MULTISTAGE DEEP LEARNING FOR AIR QUALITY INDEX PREDICTION

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Abstract— Air quality prediction is a challenging but practical research topic in machine learning and data analytics. Since air quality directly affects human health and life in the long term, predicting its index values has always attracted much attention from researchers and government agencies. Today, many ground-based stations are established to provide air quality index values in monitored areas. Meanwhile, Unmanned Aerial Vehicles (UAVs) are being used more and more for surveillance applications, and become a good candidate application for air quality monitoring. However, monitoring and predicting air quality using UAVs is still a new domain and poses many challenges for the research community. To solve the problem of predicting air quality based on sensor values measured using UAV, in this paper, we propose a solution that based on a model combing an unidirectional convolutional neural network and a bi-directional long short term memory network (1DCNN-BiLSTM). Experimental results with highly efficient and practical performance have shown that our proposed method can be deployed in real monitoring applications. The proposed system can also be a useful source of data in complement with ground-based stations.

Keywords— Convolutional neural network, air quality monitoring, UAV, Bi-directional long short term memory.

I. INTRODUCTION

Nowadays, environmental issues, especially air quality are more concerned by most people than ever. Air pollution is a major challenge for cities and industrial zones, with serious impacts on human health. According to the World Health Organization, 7 million people are exposed to health risks from air pollution [1]. It is the leading risk factor for most health problems such as asthma, skin infections, heart, throat, lung cancer, and diseases of the respiratory system. Besides, it is also a serious threat to our planet. Pollution emitted from various sources such as vehicles and industrial zones is the primary cause of the greenhouse effect, and CO2 emissions are one of the most important causes of the greenhouse effect [2]. Climate change has been widely discussed in global forums and has remained a burning issue for the world for the past two decades, which results in the increasing of smog and ozone layer damage. Air quality index estimation is an important way to monitor and control air pollution. Some air pollutants, known as standard air pollutants, can cause damage to health, the environment, and property. The most significant pollutants are Carbon Monoxide (CO), Lead (Pb), Nitrogen Dioxide (NO2), Ozone (O3), Particulate matter (PM), and Sulfur Dioxide (SO2).

Meteorological conditions, including regional and general meteorology, play an important role in determining air pollutant concentrations [3–8]. For example, low ambient temperature accompanied by solar radiation slows down the photochemical reaction and leads to fewer secondary air pollutants, such as O3 [9]. Increased wind speed can increase or decrease the concentration of pollutants in the air. For example, when wind speed are low, traffic-related pollutants have the highest concentrations [10, 11]. However, strong wind speed can form dust storm by blowing up terrestrial particles [12]. High concentration of some air pollutants (such as PM, CO, and SO2), is often associated with high humidity. But for other air pollutants (such as NO2 and O3), high humidity leads to low concentration [11]. In addition, high humidity can be an indicator of precipitation phenomena, leading to strong wet deposition which reduces air pollutant concentrations [13]. Clouds can scatter and absorb solar radiation, which has implications for the formation of some air pollutants (eg, O3) [9, 14]. Therefore, meteorological variables are important parameters to predict the concentration of pollutants in the air. Fortunately, these meteorological parameters can be measured easily and efficiently with an UAV carrying the corresponding sensors.

The typical idea for monitoring air quality is to use sensors fixed at several important locations, to measure the concentration of air components. The air quality information is then sent to a data center for storage and analysis. However, this approach is quite expensive and difficult to implement in some locations. On the other hand, since the number of sensors is limited, the air quality monitoring is only done at fixed locations, we cannot have

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detailed air quality information over a large area, and thus cannot get an overview of the air quality for that area.

On the other hand, predicting air quality is also an important requirement for environmental monitoring systems. There are many methods to predict air quality, of which using Machine learning algorithms are a popular choice. For example, in a recent study [15], Zhou et al. presents a method using artificial intelligence based on the Deep Multi-Output LSTM (DM-LSTM) neural network model to predict the air quality in the Taipei city, Taiwan. The study is promising, but the data used in the study was generated by five fixed air quality monitoring stations in the city. Therefore, these data sets do not reflect pollution concentrations at a detailed level at each area. Similarly, other data-based methods have been used to predict air quality such as DEA (data envelopment analysis) in [16], however, the information being used comes from fixed data sources, not portable sensor units that can be carried on a daily basis.

To solve the above-mentioned problems, in this paper, we proposing a method which focus on using the 1DCNN - BiLSTM model for air quality prediction problem. Our study used sensor data collected using UAVs to train and validate the propose model. Our contribution consists of three main parts:

- Proposed CNN model, 1DCNN-BiLSTM extracts features from data collected by sensors on unmanned aerial vehicles.
- Building of a database (dataset) on air quality in separate areas. Then we evaluate the proposed method on the collected dataset and analyze the results.
- Development of a prototype to prove the feasibility and efficiency the proposed method as shown in Figure 1.

