from ground monitoring stations, public feedback on social media, and traffic flow information. A total of approximate 2 terabytes data was collected covering a period from January 2018 to December 2022. Satellite remote sensing data included high-resolution images obtained from the National Remote Sensing Center of China (NRSCC) (Beijing, China). Ground monitoring data comprised hourly measurements of air pollutants such as PM2.5, NO_2, SO_2, CO, and O_3 from monitoring stations managed by China Ministry of Ecology and Environment (Beijing, China). Social media information capturing public reports and feedback on environmental conditions was collected through application programming interfaces (APIs) provided by platform of Weibo ((https://open.weibo.com). These data were diverse and complex and needed to be cleaned and standardized by efficient teleprocessing methods to accommodate subsequent deep learning model analysis. The data processing steps included removal of outliers, filling in missing values, normalization, and feature engineering to improve data quality and analysis efficiency. The dataset was split into 70% for training, 15% for validation, and 15% for testing to ensure a robust evaluation of the model's performance and generalization ability and improve the training efficiency and prediction accuracy of the model. Through these strict data processing steps, the stability of model training and the reliability of monitoring results could be ensured to provide solid data support for urban pollution control [10].

Computational and statistical environments

Python (https://www.python.org/) with libraries such as TensorFlow and Keras for deep learning model development was employed for this study. R (https://www.r-project.org/) was applied for statistical analysis, while ArcGIS (https://www.esri.com/) was used for geographical data processing and visualization. MATLAB (https://www.mathworks.com/) was used for numerical computing and algorithm development. QGIS (https://www.qgis.org/) was employed for open-source geographical information system analysis. The input feature data of CNN model training was divided into three regions of A, B, and C with three communities of X, Y, Z being investigated. The region A located in Beijing, China with X community located in Haidian District that had a high population density of about 3 million residents, a mix of residential and educational institutions, and urban type environment with traffic and industrial activities causing pollution. Area B Located in Shanghai, China with Y community located in the Pudong New Area that had a population of about 2.5 million and was a financial center with a high concentration of commercial activities and tall buildings, leading to urban pollution challenges. Area C located in Guangzhou (Guangdong, China) with Z community located in Tianhe District that had about 2 million residents, was known for its blend of residential areas and technology industries, and the subtropical climate that affected environmental conditions. These regions and communities were selected because of their different demographic and environmental characteristics, which exhibited different environmental conditions and population dynamics that influenced the pollution data used in the study and might affect the applicability of pollution levels and performance evaluation metrics when evaluating the effectiveness of the CNN model. Population density, industrial activity, traffic volume, and climatic conditions were the key factors that influenced pollution outcomes. Detailed data on these factors were integrated into the CNN model to improve the accuracy and reliability of pollution prediction and monitoring.

Model architecture selection

An effective architecture choice was based on the already widely proven LeNet architecture, which was particularly suitable for processing image data due to its relatively simple and efficient properties. LeNet architecture mainly included several convolution layers, pooling layers, and fully connected layers. A basic LeNet style CNN architecture formula was as follows.

$$L_1 = \mathrm{ReLU}(W_1 * I + b_1) \tag{1}$$

$$P_1 = \mathrm{MaxPool}(L_1) \tag{2}$$

$$L_2 = \mathrm{ReLU}(W_2 * P_1 + b_2) \tag{3}$$

$$P_2 = \mathrm{MaxPool}(L_2) \tag{4}$$

$$F = \mathrm{Flatten}(P_2) \tag{5}$$

$$O = \mathrm{Softmax}(W_3 F + b_3) \tag{6}$$

where I was the input image data. W_i and bi were the weights and biases of layer I, respectively. * was the convolution operation. *ReL* was the nonlinear activation function. *MaxPool* was the maximum pooling operation. Flatten flattened the two-dimensional feature map to one dimension. *Softmax* was used for the output layer, usually for multi-classification problems. The *LeNe*t style CNN model was chosen mainly because its structure was flexible enough to adapt to different input data and monitoring requirements by adjusting the configuration of the convolution layer and the pooling layer. Through this framework, the model could effectively capture the spatial hierarchical features in the image, which was helpful to identify and analyze the urban pollution pattern and change trend more accurately [11].

