

Retraction

Retracted: Urban Ecological Monitoring and Prediction Based on Deep Learning

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] J. H. Yang and C. P. Chan, "Urban Ecological Monitoring and Prediction Based on Deep Learning," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1973777, 6 pages, 2022.

Research Article

Urban Ecological Monitoring and Prediction Based on Deep Learning

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Obtaining comprehensive and accurate air quality information is conducive to people's daily travel and living arrangements, especially to protect people's health from air pollutants. Due to the limited number of air quality monitoring stations and the lack of training samples, the generalisation performance of air quality estimation model is often not good enough. Therefore, we propose an urban air quality index (AQI) prediction and AQI level estimation method based on deep multi-task learning. We consider various urban big data information related to air quality (meteorology, transportation, enterprise self-test, POI, road network, etc.), and use machine learning methods such as deep learning and graph embedding learning to learn the representation of relevant information, and establish the relationship between these related representations and air quality. Experiments show that this scheme can estimate the level of urban air quality index joint prediction task and air quality index, and the model has generalisation performance.

1. Introduction

With industrial development and population expansion, various harmful substances are emitted into the air, causing air pollution. Having comprehensive and accurate information on air quality helps to protect the ecological environment and human health from the dangers of air pollution [1]. Many cities have set up air quality monitoring stations to monitor air quality in real time. However, the number of air quality monitoring stations is limited. It is not possible to know with certainty the air quality at locations where no air quality monitoring stations have been set up, and air quality monitoring stations cannot predict future air quality [2]. Therefore, estimating air quality in areas without monitoring stations and predicting future air quality at monitoring stations can provide comprehensive air quality informa-

tion in space and time, helping people to rationalise their travel plans and assisting relevant organisations in making environmental decisions. Existing air quality estimation methods are based on urban data related to air quality (e.g., meteorological, road network, and POI) to establish the relationship between air quality in two areas, thus using the air quality in areas with monitoring stations to estimate the air quality in areas without monitoring stations [3]. However, existing air quality estimation methods do not adequately consider data related to air quality, and do not take into account information such as company self-measurement and the angle of relative location between areas. Secondly, existing work has defined and extracted features manually, which are often incomplete and take a lot of time to design and verify their validity [4]. Also, due to the limited number of monitoring sites and the lack of

training samples, the models often fail to achieve good generalisation performance [5].

To address these problems, this paper proposes a deep multi-task learning-based urban air quality prediction and estimation method, which integrates a variety of air quality-related urban big data information (meteorology, enterprise self-measurement, road network, POI, etc.), learns the representation of this related information through deep learning and machine learning methods such as graph embedding learning, and improves the generalisation performance of single-task models by combining air quality prediction and estimation tasks through multi-task learning [6].

2. Related Work

2.1. Air Quality Estimates. Existing air quality estimation methods include mainly physical dispersion simulation-based methods and statistical and data-driven methods.

Physical dispersion simulation-based methods estimate the distribution of pollutants by simulating the pattern of pollutant dispersion [7, 8]. Linear statistical model-based methods use linear models such as spatial interpolation or land-use regression combined with land-use related characteristics to estimate air quality. For example, the kriging-based air quality estimation method [9] uses a spatial interpolation method called fuzzy genetic linear member kriging to estimate the geospatial distribution of air quality. The land-use regression-based approach [10] uses a land-use regression model to establish the relationship between land-use related characteristics (e.g., land use, traffic patterns, and population density) and air quality.

As linear statistical models are unable to establish non-linear relationships between urban air quality and land-use related characteristics, non-linear statistical models are also widely used in air quality estimation [11]. Established methods based on non-linear statistical models include those based on supervised learning and those based on semi-supervised learning [12].

Methods based on supervised learning include those based on generalised additive models and those based on Gaussian process regression. For example, [13] used generalised additive models to establish the relationship between air quality and the relevant explanatory variables. [14] used Gaussian process regression to establish relationships between characteristics such as traffic flow, population density, temperature, and air quality. Such non-linear models also fail to achieve good estimation performance due to the limited number of training samples [15]. [16] proposed an air quality estimation method based on a collaborative training algorithm, which combines a variety of data such as meteorology, traffic flow, road network structure, and POI in cities, and uses conditional random fields and artificial neural networks to model the relationship between relevant features and urban air quality. [17] used unlabelled data to increase the number of training samples through the collaborative training algorithm; however, the collaborative training algorithm did not control the noise introduced during the iterative training process, and therefore, the model could not achieve better results.

2.2. Air Quality Forecasting Methodology. Existing air quality prediction methods are divided into those based on physical dispersion modelling and those based on statistical and data-driven methods.