II. RELATED WORKS

In previous studies related to monitoring and predicting air quality, there are two main categories: deterministic and statistical models. Deterministic models use meteorology, physics, and chemistry to simulate the transfer, diffusion, or elimination of pollutants. The deterministic models can be mentioned as CMAQ (Community Multiscale Air Quality) [17] and WRF-Chem (Weather Research and Forecasting model coupled with Chemistry) [18]. These theoretical analysis-based models are widely used in the environmental and atmospheric research community [19, 20]. However, due to factors such as data errors, complex geographical conditions, and weak theoretical foundations, these methods often have limited accuracy [21, 22]. On the other hand, the above methods do not solve the real-time prediction problem because they require specific calculations with all the non-linear points in the complex atmosphere, resulting in long computation times. Meanwhile, statistical modeling relies on data to compute and predict the results, giving more accuracy but requiring careful annotation process. Previously, traditional machine learning methods were widely applied to air quality data processing such as SVM, decision tree, or random forest. These machine learning methods require a feature extraction step for the data before it can be input for the models. Recently, deep learning models are becoming more and more popular in many research fields, including air quality analysis and prediction. Deep learning models do not require separate feature extraction step, but this process will rather be trained inside the deep learning model.

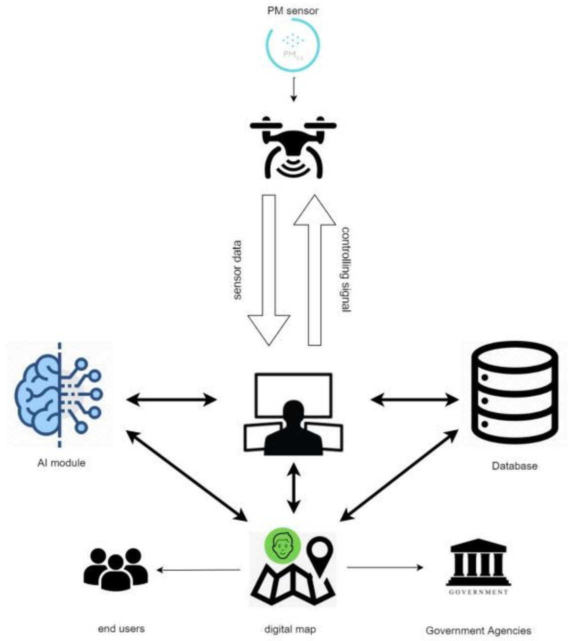

Figure 1: System overview

A. Machine learning.

To overcome the problems of deterministic models, many studies have applied machine learning algorithms to predict air quality. Machine learning models do not require complex physical and chemical processing like deterministic models but use previously collected air data to predict air quality in the near future. In addition, the machine learning approach helps to solve the non-linear problem and improves the performance and accuracy of the model. Linear regression is a fundamental model in machine learning. Some researchers have applied this model to the air quality prediction problem. For example, Rajput et al used a multiple linear regression model to predict air quality in India [23]. However, air pollutants have a nonlinear relationship with their influencing factors. Singh et al. [24] compared linear and nonlinear methods and found that nonlinear methods can capture complex nonlinearities in air quality data. Therefore, nonlinear models, such as artificial neural networks (ANNs) [25] are more suitable than linear models. Azid et al. [26] combined Principal Component Analysis (PCA) and ANN to predict air quality in Malaysia. De Vito et al. [27] improved ANN with a dynamic approach. Kang [28] used Lanzhou data and genetically simulated annealing ANN to predict air quality. Paoli et al [29] used ANN to predict O3 in Corsica. Mahajan et al [30] used a clustering method based on the geographical distance to improve the performance of ANNs in 4 cities in Taiwan. Another nonlinear method is the Support Vector Machine (SVM) [31] which is also favored by researchers because it has better generalization ability than ANN. Sánchez et al. [32] found that SVM often outperformed ANN by comparing SVM with different kernels and ANNs. Nieto et al [33] used a PSO-SVM-based method to predict air quality over northern Spain. Gu et al. [34] extracted the sequential information of the prediction by applying the regression method to the SVM.

B. *Deep learning.*

Despite the improved performance compared to deterministic models, traditional machine learning models often have to use complex methods to preprocess data and extract features manually. Data in air quality monitoring issue are often characterized by spatial and temporal correlations. Capturing these dependencies is a critical task for building an accurate model. Deep learning is a promising method to solve this problem, due to its ability in automatically extracting of features and complex relationships of inputs. For example, in [35] Li et al. uses a stacked autoencoder (SAE) to extract information from 12 stations and then feed the extracted information into a linear regression (LR) to predict air quality at 12 stations simultaneously.