Layer configuration

The layer configuration determined the performance and accuracy of the model. The specific layer configuration and corresponding formulas were shown below.

(1) Convolution layer

Convolution layer was the core of CNN used to extract local features in images. Each convolution layer processed the input image or the output of the previous layer by applying multiple filters or convolution nuclei. For environmental monitoring models, multiple convolution layers were employed to capture features ranging from simple to complex with the formula as follows.

$$L_k = \mathrm{ReLU}(W_k * L_{k-1} + b_k) \tag{7}$$

(2) Pooling layer

Pooling layers followed by convolution layers were used to reduce the spatial dimension of features, thereby reducing the computational effort and the risk of overwriting. Maximum pooling was a common pooling method that extracted the maximum value from the covered area with the formula below.

$$P_k = \mathrm{MaxPool}(L_k) \tag{8}$$

(3) Fully connected layer

The fully connected layer was used to integrate all the previously extracted features for a final classification or regression analysis after the convolution and pooling layers. In a fully connected layer, each input was connected to the output that was calculated by an activation function to calculate the probabilities of different categories with the formula as follows.

$$F_k = \mathrm{Flatten}(P_{k_{\mathrm{final}}}) \tag{9}$$

$$O = \mathrm{Softmax}(W_f F_k + b_f) \tag{10}$$

The design of layer configuration considered the need to effectively extract spatial and abstract features from the data, while maintaining the sensitivity and accuracy of the identification of different pollution sources, which was very suitable for complex urban environmental pollution monitoring scenarios.

Activation function and regularization strategy

The role of the activation function was to introduce nonliterary into the model, allowing the network to learn and perform more complex tasks. *ReLU* was used for the CNN model of environmental pollution monitoring because of its faster convergence rate in practice and effectively reduces the problem of gradient disappearance. The *ReLU* function was defined as follows.

$$f(x) = \max(0, x) \tag{11}$$

This function outputted the value directly if the input was greater than 0, and the 0 value if it was less than 0 and was applied after each convolution layer as well as in the fully connected layer except for the final output layer. Regularization was a technique used to prevent overwriting of a model, especially when the amount of data was limited, or the model was very complex. Two regularization strategies including dropout and L2 regularization were adopted in this study. During the training process, some weights in the network were randomly discarded temporarily, which could be regarded as a sample perturbation during training, increasing the generalization ability of the model. Dropout was used in a fully connected layer with the formula below.

$$O = \mathrm{Dropout}(F, p) \tag{12}$$

where *F* was the input feature. *p* was the dropout ratio, representing the probability of randomly dropping neurons. L2 regularization, also known as weight attenuation, was to add the square term of weight to the loss function to control the size of the weight value and avoid excessive weight resulting in overwriting of the model. It could be expressed in the loss function as follows.

$$L_{\mathrm{new}} = L_{\mathrm{original}} + \lambda \sum_i w_i^2 \tag{13}$$

where original was the original loss function. w_i was the model weight. Lambda was the regularization parameter, which was used to adjust the influence strength of the regularization term. By combining the *ReLU* activation function with Dropout and *L2* regularization strategies, the performance and stability of the urban ecological environmental pollution monitoring model could be effectively improved, while preventing overwriting and ensuring good generalization ability of the model in practical applications. The regularized loss function L_{new} was calculated based on the dynamic concentration changes of different pollutants. The original loss function L_{original}, based on the mean square error between the model prediction and the actual value, was calculated as follows.

$$L_{\mathrm{original}} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{14}$$

Weight initialization and optimizer selection

Weight initialization and optimizer selection were two key technical decisions, which significantly affected the training efficiency and performance of the model. The purpose of weight initialization was to prevent gradient disappearance or gradient explosion in the network at the beginning of training, which would prevent the network from learning effectively from the training data. One commonly used method was He initialization, which was particularly suitable for networks of *ReLU* activation functions because it considered the number of neurons in the previous layer, thus adjusting the variance of the weights. The formula for He initialization was as follows.

