Enhanced Air Quality Index Prediction Using a Hybrid Convolutional Network

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Abstract. Accurate air quality forecasting is critical for decreasing pollution and protecting public health. A hybrid model combining the Temporal Convolution Network (TCN) and the Graph Convolution Network (GCN) has been developed to predict air pollution with high accuracy and minimise the associated health risks. Because air quality data has two crucial components: temporal trends and spatial linkages, the combination of TCN and GCN is required. The GCN model learns the complicated architecture of each observatory, whereas the TCN model uses past data to detect deviations. The Graph Temporal Convolution Network (GTCN) model was evaluated using six important variables: station names, Air Quality Index (AQI), data timestamps, longitude, and latitude. Our GTCN outperformed other researchers' models on real-world data between February and July 2021. The results demonstrated the lowest Mean Absolute Error (MAE) of approximately 4.78 and the lowest Root Mean Square Error (RMSE) of approximately 6.67. Through precise air quality forecasting, people can pre-know how to protect themselves and prepare outdoor dresses well to reduce exposure to air pollution and related health hazards.

Keywords: Air Quality Index · Graph Convolution Network · Temporal Convolution Network · Uncertainty · Prediction Model

1 Introduction

In recent years, public health, environmental sustainability, and economic growth have all been significantly affected by air quality [1]. Due to rapid industrialization and urbanization in many parts of the world, air pollution has become a serious problem that requires immediate action [2]. Precise air quality forecast extends beyond short-term projections, considering spatial relationships, historical trends, and a range of data sources to guide mitigation activities. Prediction is a valuable tool for taking preventive action, allocating resources properly, and raising awareness. Accordingly, precisely anticipating pollution levels is a critical indicator for air quality regulation [3]. It has the potential to influence decision-making processes ranging from personal behaviour to public policy and sustainable urban design by giving precise, timely information on pollutant concentrations

R. Ghazali et al. (Eds.): SCDM 2024, LNNS 1078, pp. 296–306, 2024.
https://doi.org/10.1007/978-3-031-66965-1_29

(4). Governments and public health organisations can utilise precise projections to act immediately to safeguard individuals from high levels of pollution.

Traditional air quality forecasts often utilise statistical models based on mathematical equations to simulate the physical factors that control air pollution [5]. These models often rely on historical data and a restricted set of variables, such as traffic, weather, and industrial pollution. These models may not always fully reflect the complex and dynamic interactions between these variables, but they can still be useful for learning about air quality. When compared to conventional models, machine learning techniques provide a more sophisticated and flexible approach to forecasting air quality [6]. However, they do necessitate the ability to understand and analyse data, as well as a large volume of high-quality data. Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Deep Learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are among the most utilised machine learning techniques for predicting air quality [7–9]. Other machine learning approaches, such as Decision Trees (DT), Bayesian Networks (BN), and K-Nearest Neighbour (KNN), have also been used to forecast air quality, but less frequently [7, 10].

Graph convolutional networks (GCNs) and temporal convolutional networks (TCNs) have showed great potential in air quality prediction due to their ability to replicate complex spatial and temporal correlations in data. Zhang et al. [10] discovered that by using graph-based representations that capture the relationships between stations, GCNs may successfully depict the spatial dependencies between air quality monitoring stations. TCNs use convolutional layers to capture patterns in time series data, allowing them to accurately represent temporal dependencies in air quality data. It has been established that combining GCNs and TCNs in air quality prediction models improves forecast accuracy and enables the identification of potential pollution sources. A GCN-TCN model was used to forecast Beijing, China's air quality [10, 11]. The method beat earlier machine learning models in terms of prediction accuracy and was able to determine how different pollution sources affected the overall air quality.

This article proposes using the GCN and TCN techniques to forecast future AQI using the latitude and longitude of the observation station, as well as prior AQI readings. This study uses spatial and temporal correlations to forecast AQIs for future time points. Because air pollutants are mobile in the atmosphere and travel to different places depending on meteorological circumstances, there are both temporal and spatial correlations involved. The suggested model employs temporal convolutional networks to learn minor dynamic changes in historical data and graph convolutional networks to learn complicated topology patterns between observation stations. This model can forecast the AQI at future time points, acting as an early warning system for people to take appropriate action and giving the government information on the trend in air quality to help it create pertinent legislation.