However, air quality data is sequential, so models that handle sequential data better such as Recurrent neural network (RNN) give out stronger performance than SAE, ANN, and SVM in predicting air quality. Ong et al [36] also used SAE but replaced LR with RNN to provide a 12-hour prediction time. However, RNNs have two classic drawbacks: explosive gradients and vanishing gradients. Therefore, several studies have used Long Short-Term Memory (LSTM) to predict air quality. For example, use LSTM to predict air quality for the next 12 hours and 24 hours, respectively [37, 38]. Zhao et al. [39] used the information of neighboring stations to build a LTSM-based model. Wang et al. [40] also used LSTM, but they applied Granger causality to select stations with high relevance. Zhou et al [41] established an LSTM-based model to predict the air quality of several stations. Some studies have found that RNN can achieve better results than ANN and SVM [42, 43]. The Gated Recurrent Unit (GRU) is a simplified version of the LSTM, and some researchers have used it to predict air quality. Athira et al [44] compared RNN, LSTM, and GRU to predict air quality and their experiments showed that GRU had the best performance. Wang et al. [45] added a residual connection to GRU and LSTM, they found that GRU has better performance than LSTM. Instead of preprocessing the data with RNNs, which use a convolution function before including them in predictions, their experiments show that GRU has better results than LSTM, ANN, SVM, random forest, and MLR. Some studies [47, 48, 49] use a convolutional neural network (CNN) [50] to preprocess raw data and then feed them into LSTM. Soh et al. [51] used CNN to extract topographic information, for example, a mountain between stations and used LSTM and ANN to extract information from the target station and highly related stations, selected by the clustering method. In the end, they aggregated all the information to make a final prediction. Pan et al [52] established a model that includes spatial, temporal, and deduction modules. The intermediate module extracts the parameters of the space and time modules. Modules can be CNN, LSTM, or ANN models, used to make the final prediction.

III. PROPOSED METHOD

The proposed method uses CNN + Bi-LSTM model to predict the air quality value as illustrated in Figure 2. Given the input data, the proposed model uses the values at the previous t time steps to predict the time step t + 1. In each time step, we decide to use the data of N nearest points (in the map) as a characteristic of this time step. The optimal N and t are selected based on the experimental results.

The original raw data will be of the form D*D*T (where D*D is the number of points to be sampled, in this case, D = 40). This data will be processed before being fed into the training model. After preprocessing, the input data will have the form D*D*K*K*T (K is the size of the square with the center corresponding to the position of the point to be predicted). The output of the model will take the form of a feature array that is the predicted result for the time t+1 that we set earlier. The main steps are as follows:

- Input data: enter the necessary data for training the CNN-LSTM model.
- Transform the data using the nearest k points as the feature vector to be trained.
- Initialize the network: initialize the weights and offsets of each layer of the CNN-LSTM model.
- Computation at CNN layer: consecutive input data is passed through the convolution layer and batch normalization layer in the CNN layer, feature extraction of input data is performed and the output value is obtained.

- Computation at the BiLSTM layer: the output data of the CNN layer is passed through the BiLSTM layer and the output value is obtained.

- Computation at the output layer: the output value of the BiLSTM layer is passed into the dense (fully connected) layer to get the output value.

- Computation error: we compare the output value calculated by the output layer with the actual value of this data group and obtain the corresponding error. (Using MPAE).

- Save model: save the trained model.

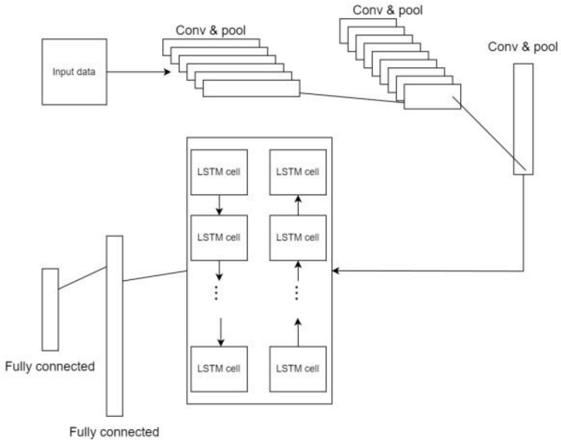

Figure 2: CNN – BiLSTM architecture

A. CNN.

CNN is a deep learning network model including convolutional layers that is widely used in image processing. It can be effectively applied to time series data prediction. CNN mainly consists of two parts: convolutional layer and pooling layer. CNN models are typically designed to operate on two-dimensional data such as images and videos. For this reason, the CNN model is often referred to as the two-dimensional (2D-CNN) or Conv2D CNN model. Recently, to solve the problems related to one-dimensional time series data, the 1-D CNN model or Conv1D has been developed. In our method, we used a 1-dimensional convolution layer (which takes input as 1-dimensional data) to extract the features of the data and use it as the input of the LSTM.

B. Bi-LSTM.

An LSTM model consists of 1 cell, 1 input gate, 1 forget gate, and 1 gate as demonstrated in Figure 3. The cell stores a value and the gates control the flow of information in and out of that cell. The specific derivative formula of LSTM is illustrated in equations (1) - (7). In our proposed method, the LSTM layer is superimposed after the CNN to learn the relationship between the number of days and the air quality of the surrounding points.

The output of LSTM is cell state ct and hidden state ht. Its input is the cell state of the previous timestep c_{t-1}, the hidden state of the previous timestep h_{t-1} and the input of the itth state (x_t).

$$sigmoid\,(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$f_t = sigmoid\,(U_f * x_t + W_f * h_{t-1} + b_f) \tag{2}$$

$$i_t = sigmoid\,(U_i * x_i + W_i * h_{t-1} + b_i) \tag{3}$$

$$o_t = sigmoid\,(U_o * x_t + W_o * h_{t-1} + b_o) \tag{4}$$

$$c_t = f_t * c_{t-1} + i_t * tanh(U_c * x_t + W_c * h_{t-1} + b_c) \tag{5}$$

$$h_t = o_t * tanh(c_t) \tag{6}$$

Where U_f, U_c, U_i, U_o are the input weight, W_f, W_c, W_i, W_o are recurrent parameters and b_f, b_c, b_i, b_o are the bias.