$$W \sim \mathrm{N}\left(0, \sqrt{\frac{2}{n_{\mathrm{l-1}}}}\right) \tag{15}$$

This initialization method helped to maintain the distribution of activation and gradient during the training process, thus speeding up the convergence speed and improving the learning effect of the network. Choosing the right optimizer was the key to ensure that the CNN model could effectively learn and converge to the optimal solution. Adam optimizer was chosen for this study, which combined the advantages of momentum and adaptive learning rate and could adjust the learning rate in different parameter dimensions, making it usually better than the traditional gradient descent method in practical application. The rules for updating Adam were as follows.

$$\theta_{t+1} = \theta_t - \frac{\eta_t}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t \tag{16}$$

By combining the He initializes and the Adam optimizer, it was possible to provide stability and efficiency when training complex CNN models, especially when dealing with large-scale data sets on urban ecological environmental pollution monitoring. This combination facilitated rapid convergence and improved the model's predictive accuracy in real-world environments. The weights needed to be initialized using He initialization formula and then updated using the

Adam optimizer. This method ensured that the variance of the weights was scaled appropriately, preventing issues such as exploding or vanishing gradients, thus facilitating more efficient and stable training of deep neural networks.

Training process

At the beginning of model training, the initial parameters were set by weight initialization. The data was processed batch by batch using the batch gradient descent method. The loss function was calculated by forward propagation, and the weights were updated by the propagation algorithm to minimize the loss. At the end of each training cycle, the model performance was evaluated using validation sets, adjusting parameters such as learning rate and regularization coefficient. This process was iterated until the model no longer significantly improved performance, or a predetermined number of iterations was reached. The model was evaluated through a test set to ensure that its generalization ability and accuracy met the actual monitoring needs [12].

Optimization policy

The key optimization strategy was to adjust and improve the model to achieve higher efficiency and accuracy. The learning rate was effectively adjusted using advanced optimizes such as Adam or RMSprop, which dynamically adjusted the learning rate using the first and second moment estimates of the gradient, helping to converge quickly and avoid falling into local minima. Early stop strategy was implemented, which prevented overwriting. Training stopped when the performance on the validation set did not improve over several successive iterations, which helped the model maintain its best performance on unseen data. In addition, learning rate decay was another commonly used strategy, and gradually reducing the learning rate as the training progresses allowed the model to decline rapidly early in training and be more stable when approaching the optimal solution. The generalization ability of the model was further enhanced through techniques such as batch normalization that speeded up the training process by normalizing inputs from layers, and Dropout that increased the robustness of the model by randomly turning off neurons in the network to reduce dependence on specific features. These strategies worked together to improve the performance and reliability of the model when processing complex environmental data [13].

Selection of evaluation indicators

The rates of accuracy and recall applied to unbalanced data sets and were used to more carefully assess the model's ability to identify a small number of classes, especially in the detection of contamination events. F1 scores provided a balanced assessment between accuracy and recall, suitable for comparing the overall performance of different models. The area under the receiver operating characteristic curve (AUC-ROC) provided a comprehensive view of the model's performance under a variety of thresholds, especially when classification thresholds were undefined or changing, and was able to measure the robustness of the model. Through the comprehensive consideration of these indicators, the model could be comprehensively evaluated and optimized to ensure its effectiveness and accuracy in practical application.

Verification methods

The validation methods included cross-validation and set-aside validation. Cross-validation was especially useful when the data set was small. By using K-fold cross-validation, the model performance was evaluated using the limited data to the full [14]. Set aside validation was suitable for large data volumes. In practice, the appropriate verification method was selected according to the characteristics and magnitude of the data. Through the application of these methods, the CNN model was evaluated and optimized effectively to ensure its reliability and accuracy in the actual environment.

Comparative analysis

Several representative benchmark models including Support Vector Machine (SVM)

(National Supercomputing Center, Guangzhou, Guangdong, China), Random Forest (RF) (Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China), Gradient Boosting Machine (GBM) (National Climate Center, Beijing, China), K-Nearest Neighbors (Environmental Monitoring Center, Shanghai, China), Deep Learning Convolutional Neural Network (Tsinghua University Center for Earth System Science, Beijing, China) were involved in comparative analysis of this study to identify the strengths and limitations of the developed models. In addition, the model's runtime and resource consumption, especially in applications that required real-time monitoring and response were also explored to better understand the application potential and improvement direction of the model in the real environment [15].