This paper is organized as follows: the first section provides the introduction. The second section introduces the related works. The experiment method is described in the third section. The experimental results and discussions are presented in the fourth section. The last section gives the conclusion and future work.

2 Related Works

The AQI is a statistic used in several countries to assess the quality of air [12]. There are also numerous researchers working on AQI furcation using various models [13–17]. In Taiwan, the Environmental Protection Agency incorporated long-standing dual air quality indicators into the AQI, such as the Air Pollution Index (PSI) and Fine Suspended Particulate Index (DAQI). The primary components include ozone (O3), suspended particles (PM10), small, suspended particulates (PM2.5), nitrogen dioxide (NO2), sulphur dioxide (SO2), and carbon monoxide (CO). The sub-indicator values of various pollutants are transformed depending on their impact on human health, and the maximum value of each sub-indicator value for the day is used to generate the AQI value for the observation station.

Many studies have focused on predicting the AQI to preserve human health, such as Lah, et al. [18] used the ARIMA model to estimate the historical AQI value. Furthermore, the relationship between the AQI and nine factors (PM2.5, PM10, SO2, NO2, CO, O3, maximum temperature, minimum temperature, and wind direction) is investigated in Jiao, et al.'s research works [19] before utilizing the LSTM model to predict the AQI using these variables. Meanwhile, a new framework, MTMC-NLSTM, is presented in Jin, et al.'s research works [20]. It employs nested LSTM, which boosts the size of each LSTM unit by one. To forecast multivariate AQI data, MTMC (multi-task multi-channel) is used. The experimental results show that the DL model with DSWT can predict events more accurately and with fewer errors. Lah, et al. [18] and Zhao, et al. [21] provide good prediction results, however, they only analyze the temporal relationship and ignore the geographical correlation.

Cui [22], on the other hand, presented a novel traffic forecasting technique. They used Graph Convolutional Networks (GCN) to learn about the intricate structure of roadways and Gated Recurrent Units (GRU) to grasp past traffic patterns. Based on experimental results and dynamic changes in the data, the suggested approach may provide spatiotemporal correlation in traffic data and can be applied to a variety of correlation-based predictions. He and colleagues proposed a new deep learning framework known as TGC-LSTM. Road interactions in the traffic network were identified using graph convolutional networks and LSTM. The findings of the experiment show that models that incorporate both temporal and spatial correlations perform better in predictions.

Deep learning has evolved substantially in recent years, resulting in much more accurate models. Gopali et al. [24] suggested a temporal convolutional network model (TCN) for detecting time series abnormalities. TCN was used to learn the typical pattern of sequence data, and anomalies were recognized using a specified threshold and the aberrant error's degree of divergence. Kipf et al. [25] investigated the performance of LSTM and TCN for detecting anomalies in time series data. The results revealed that TCN outperformed LSTM, demonstrating that it can predict data more accurately and quickly utilizing time series.

From the above works, we can see that practically all studies employed LSTM, GCN, GRU, or TCN to combine each model as TGC-LSTM, TCN + LSTM. Nevertheless, those approaches all have limitations, such as the inability to analyze the space-time situation simultaneously. Due to this reason, our study employs both GCN and TCN model to forecast Taiwan's air quality to consider more impact factors in space-time locations.

3 Experimental Method

The proposed system architectural design is shown in Fig. 1. The process began with data splitting, which divided the historical source data into latitude and longitude and AQI values. The data is then preprocessed. After training, the GCN and TCN models are used to obtain temporal and spatial correlations. Finally, obtain a model capable of forecasting AQI with temporal and geographical correlations.

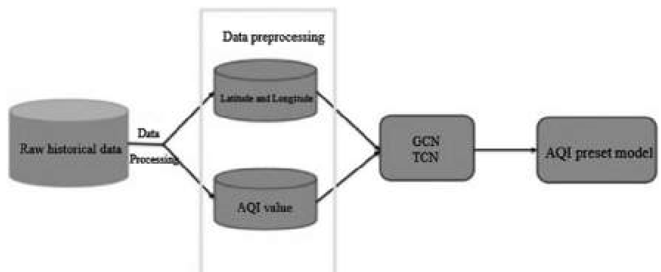

Fig. 1. System Architecture Diagram

The environmental data open platform of the Republic of China's Environmental Protection Agency serves as the primary source of experimental data in this paper. The original data contains a total of 25 observation items, such as meteorological and pollution indicators that have an impact on the AQI. The specific items have "Site Name", "Country", "AQI", "Data Creation Date", "Longitude", "Latitude", "Status", "SO2", …, "PM2.5", "Wind speed", and "Site ID". We chose six items for our experimental data that are "Site Name", "Country" (the station name), "AQI", "Data Creation Date", "Longitude", and "Latitude".