In BiLSTM, input data is processed by both forward and backward layers to utilize both forward and backward data of the current data. BiLSTM model gives better results than traditional LSTM, especially for data with closely related time and value.

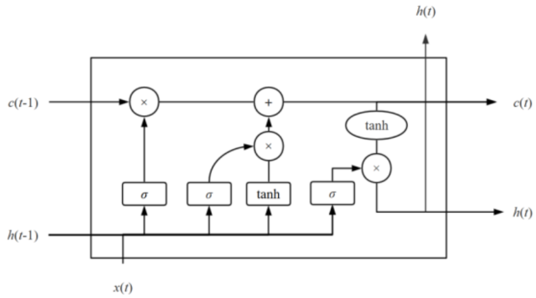

Figure 3: Architecture of LSTM cell.

IV. EXPERIMENTAL RESULTS

In this section, we focus on evaluating the CNN - BiLSTM method on the data set that has been collected by drones. We present the data collection method in section A. Next, the results are presented and evaluated in sections B and C respectively.

A. Data collection

Figure 4: UAV with sensor board to collect data

We utilized UAV in Figure 4 to perform air quality data acquisition. The benefits of using UAV for capturing air quality data include: low cost; versatility (applicable to many atmospheric research applications); flexible, time saving and easy to deploy. The UAV were built with the following basic functions: Receiving sensor signals, cameras; controlling UAV motors; storing collected data; transferring data to ground station. Data collection unit will consist of three main components:

- Measurement unit (including sensor and thermal camera): A PCB that integrates different types of sensors and thermal cameras on a system of hardware circuits that allows data acquisition of various types of data: sensor data and images from thermal cameras.
- Main processing unit: also known as Main Embedded Computer (MEC). The main function of the MEC is to receive information from the sensor, preprocess the sensor data and then store it in the memory of the UAV.

- Interface unit: Contains communication modules from the drone to the storage modules. The module is designed and manufactured according to communication protocol to easily connect from the main MEC to the storage hardware. The interface unit has two main functions: first, receive the measure signal from the air quality sensors and thermal camera, send these signals to MEC for further signal processing. And second, store the acquired data in the UAV memory.

We have selected the area of Quang Minh industrial zone, in Hanoi for data collection. Data was collected through a UAV device in the area of the industrial zone with an area of 1600x1000m divided into a grid of 40x25m cells. In this area, the flight path for the UAV is described as follows: The UAV will fly around the area once for every hour, collecting data at predefined points on that grid. For each point on the grid, the data will include the following attributes: temperature, humidity, fine dust PM 2.5, SO2, NO2, CO2, CO, NH3, O3, longitude, latitude of the data point and time of its measurement (year-month-day, hour). The data collection was taken place for 1 month so that we can make sure changes in weather are included in this period. A detailed description of each indicator is given in the Table 1 below:

Table 1: Data description

Data	Note
AQI	air quality index.
PM 2.5	particulate matter pm2.5(μg/m3).
SO_2	gas concentration (g/m3).
NO_2	gas concentration (g/m3).
CO	gas concentration (g/m3).
CO_2	gas concentration (g/m3).
NH_3	gas concentration (g/m3).
O_3	gas concentration (g/m3).
Longitude	at measurement point
Latitude	at measurement point

B. Evaluation index.

We use the mean absolute percentage error (MAPE) as the evaluation criterion for this problem. MAPE is a measure of the accuracy of a statistical prediction method. The formula of MAPE is as follows:

$$M = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (7)$$

Where F_t is the prediction value and A_t is the real value. The smaller the value of MAPE, the closer the forecast results are to reality.

C. Results.

Performance evaluation.

With this experiment, we compared the proposed CNN-BiLSTM method with previous methods including: linear regression, BiLSTM on the same data set. We compare these methods with different parameters such as number of sampling days and sampling range K (applicable to CNN-BiLSTM).

Table 2: Results with data from previous 3 days

Method	CNN-BiLSTM (K=3)	CNN-BiLSTM (K=5)	CNN-BiLSTM (K=7)	Linear Regression	LSTM
SO2	**4%**	18%	17%	5%	5%
NO2	**8%**	16%	18%	28%	8%
CO	15%	16%	17%	**7%**	8%
CO2	**11%**	14%	14%	15%	12%
NH3	**5%**	10%	12%	25%	8%
O3	**6%**	10%	12%	17%	9%
PM2.5	**8%**	14%	16%	21%	10%

Table 3: Results with data from previous 5 days

Method	CNN-BiLSTM (K=3)	CNN-BiLSTM (K=5)	CNN-BiLSTM (K=7)	Linear Regression	LSTM
SO2	**3%**	12%	14%	5%	5%
NO2	**6%**	10%	12%	17%	8%
CO	12%	15%	16%	**7%**	9%
CO2	**9%**	12%	14%	15%	10%
NH3	**4%**	8%	10%	20%	10%
O3	**5%**	9%	10%	15%	8%
PM2.5	**7%**	10%	12%	18%	12%