Tuning policies

The tuning strategy was the key to improving the performance of the model. Effective tuning strategies included parameter adjustment, model architecture improvement, and advanced feature engineering. Parameter tuning such as optimization of learning rate, batch size, and number of iterations was a basic and important adjustment that could be systematically found through grid search or Bayesian optimization methods to identify the optimal combination of parameters. Depending on the performance of the model during training and validation, the model architecture could be adjusted or simplified such as increasing or reducing the number of convolution layers and fully connected layers or introducing residual connections to improve the learning effect of the deep network. Implementing advanced feature engineering such as feature selection and generating new features could also significantly improve model performance by extracting more representative features from raw monitoring data or using autoworkers to generate deep features. In addition, applying data enhancement techniques such as rotating, scaling, and flipping image data could increase the generalization and robustness of the model. Using ensemble learning methods such as random forests or gradient hoists to combine the predictions of multiple models was also an effective strategy. These integrated methods often provided more stable and accurate predictions than a single model. Through these comprehensive tuning strategies, the performance of the model in urban environmental pollution monitoring could be effectively improved to ensure its adaptability and accuracy in complex environments.

Results and discussion

Forecast results of air quality index

The proposed CNN model demonstrated high accuracy in the prediction of the air quality index. The predicted values were compared with actual observed values at three consecutive time points including the three key pollutants PM2.5, NO_2, and O_3. The results showed that the predicted results of the model were very close to the actual data with very small error range (Figure 1). For PM2.5, the maximum prediction error was only 0.5 μg/m^3, which indicated that the model could predict the concentration level of particulate matter very accurately. The predictions for NO_2 and O_3 also showed a high degree of agreement with the actual values with maximum errors of 0.2 μg/m^3 and 0.2 μg/m^3, respectively. This high-precision forecasting capability was critical for real-time air quality monitoring systems, which could provide powerful data support for urban environmental management, help governments adjust pollution prevention and control measures in a timely manner, and provide accurate health advice to the public. The successful application of the model also demonstrated the potential of deep learning techniques in the field of environmental science, especially their effectiveness in processing and analyzing large-scale environmental data.

Source location and analysis

The predicted values of SO_2, CO, and PM10 for three different regions were compared with the actual observed values at specific points in time. The localization and analysis of pollution sources

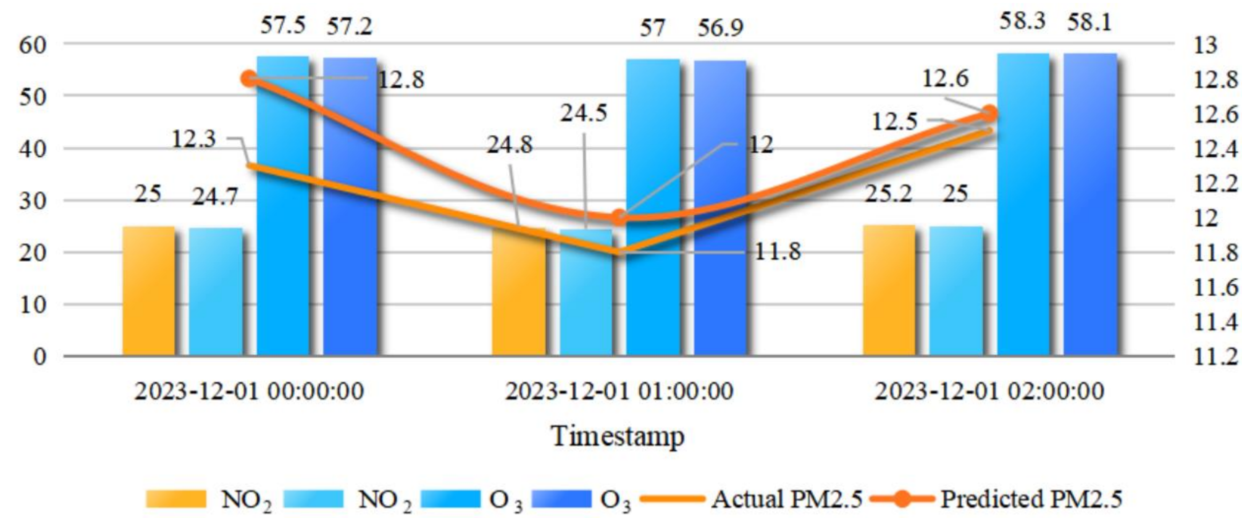


Figure 1. Air quality index prediction.