Table 1. Data included Empty Data

Area	County	AQI	Time
Daicheng	Changhua	108	2021/3/17 10:00
		111	2021/3/17 11:00
		N	2021/3/17 12:00
		N	2021/3/17 13:00
		103	2021/3/17 14:00

We utilized data from February 2021 to January 2022, as some observation stations were destroyed in 2021. We incorporated the updated information from the revised observation stations, which included the addition of several new stations. The initial phase involved organizing the original data and removing irrelevant information. For further data analysis, we retained the observation station name, AQI value, longitude, and latitude. In Table 1, we present examples of five scenarios. During the AQI processing phase, the program scanned the data and populated any empty AQI value columns with N.

Then, through Eq. (1), Eq. (2) and Eq. (3), the historical AQI value is updated. $X(t)$ represents the data at time point t. If the time point t is N, but the time point $t-1$ and the time point $t+1$ are not N, fill in the data at the time point t through Eq. (1).

$$X_{(t)} = \frac{X_{(t-1)} + X_{(t+1)}}{2}$$

$$if \quad X_{(t-1)}, X_{(t+1)} \neq N \; and \; X_{(t)} = N \tag{1}$$

If the data at time point t and time point $t+1$ are N, and the data at time point $t-1$ and time point $t-2$ are not N, then fill in the data at time point t through Eq. (2). Since the range of the AQI value is between 0 and 500, doing so can ensure that the data at the time point t will not be negative or out of range due to drastic fluctuations.

$$X_{(t)} = \frac{X_{(t-2)} + X_{(t-1)}}{2}$$

$$if \quad X_{(t-2)}, X_{(t-1)} \neq N \; and \; X_{(t)}, X_{(t+1)} = N \tag{2}$$

Similarly, if the data at time point t and time point $t-1$ are N, and the data at time point $t+1$ and time point $t+2$ are not N, fill in the data at time point t through Eq. (3). The final completed data is shown in Table 2. In Tables 1 and 2, The initial value of data N is obtained by adding 108 and 111, dividing the result by 2, and rounding to 110. Equation (2) is used to calculate this. The second data N is then calculated through Eq. (1). The result is rounded to 107 after adding 110 to 103 and dividing the total by 2.

$$X_{(t)} = \frac{X_{(t+1)} + X_{(t+2)}}{2}$$

$$if \quad X_{(t+1)}, X_{(t+2)} \neq N \; and \; X_{(t)}, X_{(t-1)} = N \tag{3}$$

The filling formulas in Eqs. 1–3 represent better filling strategies. It can prevent the AQI from quickly rising or falling due to emergencies while also ensuring that the AQI does not drop below zero.

Table 2. Filled empty data to complete information.

Area	County	AQI	Time
Daicheng	Changhua	108	2021/3/17 10:00
		111	2021/3/17 11:00
		110	2021/3/17 12:00
		107	2021/3/17 13:00
		103	2021/3/17 14:00

3.1 The GCN Model

Deep learning has recently gained prominence in a variety of industries. However, their research subjects are frequently limited to Euclidean data, even though many essential data sets exist in the actual world as graphs. Because the distances between observation stations in different locations are not equal, a graph-structured topology network is established, indicating that it is difficult to utilise CNN to process such non-Euclidean data to derive spatial correlation. As a result, we use graph convolutional networks, which can handle data with non-Euclidean structures.

We use an undirected graph $\boldsymbol{G}$ to represent the relationship between observation stations and observation stations. Use the unweighted graph $\boldsymbol{G} = (\mathrm{V,E})$ to describe the topological structure between the geographical locations of the observation stations in each region. Each observatory represents a node, and is the set of all nodes, which means $= \mathrm{V}\{v_1, v_2, v_3 \ldots, v_n\}$. is the set of all observatories and the connected edges between them.