Methods based on physical dispersion modelling predict the distribution of pollutants by simulating the pattern of pollutant dispersion, such as Gaussian models [18], dynamic street canyon models, and computational fluid dynamics [19], which mostly use functions related to meteorology, street geography, receptor location, traffic flow, and dispersion factors to simulate the dispersion of pollutants. However, such methods usually require empirical assumptions to be met and parameter settings are not generalisable.

Linear statistical modelling-based approaches use linear models to model the linear relationship between air quality over its own time series or with other characteristics to make predictions about future air quality. For example, [20] used an autoregressive sliding average model to model the trend in air pollutant concentrations over their own time series to predict future average air pollutant concentrations. For example, [12] used polynomial regression combined with meteorological data to predict daily maximum concentrations O_3 and [13] used kernel regression combined with meteorological data to predict daily maximum concentrations. [14] used artificial neural networks and linear regression to predict future air quality in NO_2 the area to be predicted by combining meteorological and historical air quality from the area to be predicted and from the surrounding air quality monitoring stations.

3. Learning of Regional Non-Temporal Information Representation Based on Graph Embedding Methods and Convolutional Neural Networks

The POI category and density of an area tend to reflect the land use and traffic patterns of the area, and are directly or indirectly related to the air quality of the area; for example, areas with factories tend to have poorer air quality, and areas with parks tend to have better air quality. Road network structure and traffic patterns are strongly correlated, with traffic-generated emissions being a source of urban air pollutants, and the road network structure to some extent reflecting the air quality of the region. The traditional method extracts relevant features such as road network and POI, simply counts the number of various types of POI contained in each area and the length of various types of road network as relevant features, ignoring the hierarchical information between different categories of POI/road network, and when there are more categories of POI, the statistical features extracted by the traditional method are rather sparse. The graph embedding method LINE is a method of embedding an information network into a low-dimensional vector space by representing each vertex in the network with a vector in the low-dimensional space. In this paper, the LINE method is used to embed the non-temporal information of each region into a low-dimensional vector by

combining the information network graph consisting of coordinates, road network, and non-temporal data such as POI of all regions to be estimated and regions to be predicted. In order to extract more non-temporal features relevant to AQI prediction and AQI class estimation, the low-dimensional vector of non-temporal information is further processed by a convolutional neural network to extract local features, and the output of the convolutional neural network is used as the final regional non-temporal information representation for subsequent AQI prediction and AQI class estimation tasks.

3.1. Learning Non-Temporal Information Representation of Regions Based on the Graph Embedding Method LINE

Definition 1. Area-region diagram. The region-area diagram $G_{dd} = (D \cup D, \varepsilon_{dd})$, representing the physical distance relationship between grid regions, is shown in Figure 1, where D denotes the set of grid regions, ε_{dd} denotes the set of edges between grid regions, and each grid region d_i and grid region d_j is separated by an edge e_{ij} , with edge weight w_{ij} defined as the physical distance between d_i and d_j .

Definition 2. Area-POI diagram. The region-POI diagram $G_{dp} = (D \cup P, \varepsilon_{dp})$, representing the distribution of POIs within a grid influence region, is shown in Figure 2, where D denotes the set of grid regions, P denotes the set of POI categories, and ε_{dp} denotes the set of edges of grid regions and POI categories. If the grid region d_i has POIs of category P_j within the grid influence region, an edge e_{ij} exists between grid region d_i and P_j POI categories; the edge weight w_{ij} is defined as the number of POIs of category P_j contained within the grid influence region of d_i .

Definition 3. Area-road network diagram. The region-road network diagram $G_{dr} = (D \cup RD, \varepsilon_{dr})$ represents the distribution of road sections within the grid influence area, as shown in Figure 3, where D denotes the set of grid regions, RD denotes the set of road section categories, and ε_{dr} denotes the set of edges between grid regions and road section categories. If there are road sections of category r_j within the grid influence area of grid region d_i , there exists an edge e_{ij} between grid region d_i and road section category r_j , and the edge weight w_{ij} is defined as the total length of road sections of category r , contained within the grid influence area of d_i . According to the Chinese urban planning guidelines, this paper classifies urban roads into four classes as shown in Table 1.