Table 4: Results with data from previous 7 days

Method	CNN-BiLSTM (K=3)	CNN-BiLSTM (K=5)	CNN-BiLSTM (K=7)	Linear Regression	LSTM
SO2	**5%**	18%	18%	6%	6%
NO2	**9%**	16%	19%	25%	9%
CO	14%	17%	15%	**9%**	10%
CO2	**9%**	12%	10%	11%	10%
NH3	**6%**	12%	14%	20%	10%
O3	**6%**	12%	13%	18%	10%
PM2.5	**8%**	12%	14%	20%	12%

Table 5: Results with data from previous 30 days

Method	CNN-BiLSTM (K=3)	CNN-BiLSTM (K=5)	CNN-BiLSTM (K=7)	Linear Regression	LSTM
SO2	**4%**	17%	15%	6%	6%
NO2	**7%**	15%	16%	25%	9%
CO	14%	16%	13%	**8%**	11%
CO2	**9%**	10%	10%	10%	10%
NH3	**6%**	11%	13%	15%	8%
O3	**6%**	10%	11%	12%	10%
PM2.5	**7%**	9%	15%	17%	12%

Table 6: Results with data from previous 45 days

Method	CNN-BiLSTM (K=3)	CNN-BiLSTM (K=5)	CNN-BiLSTM (K=7)	Linear Regression	LSTM
SO2	**4%**	16%	14%	5%	6%

NO2	**7%**	14%	15%	22%	9%
CO	14%	15%	13%	**8%**	10%
CO2	**8%**	11%	10%	9%	9%
NH3	**6%**	10%	12%	14%	8%
O3	**6%**	11%	10%	11%	9%
PM2.5	**7%**	9%	14%	18%	11%

In overall, the results in Table 2, Table 3, Table 4, Table 5, and Table 6 show that the accuracy of CNN-BiLSTM are superior compared to previous methods (LSTM, Linear Regression). The proposed method can result in the best MAPE values for SO2, NO2, CO, CO2, NH3, O3, and PM2.5 are 3%, 6%, 12%, 9%, 4%, 5%, and 7% respectively. In the case of data taken from previous 7 days in Table 4. Only linear regression method can give better result than the proposed Bi-LSTM method in case of CO gas prediction. With other methods, the accuracy decreases when the number of sampling days increase. However, with the CNN-BiLSTM method, the results tend to be good when increasing the number of sampling days and decreasing the size of the neighborhood points used to sample at each point or most type of gases (SO2, CO2, CO, NH3, O3) and PM2.5. When compared with the most common method for time series problems, the LSTM, we find that for a small number of days, the LSTM achieves comparable or even better accuracy for some gases. However, when the number of sampling days increases, the strengths of CNN-BiLSTM are clearly revealed and the error is minimal. In addition, when the number of sampling days is 5 days, the result of the proposed method is the best. A neighborhood size of 3 also gives good results compared to a neighborhood size of 5 and 7. In addition, the data is shown in Table 5 and Table 6 prove that the longer data is used the better performance the model can achieve. This can be explained by the fact that, the air pollution index is heavily influenced by the season of the year. If the data is collected in the duration of one year, the experimental result can be much improved.

Inference time

Inference time is calculated from when the model starts to process input data until the model gives the predictive results. A model is considered good if and only if it has good inference time and accuracy. We often need to make a trade-off between the inference time and the accuracy of the model because the model needs more parameters to make more accurate predictions. In addition, a model with fast enough inference time can be practical for daily usage. In this comparison, M is used as a changing parameter, which is the number of days in the past used to predict future sensor values. The inference time of different methods is given in Table 5 as follows:

Table 7: Inference time for 1 data point

Method		Time
CNN - BiLSTM	M = 3	0,057s
	M = 5	0,062s
	M = 7	0,077s
Linear Regression		0,00035s
LSTM		0,067s

It is worth noting that the above inference time is calculated when the model predicts one data point. When the number of data points to predict increases, this inference time also increases. However, the inference time does not increase linearly with the number of data points to be predicted. Below is the inference time to predict the 16000 data points corresponding to the 10 areas which have size of 40 x 40 each that we used during model training.

Table 8: Inference time for 16000 data points

Method		Time
CNN - BiLSTM	M = 3	16,6s
	M = 5	30,1s
	M = 7	74,7s
Linear Regression		0,01s
LSTM		24,2s

It can be seen from Table 8 that the CNN-BiLSTM model has the longest inference time, which is quite understandable because it needs more parameters to predict and its accuracy is also the highest. However, the above inference time may still be suitable for use in practical applications. When compared with the LSTM model, the CNN–BiLSTM model with M = 1 and M = 3 proved to be superior when having the same or smaller inference time while providing higher accuracy.