In the past related papers [19] the process of graph convolution uses the Chebyshev polynomial $T_k(x)$ to do the approximation. The Chebyshev polynomial is defined recursively. The definition formula is Eq. (4), and the graph convolution formula approximated by Chebyshev polynomials can be redefined as Eq. (5).

$$T_0(x) = 1, T_1(x) = x, T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x), x \in [-1, 1] \tag{4}$$

$$y = g_{\theta\prime *}x \approx \sum_{k=0}^{k} \theta'_k T_k\big(\tilde{L}\big)x \tag{5}$$

Next, to reduce the time complexity in the process of model training and learning, we set k to 1, that is, only consider the adjacent one-step nodes each time, so the whole formula can be rewritten as Eq. (6).

$$y = \theta'_0 x + \theta'_1 \tilde{L}x \tag{6}$$

Among them, $\tilde{L} = \frac{2L}{\lambda\max} - I$. So, the formula can be rewritten as Eq. (7).

$$y = \theta'_0 x + \theta'_1 (\frac{2L}{\lambda\max} - I)x \tag{7}$$

L represents the normalized Laplacian matrix, then further set λ max to 2 and define $L = I - D^{-\frac{1}{2}}WD^{-\frac{1}{2}}$ through the normalized Laplacian matrix, rewrite the formula as Eq. (8).

$$y = \theta_0' x - \theta_1' \left(D^{-\frac{1}{2}} W D^{-\frac{1}{2}} \right) x \tag{8}$$

Finally, to reduce the parameters of the model, let $\theta_0\prime = -\theta_1\prime$, and re-normalize, rewrite the formula as Eq. (9), where $\tilde{W} = W + I$, $\tilde{D}_{ii} = \Sigma_j \tilde{W}_{ij}$ is the adjacency matrix, and D is the degree matrix.

$$y = \theta \left(\tilde{D}^{-\frac{1}{2}} \tilde{W} \tilde{D}^{-\frac{1}{2}} \right) x \tag{9}$$

In the experiment, the adjacency matrix W is calculated through latitude and longitude. First, we take out the latitude and longitude of 81 observation stations in the original data. The distribution of observation stations' latitude and longitude data (partial data) are shown in Table 3.

Table 3. Observation station latitude and longitude

Area	County	Longitude	Latitude
Erlin	Changhua	120.4097	23.92518
Sanchong	New Taipei	121.4938	25.07261
Sanyi	Miaoli	120.7588	24.38294
Tucheng	New Taipei	121.4519	24.98253

Since the atmosphere on the Earth belongs to a system that changes at any time, there are different degrees of influence between the observation stations. First, we use Eq. (10) to calculate the observation stations (w, x) and the distance between Observation stations (y, z) on the earth. The calculated distance (partial data) is shown in Table 4.

$$dist = 2r * \arcsin\left(\sqrt{\left(\sin \frac{w-y}{2} \right)^2 + \cos w * \cos y * \left(\sin \frac{x-z}{2} \right)^2} \right) \tag{10}$$

Among them, w and y represent latitude, x and z represent longitude, and r represents the radius of the earth. Then we use the distance calculated by Eq. (10) and substitute it with Eq. (11) to calculate the distance between the stations. Weight k, the range of k is between 0 and 1. 0 means the distance between two points is farther, and 1 means the distance between two points is closer. To prevent excessive dependence between points, we set the parameter z at 0.5, , and the final adjacent matrix (partial data) is shown in Table 5.

$$W(a, b) = \begin{cases} 1 \; if \;\; a = b \\ 0 \; if \;\; k < z \\ k \; if \;\; k \geq z \end{cases}, k = \exp\left(-\frac{(dist(a, b))^2}{\sigma^2} \right) \tag{11}$$

Table 4. The distance between observation stations

		Erlin	Sanchong	Sanyi	Tucheng
		Changhua	New Taipei	Miaoli	New Taipei
Erlin	Changhua	00.00	168.01	61.89	157.74
Sanchong	New Taipei	168.01	0.00	106.60	10.84
Sanyi	Miaoli	61.89	106.61	00.00	96.59
Tucheng	New Taipei	157.74	10.84	96.59	00.00