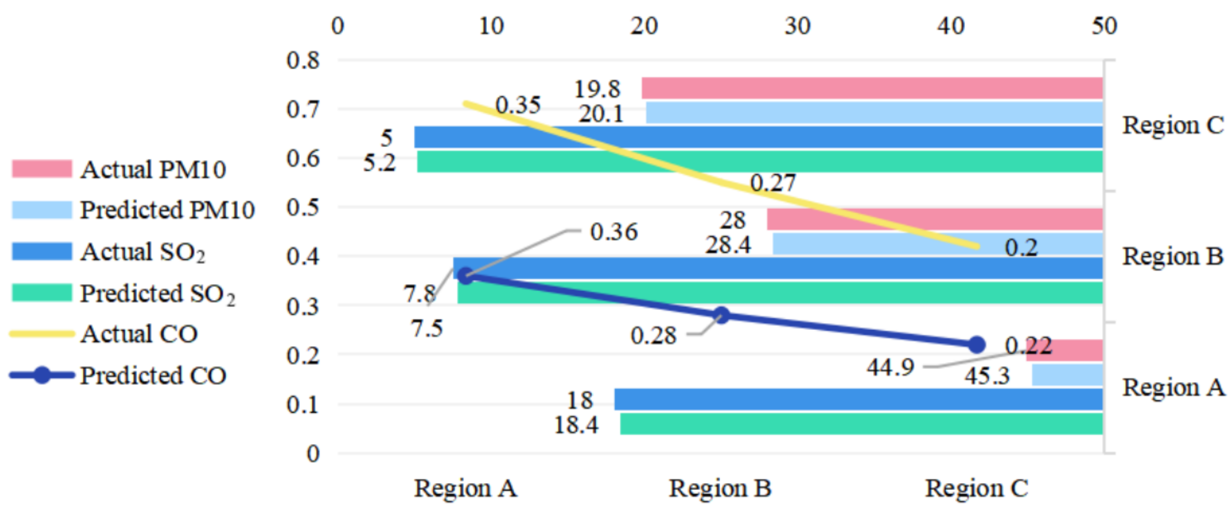
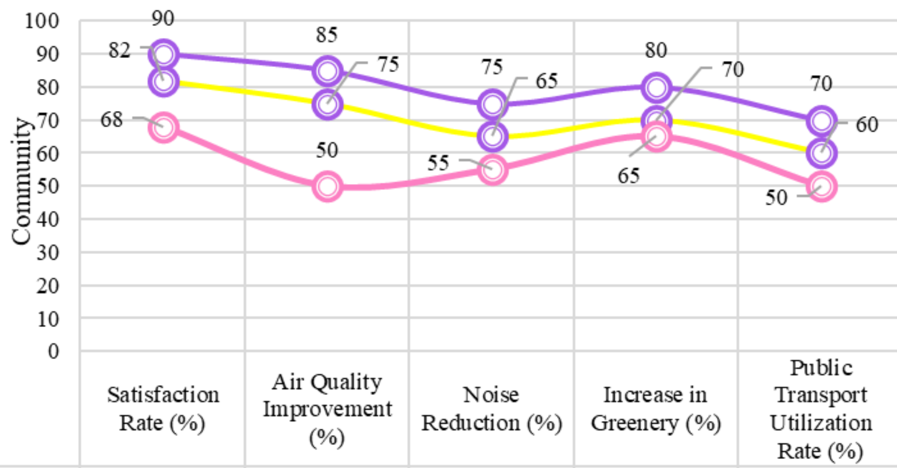


Figure 2. Pollution source localization and analysis.