V. CONCLUSION

In this paper, we have collected a data set of air quality measurement in Quang Minh industrial zone, Hanoi to experiment with our proposed model, as well as other common used models. The experimental results show that the proposed model works well with the dataset, proving its efficiency and feasibility when deployed in real-world application. In addition, in this work, we have also built a complete system which including an UAV, a ground station control, a data processing server, and a digital map. Although the experiments conclude with promising results, this study still has some limitations that can be overcome and improved in future. We will conduct a data collection on a wider and more diverse terrain, in order to evaluate the air quality more objectively and multidimensionally, then analyzing deeper the errors of the measurement. Our team also aims to build a multi-task machine learning model that can both predict future air quality and be able to eliminate and correct errors in measurements. Correction of measurement errors is necessary when implementing the application in real field. This is because the air quality data measured by sensors always have outliers, missing data. In addition, we also aim to solve the problem of optimizing the flight trajectory of the UAV to improve mesurment efficiency and save energy.

REFERENCE

[1] 7 million deaths linked to air pollution annually. [Online]. Available: https://www.who.int/phe/eNews_63.pdf

[2] Moore, Frances. "Climate change and air pollution: exploring the synergies and potential for mitigation in industrializing countries." Sustainability 1.1 (2009): 43-54.

[3] Kalkstein, L.S.; Corrigan, P. A synoptic climatological approach for geographical analysis: Assessment of sulfur dioxide concentrations. Ann. Assoc. Am. Geogr. 1986, 76, 381–395.

[4] Comrie, A.C. A synoptic climatology of rural ozone pollution at three forest sites in Pennsylvania. Atmos. Environ. 1994, 28, 1601–1614.

[5] Eder, B.K.; Davis, J.M.; Bloomfield, P. An automated classification scheme designed to better elucidate the dependence of ozone on meteorology. J. Appl. Meteorol. 1994, 33, 1182–1199.xxx

[6] Zelenka, M.P. An analysis of the meteorological parameters affecting ambient concentrations of acid aerosols in Uniontown, Pennsylvania. Atmos. Environ. 1997, 31, 869–878.xxx

[7] Laakso, L.; Hussein, T.; Aarnio, P.; Komppula, M.; Hiltunen, V.; Viisanen, Y.; Kulmala, M. Diurnal and annual characteristics of particle mass and number concentrations in urban, rural and Arctic environments in Finland. Atmos. Environ. 2003, 37, 2629–2641.xxx

[8] Jacob, D.J.; Winner, D.A. Effect of climate change on air quality. Atmos. Environ. 2009, 43, 51–63.x

[9] Akbari, H. Shade trees reduce building energy use and CO2 emissions from power plants. Environ. Pollut. 2002, 116, S119–S126.x

[10] DeGaetano, A.T.; Doherty, O.M. Temporal, spatial and meteorological variations in hourly PM 2.5 concentration extremes in New York City. Atmos. Environ. 2004, 38, 1547–1558.x

[11] Elminir, H.K. Dependence of urban air pollutants on meteorology. Sci. Total Environ. 2005, 350, 225–237.x

[12] Natsagdorj, L.; Jugder, D.; Chung, Y.S. Analysis of dust storms observed in Mongolia during 1937–1999. Atmos. Environ. 2003, 37, 1401–1411.x

[13] Seinfeld, J.H.; Pandis, S.N. Atmospheric Chemistry and Physics: From Air Pollution to Climate Change; John Wiley & Sons: Hoboken, NJ, USA, 2016.x

[14] Twomey, S. The influence of pollution on the shortwave albedo of clouds. J. Atmos. Sci. 1977, 34, 1149–1152x

[15] Zhou, Y., Chang, F.J., Chang, L.C., Kao, I.F., Wang, Y.S., 2019. Explore a deep learning multi-output neural network for regional multi-step-ahead air quality forecasts. J. Clean. Prod. 209, 134e145. http://www.sciencedirect.com/science/article/pii/S0959652618332694.
https://doi.org/10.1016/j.jclepro.2018.10.243.x

[16] Zhou, Z., Guo, X., Wu, H., Yu, J., 2018. Evaluating air quality in China based on daily data: application of integer data envelopment analysis. J. Clean. Prod. 198, 304e311. http://www.sciencedirect.com/science/article/pii/S0959652618318304.
https://doi.org/10.1016/j.jclepro.2018.06.180.x

[17] D. Byun, K.L. Schere. Review of the governing equations, computational algorithms, and other components of the models-3 community multiscale air quality (cmaq) modeling system Appl. Mech. Rev., 59 (2006), p. 51, 10.1115/1.2128636x

[18] Close M. Shrivastava, J. Fast, R. Easter, W.I. Gustafson, A. Hodzic. Modeling organic aerosols in a megacity: comparison of simple and complex representations of the volatility basis set approach Atmos. Chem. Phys., 11 (2011), pp. 6639-6662, 10.5194/acpd-10-30205-2010x

[19] L.T. Wang, Z. Wei, J. Yang, Y. Zhang, F.F. Zhang, J. Su, et al. The 2013 severe haze over southern hebei, China: model evaluation, source apportionment, and policy implications Atmos. Chem. Phys., 14 (2014), pp. 3151-3173x

[20] Q. Zhang, D. Xue, X. Liu, X. Gong, H. Gao Process analysis of pm2.5 pollution events in a coastal city of China using cmaq J. Environ. Sci., 31 (2019), pp. 225-238