For the three diagrams defined above, using the LINE method to learn the low-dimensional vector representation of all vertices in each diagram, the diagrams G_{dd} , G_{dp} , and G_{dr} correspond to the objective functions $L(G_{dd})$, $L(G_{dp})$, and $L(G_{dr})$, respectively, and the total objective

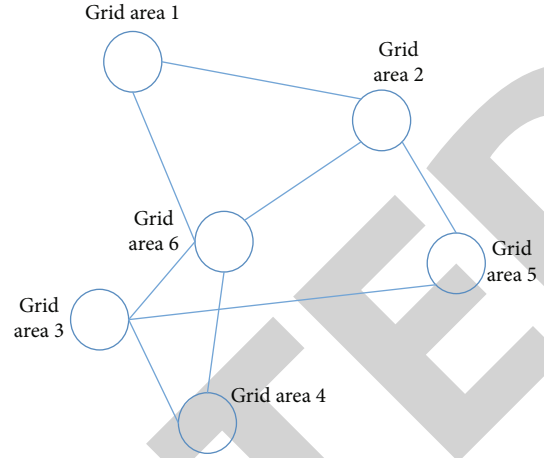


FIGURE 1: Area-region map.

function $L(G)$ as shown in the following equation.

$$\begin{aligned}
 L(G_{dd}) &= - \sum_{e_{ij} \in \varepsilon_{dd}} w_{ij} \log p(v_j | v_i), \\
 L(G_{dp}) &= - \sum_{e_{ij} \in \varepsilon_{dp}} w_{ij} \log p(v_j | v_i), \\
 L(G_{dr}) &= - \sum_{e_{ij} \in \varepsilon_{dr}} w_{ij} \log p(v_j | v_i), \\
 L(G) &= L(G_{dd}) + L(G_{dp}) + L(G_{dr}).
 \end{aligned} \tag{1}$$

In the calculation reference formula of $p(v_j | v_i)$, by optimizing the objective function $Z(g)$, the low-dimensional vector representation of all vertices in the graph can be obtained; that is, the low-dimensional vector representation $u^{d_i} \in R^{\varphi}, R^{\varphi}$ of non-temporal information of each region d_j can be obtained, which represents the vector space of φ , and the connection relationship of regional location, POI, and road network in the graph can be embedded into the low-dimensional vector, in order to extract more non-temporal information related to AQI prediction and AQI level estimation tasks.

3.2. AQI Forecasting Tasks. In this paper, multiple complex factors related to air quality are taken into account when predicting the AQI of a region to be predicted: historical meteorological, historical air quality, historical traffic, historical business self-measurement, and weather forecast data of the region to be predicted; non-temporal data such as coordinates, POI, and road network of the region to be predicted; and historical meteorological and historical air quality data of the region of global influence. A graph embedding method and a CNN are used to learn the representation of this relevant non-temporal information, and a recurrent neural network is used to learn the representation of this relevant temporal information, and based on these relevant representations, the AQI of the area to be predicted at multiple times in the future [21–23].

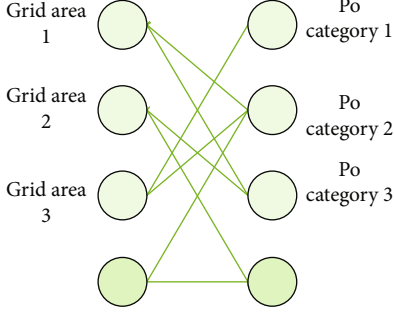


FIGURE 2: Area-POI diagram.

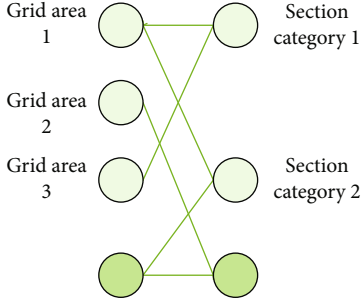


FIGURE 3: Regional-road network map.

TABLE 1: Classification of urban roads.

Road grade	Vehicle speed (km/h)	Road width (m)
1	60-80	40-70
2	40-60	30-60
3	30-40	20-40
4	0-30	16-30

The output LSTM is called the output LSTM, based on μ^{d_f} , $F_h^{d_f}$, $F_{h_t}^{d_f}$, $F_{c_t}^{d_f}$, G_h^g and $G_{h_t}^g$. This paper uses a one-layer LSTM to predict d_f the AQI at z future moments. First, all the vectors in $F_h^{d_f}$ and G_h^g are joined together to obtain μ^{d_f} a linear transformation $FALL_{h_t}^{d_f}$ and the output of the linear transformation is non-linearly processed by the tanh function to obtain $h_t^{d_f}$ as shown in equation (2), as the initial hidden state information of the output LSTM.

$$h_t^{d_f} = \tanh \left(W_h^{d_f} FALL_{h_t}^{d_f} \right). \quad (2)$$

Similarly, all the vectors in $F_{c_t}^{d_f}$ are concatenated to obtain $FALL_{c_t}^{d_f}$, and after a linear transformation and non-linear processing, $c_t^{d_f}$ is obtained as the initial memory cell information for the output LSTM.

When the input sequence of the input recurrent neural network is too long, the output LSTM is often not good enough when the output LSTM is initialized with only the output of the input recurrent neural network at the last moment, so in this paper, when using the output LSTM to

TABLE 2: Comparison of classification results of different urban air quality estimation methods.