through deep learning models revealed the model's efficient ability to accurately predict pollution levels in different regions. The prediction results of SO_2, CO, and PM10 concentrations by proposed model were very close to the actual data (Figure 2), which indicated that the proposed model had high accuracy and reliability. The results showed that the pollution level of region A was significantly higher than that of the other two regions, which might be due to more industrial activity or traffic flow in the region. The lower pollution levels in regions B and C were associated with fewer industrial facilities and lower population density. The data not only helped identify major sources of pollution, but also supported more targeted environmental management and pollution control measures. The application of the model demonstrated the potential of deep learning technology in the field of environmental monitoring, especially in the effectiveness of complex data analysis and real-time monitoring. By further optimizing and adjusting the model, the prediction accuracy and generalization ability



	Satisfaction Rate (%)	Air Quality Improvement (%)	Noise Reduction (%)	Increase in Greenery (%)	Public Transport Utilization Rate (%)
Community X	82	75	65	70	60
Community Y	68	50	55	65	50
Community Z	90	85	75	80	70

Figure 3. Community feedback and environmental improvement monitoring.

could be improved, and more accurate decision support could be provided for urban environmental management.

Community feedback and environmental improvement monitoring results

The feedback satisfaction and improvement of various environmental indicators in three different communities after the implementation of environmental improvement measures were shown in Figure 3. Community Z had achieved high improvement in air quality improvement, noise reduction, greening increase, and public transportation utilization rate. The feedback satisfaction of residents in this community also reached 90%, which indicated that the environmental improvement measures had the most significant effect in this community. In contrast, community Y showed less improvement in various indicators and relatively low feedback satisfaction, which might be related to the lack of comprehensive implementation measures in this community or the higher expectations of residents. The data reflected the immediate impact of environmental improvement measures and the actual feelings of residents, providing valuable information for assessing the effectiveness of current strategies and guiding future environmental management decisions. Through continuous monitoring and analysis of these indicators, it was possible to further understand the specific impact of different measures in different communities to optimize and adapt strategies to ensure that environmental improvement actions achieved the desired results on a wider scale and improved the quality of residents' life. The results also inspired communities to become more actively involved in environmental protection practices and contribute to the achievement of the sustainable development goals.

Problems of this study

In this study, several key problems were encountered in the process of monitoring and analyzing urban ecological environmental pollution through deep learning technology. A good model training depended on a large number of high-quality and diverse data sources. Insufficient or poor data quality directly affected the performance and reliability of the model. The complexity and computational cost of the model was also one of the challenges, especially when monitoring and processing large-scale data in real time, which required efficient algorithms and sufficient computational resources. In addition, the generalization ability of the model was an important problem as well. In different urban environments, the same model might show performance differences due to different environmental conditions and pollution sources. Another issue was the implementation and regulation of environmental policies. While technology could provide accurate monitoring and forecasting, it remained a challenge to translate these technological achievements into effective policy measures and to ensure that these measures were properly implemented and monitored. Moreover, community participation and feedback mechanism were also issues that needed to pay attention to in the implementation of the project. Increasing community awareness and participation in environmental issues, as well as establishing effective feedback and communication mechanisms, were the key factors to ensure the success of environmental improvement measures. By addressing these issues, it could ensure the more effectively use of deep learning technologies to improve urban ecosystems and create a healthier and more sustainable living environment for residents.

Suggestions from this study

The study recommended the collaborations among local environmental monitoring stations, government agencies, and research institutes to obtain more extensive and detailed environmental data to enhance the quality of data collection and processing. More efficient data processioning methods should be developed to improve the accuracy and applicability of data to provide a reliable basis for model training. In addition, the prediction model should be continuously optimized and updated, especially the development of new algorithmic frameworks that could better handle nonlinear and large-scale data. Self-learning and adaptive adjustment of the model should be realized to cope with environmental changes and new pollution factors. The model integration strategies should be continuously explored to improve the accuracy and robustness of overall predictions by combining predictions from multiple models. Model integration not only leveraged the strengths of individual models, but also reduced the risk of deviations from a single model. The effect of environmental policies should be further studied. Deep learning technology needed to be used to analyze the actual effects of policy measures, provide data support for policy formulation, and ensure the scientific and effective environmental governance strategies. Strengthen the interaction with the community and establish an effective communication mechanism was promoted by the results of this study. To raise public awareness of environmental issues, residents should be encouraged to participate in environmental monitoring and protection activities. The feedback from residents should be collected promptly to optimize environmental governance strategies and jointly promote sustainable improvement of the urban environment. Through these comprehensive measures, deep learning technology could be applied more comprehensively in urban environmental management, and more accurate and efficient pollution monitoring.