[21] X. Jin, A.M. Fiore, G. Curci, A. Lyapustin, K. Civerolo, M. Ku, et al. Assessing uncertainties of a geophysical approach to estimate surface fine particulate matter distributions from satellite-observed aerosol optical depth Atmos. Chem. Phys. Discuss., 19 (2019)x

[22] R. Kumar, M.C. Barth, G.G. Pfister, M. Naja, G.P. Brasseur Wrf-chem simulations of a typical pre-monsoon dust storm in northern India: influences on aerosol optical properties and radiation budget Atmos. Chem. Phys., 14 (2014), pp. 2431-2446x

[23] T. S. Rajput and N. Sharma, ''Multivariate regression analysis of air quality index for Hyderabad city: Forecasting model with hourly frequency,'' Int. J. Appl. Res., vol. 3, no. 8, pp. 443–447, 2017.

[24] K. P. Singh, S. Gupta, A. Kumar, and S. P. Shukla, ''Linear and nonlinear modeling approaches for urban air quality prediction,'' Sci. Total Environ., vol. 426, pp. 244–255, Jun. 2012.

[25] S. Dreiseitl and L. Ohno-Machado, ''Logistic regression and artificial neural network classification models: A methodology review,'' J. Biomed. Inform., vol. 35, nos. 5–6, pp. 352–359, 2002.

[26] A. Azid et al., ''Prediction of the level of air pollution using principal component analysis and artificial neural network techniques: A case study in Malaysia,'' Water, Air, Soil Pollution, vol. 225, no. 8, p. 2063, 2014.

[27] S. De Vito et al., ''Dynamic multivariate regression for on-field calibration of high speed air quality chemical multi-sensor systems,'' in Proc. AISEM Annu. Conf., Feb. 2015, pp. 1–3.

[28] Z. Kang and Z. Qu, ''Application of BP neural network optimized by genetic simulated annealing algorithm to prediction of air quality index in Lanzhou,'' in Proc. IEEE Comput. Intell. Appl. (ICCIA), Sep. 2017, pp. 155–160.

[29] C. Paoli, G. Notton, M. Nivet, M. Padovani, and J. Savelli, ''A neural network model forecasting for prediction of hourly ozone concentration in Corsica,'' in Proc. Environ. Elect. Eng. (EEEIC), May 2011, pp. 1–4.

[30] S. Mahajan, H. M. Liu, T. C. Tsai, and L. J. Chen, ''Improving the accuracy and efficiency of PM2.5 forecast service using cluster-based hybrid neural network model,'' IEEE Access, vol. 6, pp. 19193–19204, 2018.

[31] C. Cortes and V. Vapnik, ''Support-vector networks,'' Mach. Learn., vol. 20, no. 3, pp. 273–297, 1995.

[32] A. S. Sánchez, P. J. G. Nieto, P. R. Fernández, J. J. del Coz Díaz, and F. J. Iglesias-Rodríguez, ''Application of an SVM-based regression model to the air quality study at local scale in the Avilés urban area (Spain),'' Math. Comput. Model., vol. 54, nos. 5–6, pp. 1453–1466, 2011.

[33] P. J. G. Nieto, E. Garcia-Gonzalo, F. S. Lasheras, and F. J. de Cos Juez, ''Hybrid PSO–SVM-based method for forecasting of the remaining useful life for aircraft engines and evaluation of its reliability,'' Rel. Eng. Syst. Saf., vol. 138, pp. 219–231, Jun. 2015.

[34] K. Gu, J. Qiao, and W. Lin, ''Recurrent air quality predictor based on meteorology- and pollution-related factors,'' IEEE Trans. Ind. Informat., vol. 14, no. 9, pp. 3946–3955, Sep. 2018

[35] X. Li, L. Peng, Y. Hu, J. Shao, and T. Chi, ''Deep learning architecture for air quality predictions,'' Environ. Sci. Pollut. Res., vol. 23, no. 22, pp. 22408–22417, 2016.

[36] B. T. Ong, K. Sugiura, and K. Zettsu, ''Dynamic pre-training of deep recurrent neural networks for predicting environmental monitoring data,'' in Proc. IEEE Big Data, Oct. 2014, pp. 760–765.

[37] V. Chaudhary, A. Deshbhratar, V. Kumar, and D. Paul. Time Series Based LSTM Model to Predict Air Pollutant's Concentration for Prominent Cities in India. Accessed: Jan. 25, 2019. [Online]. Available: http://philippefournier-viger.com/utility_mining_workshop_2018/PAPER1.pdf

[38] E. Pardo and N. Malpica, ''Air quality forecasting in Madrid using long short-term memory networks,'' in Proc. Int. Work-Conf. Interplay Between Natural Artif. Comput., 2017, pp. 232–239.

[39] J. Zhao, F. Deng, Y. Cai, and J. Chen, ''Long short-term memory-fully connected (LSTM-FC) neural network for PM2.5 concentration prediction,'' Chemosphere, vol. 220, pp. 486–492, Apr. 2019.