Urban air quality estimation method	MAP
U-Air	0.713 \pm 0.008
Semi-EP ($k=1$)	0.674 \pm 0.003
Semi-EP ($k=2$)	0.714 \pm 0.002
Semi-EP ($k=3$)	0.732 \pm 0.002
Semi-EP ($k=4$)	0.736 \pm 0.004
DAFE	0.761 \pm 0.003

predict the AQI at z future moments, an attention mechanism is introduced, and at each step of generating the sequence of AQI prediction values, the input recurrent each position of the input sequence of the neural network is searched, and the most relevant part of the output LSTM at the current moment is selected to calculate the context vector, and the AQI prediction value at the current moment is calculated based on this context vector. Let h_j denote the output of the output LSTM at moment y , and let $METL_{c_j}^{d_f}$ denote the context vector associated with the d_f long-term sequence of weather data at moment y for which the attention mechanism has been introduced, $METL_{c_j}^{d_f}$ as shown in the following equation.

$$\begin{aligned} METL_{c_j}^{d_f} &= \sum_{n=1}^l METL_{\alpha_{jn}^{d_f}} METL_{h_n}^{d_f}, \\ METL_{\alpha_{jn}^{d_f}} &= \exp \left(\text{score}_{h_j, METL_{hh_n}^{d_f}} \right) \sum_{n'} \exp \left(\text{score} \left(h_j, METL_{h_n}^{d_f} \right) \right), \\ \text{score} \left(h_j, METL_{hh_n}^{d_f} \right) &= h_j^T METL_{h_n}^{d_f}. \end{aligned} \quad (3)$$

where $METL_{hh_n}^{d_f}$ represents the hidden state output of the input recurrent neural network at moment n when a long-term sequence of d_f weather data is used as the input sequence of the input recurrent neural network, $METL_{\alpha_{jn}^{d_f}}$ represents the weight of $METL_{hh_n}^{d_f}$, score is a scoring function to calculate the correlation between the hidden state output of the input recurrent neural network at moment n and the output of the output LSTM at/moment, and $METL_{c_j}^{d_f}$ is the weighted sum of the hidden states of the input recurrent neural network at all moments.

4. Experimental Comparison of Relevant Urban Air Quality Estimation Methods

The results of the different urban regional air quality estimation methods are shown in Table 2. The results demonstrate that for the Semi-EP method, its average classification accuracy is highest at $fc=3$, which is consistent with the results of [15]. The results in Table 2 show that the performance of the proposed method is significantly better than that of U-Air and Semi-EP on the dataset used in this paper, which may

TABLE 3: Comparison results of different urban air quality prediction methods.

Method	MAE			
	1-6H	7-12H	13-24H	25-48H
FFA	20.59 ± 0.294	25.96 ± 0.258	34.75 ± 0.489	37.71 ± 0.534
DAFE	18.26 ± 0.485	21.65 ± 0.681	22.59 ± 0.717	24.52 ± 0.849

be due to the fact that, compared to U-Air and Semi-EP, features are defined and constructed manually and the proposed method uses graph embedding methods to classify the features. The non-temporal and temporal feature representations learned by the proposed method using graph embedding and deep neural networks are more representational [24, 25].

The FFA method uses a linear regressor to model the relationship between local characteristics such as historical air quality, current weather, and weather forecasts at the site to be predicted and the future air quality at the site to be predicted, and an artificial neural network to model the relationship between current weather and global characteristics such as historical air quality at neighbouring monitoring sites and the future air quality at the site to be predicted. The results of the two models are then integrated using a regression tree. For the classification of the global impact space, the same approach as for FFA is adopted. The results of the different AQI prediction methods are shown in Table 3. The results in Table 3 show that the mean absolute error of the proposed method is smaller than the mean absolute error of the FFA method. This may be due to the fact that the method proposed in this paper establishes a better non-linear relationship between the air quality of the site to be predicted and the local factors than the FFA method, and the change in the mean absolute error of the FFA method is greater than that of the method proposed in this paper as the distance between the time to be predicted and the current time increases. This may be due to the fact that the relevant feature representations learned by the proposed method using graph embedding and deep neural networks are more representational and take into account the previous AQI prediction when predicting the null AQI at a certain time, introducing more information.

5. Conclusions

This paper proposes a deep multi-task learning-based approach for urban AQI prediction and AQI class estimation. On the one hand, a variety of urban big data information related to air quality (meteorology, traffic, enterprise self-measurement, POI, road network, etc.) is considered, and machine learning methods such as deep learning and graph embedding learning are used to learn representations of relevant information and establish relationships between these relevant representations and air quality, so as to estimate AQI levels in areas without air quality monitoring stations and to estimate AQI levels in areas with air quality monitoring stations, AQI prediction for regions with air quality monitoring stations.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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