Table 5. The Weight of Distance

		Erlin	Sanchong	Sanyi	Tucheng
		Changhua	New Taipei	Miaoli	New Taipei
Erlin	Changhua	1	0	0.6732	0
Sanchong	New Taipei	0	1	0	0.9879
Sanyi	Miaoli	0.6732	0	1	0
Tucheng	New Taipei	0	0.9879	0	1

3.2 The TCN Model

The Time Convolutional Network (TCN) is derived from the Convolutional Neural Network (CNN) model and is utilized in this paper to process time series data. It comprises key components such as one-dimensional convolutional network, atrous convolution, causal convolution, and residual connection. To ensure consistency between input and output layers' lengths, the TCN employs hole convolution. This technique adapts the sequence length of each hidden layer to match the input sequence length, with the hole convolution employing exponentially increasing values (e.g., 1, 2, 4, 8…) to determine the number of spaces between messages that need to be traversed to reach the next layer.

To prevent the information from being leaked during the training process of the model, the temporal convolutional network adopts causal convolution, so that the output y_t at the time point t will only receive the information x_t at the time point t and the information before the time point t influenced by $x_1, x_2, \ldots x_{t-1}$. With the increase of the neural network layer, many problems may be encountered when the depth is deeper. This is such as gradient disappearance and gradient explosion, resulting in no way to update the weight, and eventually the accuracy decreases. TCN uses residual poor connections to solve this problem. It makes the entire network architecture achieve good results when the number of layers is very deep.

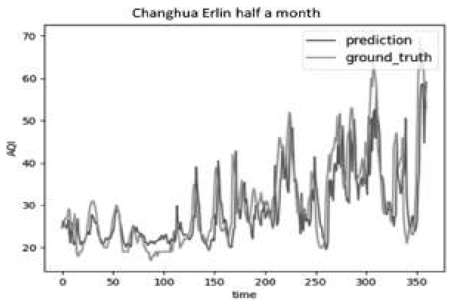

Fig. 2. AQI prediction

Table 6. The data from February to July.

Method	MAE	RMSE
ARIMA	23.97	29.92
LSTM	5.22	7.33
GCN	4.91	6.92
GRU	4.83	7.16
TGCN	4.86	6.74
TCN	5.24	7.82
GCTN	**4.78**	**6.67**

4 Experimental Result and Discussion

The data set is divided into three parts: training, validation, and testing, in the ratio 7:1:2. Then we use the geographical location to find Changhua Erlin in central Taiwan. In the following trials, we made predictions with the Chang-hua Erlin as our goal. In Fig. 2, the x-axis indicates the future time point, indicating that the prediction is based on the first data point in the test set data; the unit is an hour; and the y-axis shows the AQI value. Figure 2 illustrates the real values and forecasted value map, which were generated by dividing the data set by half a year, from February to July of the next year, 2021. The following experiment describes how to use the training and verification sets to predict the test sets AQI.

We compare the model incorporating temporal and space correlation to the ARIMA, LSTM, GCN, GRU, TGCN, and TCN models. In Table 6, statistics from half a year are used to forecast the next half month. We can see that the model's prediction value when paired with TCN and GCN is lower. This suggests that our GCTN model performs better in predicting Changhua Erlin's AQI.

5 Conclusion

In this study, we introduce a novel approach, the GTCN model, for predicting Taiwan's AQI by incorporating both temporal and spatial correlations. Unlike traditional methods that focus solely on temporal correlation, the GTCN model analyzes complex temporal and spatial correlations among multiple observation stations across various counties and cities. From our experiments, the GTCN model demonstrates superior predictive accuracy in both short- and long-term settings compared to existing models. By leveraging real datasets and strict comparisons with other researchers' models, we established the effectiveness of the GTCN model in accurately forecasting AQIs. In particular, the GTCN model achieves the smallest mean absolute error (MAE) of about 4.78 and the smallest root mean square error (RMSE) of about 6.67 when tested on data from February to July 2021, outperforming other models during this period. Our research works emphasize the potential of the GTCN model as a valuable tool for environmental protection and public health improvement. In future works, we would like to develop predictive applications that continuously analyze AQIs in real-time. These applications will not only provide users with up-to-date AQI statistics but also offer guidance on preventive measures against air pollution at various levels.

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