[40] J. Wang and G. Song, ''A deep spatial-temporal ensemble model for air quality prediction,'' Neurocomputing, vol. 314, pp. 198–206, Nov. 2018.
[41] Y. Zhou, F.-J. Chang, L.-C. Chang, I.-F. Kao, and Y.-S. Wang, ''Explore a deep learning multi-output neural network for regional multi-step ahead air quality forecasts,'' J. Clean Prod., vol. 209, pp. 134–145, Feb. 2019.
[42] M. Kim, Y. Kim, S. Sung, and C. Yoo, ''Data-driven prediction model of indoor air quality by the preprocessed recurrent neural networks,'' in Proc. IEEE ICCAS-SICE, Aug. 2009, pp. 1688–1692.
[43] İ. Kök, M. U. Şimşek, and S. Özdemir, ''A deep learning model for air quality prediction in smart cities,'' in Proc. IEEE Big Data, Dec. 2017, pp. 1983–1990.
[44] V. Athira, P. Geetha, R. Vinayakumar, and K. P. Soman, ''DeepAirNet: Applying recurrent networks for air quality prediction,'' Procedia Comput. Sci., vol. 132, pp. 1394–1403, Dec. 2018.
[45] B. Wang, Z. Yan, J. Lu, G. Zhang, and T. Li, ''Deep multi-task learning for air quality prediction,'' in Proc. Int. Conf. Neural Inf. Process., 2018, pp. 93–103.
[46] X. Sun, W. Xu, and H. Jiang, ''Spatial-temporal prediction of air quality based on recurrent neural networks,'' in Proc. 52nd Hawaii Int. Conf. Syst. Sci., 2019, pp. 1–10.
[47] S. Du, T. Li, Y. Yang, and S.-J. Horng. (2018). ''Deep air quality forecasting using hybrid deep learning framework.'' [Online]. Available: https://arxiv.org/abs/1812.04783
[48] F. Feng, J. Wu, W. Sun, Y. Wu, H. Li, and X. Chen, ''Haze forecasting via deep LSTM,'' in Proc. Asia–Pacific Web (APWeb) Web-Age Inf. Manage. (WAIM) Joint Int. Conf. Web Big Data, 2018, pp. 349–356.
[49] C.-J. Huang and P.-H. Kuo, ''A deep CNN-LSTM model for particulate matter (PM2.5) forecasting in smart cities,'' Sensors, vol. 18, no. 7, p. 2220, 2018.
[50] Y. LeCun and Y. Bengio, ''Convolutional networks for images, speech, and time series,'' in The Handbook of Brain Theory and Neural Networks, vol. 3361, no. 10. Cambridge, MA, USA: MIT Press, 1995.
[51] P.-W. Soh, J.-W. Chang, and J.-W. Huang, ''Adaptive deep learning-based air quality prediction model using the most relevant spatial-temporal relations,'' IEEE Access, vol. 6, pp. 38186–38199, 2018.
[52] Z. Pan, Y. Liang, J. Zhang, X. Yi, Y. Yu, and Y. Zheng. (2018). ''HyperSTNet: Hypernetworks for Spatio-temporal forecasting.'' [Online]. Available: https://arxiv.org/abs/1809.10889

MÔ HÌNH HỌC SÂU ĐA TẦNG CHO DỰ ĐOÁN CHỈ SỐ CHẤT LƯỢNG KHÔNG KHÍ.

Tóm tắt: Dự đoán chất lượng không khí là một chủ đề nghiên cứu đầy thách thức nhưng thiết thực trong lĩnh vực học máy và phân tích dữ liệu. Vì chất lượng không khí ảnh hưởng trực tiếp đến sức khỏe và cuộc sống của con người về lâu dài nên việc dự đoán các giá trị chỉ số của nó luôn thu hút nhiều sự quan tâm của các nhà nghiên cứu và các cơ quan chính phủ. Hiện nay trên thực tế đã có nhiều trạm giám sát mặt đất được thiết lập để cung cấp các giá trị chỉ số chất lượng không khí trong các khu vực. Đồng thời, các phương tiện bay không người lái (UAV) ngày càng được sử dụng nhiều hơn cho các ứng dụng giám sát và trở thành một ứng cử viên sáng giá cho việc giám sát chất lượng không khí. Mặc dù vậy, giám sát và dự đoán chất lượng không khí bằng UAV vẫn là một lĩnh vực mới và đặt ra nhiều thách thức cho cộng đồng nghiên cứu. Để giải quyết vấn đề dự đoán chất lượng không khí dựa trên các giá trị cảm biến được đo bằng UAV, trong bài báo này, chúng tôi đề xuất một giải pháp dựa trên mô hình kết hợp mạng nơ ron tích chập một chiều và mạng bộ nhớ ngắn hạn và dài hạn hai hướng (1DCNN-BiLSTM) . Kết quả thực nghiệm với hiệu quả cao và mang tính thực tiễn cao đã cho thấy phương pháp đề xuất của chúng tôi có thể được triển khai trong các ứng dụng giám sát thực tế. Hệ thống được đề xuất cũng có thể là một nguồn dữ liệu hữu ích bổ sung cho các trạm trên mặt đất.

Từ khóa: Mạng nơ ron tích chập, CNN, giám sát chất lượng không khí, UAV, Mạng trí nhớ dài hạn và ngắn hạn hai chiều, LSTM.

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