Conclusion

This study deeply discussed the monitoring and treatment strategies of urban ecological environmental pollution based on deep learning, aiming to improve the efficiency and accuracy of urban environmental quality monitoring. By constructing and optimizing convolution neural networks, this study successfully applied multi-source data fusion, model training, and performance evaluation methods to achieve accurate prediction of urban air quality and effective location of pollution sources. By integrating multiple data sources from satellite remote sensing, ground monitoring stations, and social media, and utilizing CNN's powerful image and data processing capabilities, this study provided a comprehensive perspective for urban pollution monitoring. The rigorous implementation of data teleprocessing and feature engineering ensured a high-quality basis for model training, and the efficient model architecture design and weight initialization strategy further enhanced the learning efficiency and prediction accuracy of the model. The accuracy rate, recall rate, F1 score, and AUC-ROC were comprehensively evaluated to confirm the effectiveness of the model in handling environmental monitoring tasks. In addition, through comparative analysis and the application of tuning strategies, the model showed good generalization ability and adaptability in the real environment. The study highlighted the important role of policy makers and community members in environmental governance. Through analyzing the effect of policy implementation and community feedback, suggestions were put forward to optimize environmental policies and improve public participation. The implementation of these strategies could improve not only the urban environment, but also the quality of life and health of residents. This study demonstrated the application potential of deep learning technology in urban ecological environment monitoring and governance and provided valuable experience and methodology guidance for future related research. It is expected to drive more effective environmental management practices globally.

References

1. Forman RTT, Carnevale FA, Baker ME. 2016. Urban ecology principles: Are urban ecology and natural area ecology really different? Landsc Ecol. 31(8):1653-1662.
2. Wu JG, Xiang WN, Zhao JZ. 2014. Urban ecology in China: Historical developments and future directions. Landsc Urban Plan. 125:222-233.
3. McPhearson T, Pickett STA, Grimm NB, Niemelä J, Alberti M, Elmqvist T, *et al*. 2016. Advancing urban ecology toward a science of cities. BioScience. 66(3):198-212.
4. Shillington LJ, Murnaghan AMF. 2016. Urban political ecologies and children's geographies: queering urban ecologies of childhood. Int J Urban Reg Res. 40(5):1017-1035.
5. Niemelä J. 1999. Ecology and urban planning. Biodivers Conserv. 8(1):119-131.
6. Cilliers SS, Siebert SJ. 2012. Urban ecology in Cape Town: South African comparisons and reflections. Ecol Soc. 17(3):33.
7. Heynen N. 2014. Urban political ecology I: The urban century. Prog Hum Geogr. 38(4):598-604.
8. Pickett S, Cadenasso M. 2017. How many principles of urban ecology are there? Landsc Ecol. 32(4):699-705.
9. Granjou C, Cavin JS, Boisvert V, Chalmandrier M, Flaminio S, Kull C, *et al*. 2023. Researching cities, transforming ecology: An investigation into urban ecology agendas. Nat Cult. 18(2):148-174.
10. Al Nasiri N, Al-Awadhi T, Hereher M, Ahsan R, AlRubkhi ALG, Charabi Y. 2020. Changing urban ecology: A challenge for coastal urban resilience: a study on Muscat. Environ Urban Asia. 11(1):10-28.
11. Haeri S, Esmaeeldokht M. 2022. Scales of interactions between urban landscape with urban ecology in urban development programs. Manzar. 14(59):54-67.
12. Bridge G. 2001. Everyday ecologies: Cities, nature, and teaching urban ecology. J Geogr. 100(4):154-165.
13. Heynen N. 2016. Urban political ecology II: The abolitionist century. Prog Hum Geogr. 40(6):839-845.
14. Pickett STA, Frantzeskaki N, Andersson E, Barau AS, Childers DL, Hoover FA, *et al*. 2024. Shifting forward: Urban ecology in perspective. Ambio. 53(6):890-897.
15. [15] Coogan SCP, Raubenheimer D, Zantis SP, Machovsky-Capuska GE. 2018. Multidimensional nutritional ecology and urban birds. Ecosphere. 9(4):e02177.