Real-time Air Pollution prediction model based on Spatiotemporal Big data

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Abstract—Air pollution is one of the most concerns for urban areas. Many countries have constructed monitoring stations to hourly collect pollution values. Recently, there is a research in Daegu city, Korea for real-time air quality monitoring via sensors installed on taxis running across the whole city. The collected data is huge (1-second interval) and in both Spatial and Temporal format. In this paper, based on this spatiotemporal Big data, we propose a real-time air pollution prediction model based on Convolutional Neural Network (CNN) algorithm for image-like Spatial distribution of air pollution. Regarding to Temporal information in the data, we introduce a combination of a Long Short-Term Memory (LSTM) unit for time series data and a Neural Network model for other air pollution impact factors such as weather conditions to build a hybrid prediction model. This model is simple in architecture but still brings good prediction ability.

Keywords—air pollution, real-time, spatiotemporal, big data

I. INTRODUCTION

Outdoor air pollution is now threatening seriously to the human health and life in big cities, especially to elderly and children [2]. This is not a private problem of one country but a global problem. Therefore, many countries in the world have constructed air pollution monitoring stations around major cities to observe air pollutants such as PM2.5, PM10, CO, NO2, SO2 [1] and alert to their citizens if there is a pollution index which exceeds the quality threshold. We briefly describe these air pollutants. PM2.5 is fine atmospheric particulate matter (PM) that have a diameter of less than 2.5 micrometers. PM10 is coarse particulate that is 10 micrometers or less in diameter. CO refers to Carbon Monoxide which is a product of combustion of fuel such as natural gas, coal or wood. Vehicular exhaust contributes to the majority of carbon monoxide let into our atmosphere. NO2 refers to Nitrogen Oxides, expelled from high-temperature combustion. SO2 is Sulfur Oxides, produced by volcanoes and in various industrial processes. Coal and petroleum often contain sulfur compounds, and their combustion generates sulfur dioxide [1].

The pollution data are usually collected hourly which makes the air pollution prediction only is occurred by hour. In reality, air pollution could affect quickly to our health so it is important to have a real-time air pollution tracking data to make an early prediction and alerting. The research in Daegu city, Korea is to try to cope with this problem. They installed air quality sensing devices on 40 taxis running across Daegu city, one of the biggest cities in Korea, and collected sensor data every 1 minute [9]. The data include air pollutants and the weather data of temperature, humidity, and air pressure. All data are stored in a MySQL database with approximately 33.3 million rows so far (from June 2017 to March 2018).

Air pollution is not identical at every point but spatial distributed. The real-time sensor data collected from taxis running cross Daegu city could show this spatial distribution clearly. The air pollution value is aggregated and the Daegu city map is represented by a grid-map of 32x32. To see the spatial distribution of air pollution, we represent this grid-map as a grayscale image of the same dimension 32x32. The grid cell which has an aggregated PM2.5 value will be shown by a pixel has the same value and the grid cell without an accumulated value will be zero. In Fig. 1, we can see the “image” of PM2.5 pollutions spreading and changing location by location and time by time. We have already known that Convolutional Neural Network (CNN) algorithm was applied successfully for Image classification [3]. In this paper, we will also use CNN for “image-like” spatial spreading of air pollution to predict air pollution values to be Good (for health), Moderate or Unhealthy in real-time.

Fig. 1. “Image-like” spatial distribution of PM2.5 pollution values in Daegu city, Korea. y = 2 means the air pollution is Unhealthy, y = 1 means the pollution is Moderate, y = 0 means outdoor air is Good for health. i is different time stamps.

Air pollution is caused by the presentation of poison gases and substances, therefore it is impacted by the meteorological
factors of local place such as temperature, humidity, rain, wind, ... For example, cool temperature and low relative humidity often contribute to higher air pollution. Otherwise, wind speed and wind direction could move air pollutants from one place to others. To clear out this statement, we took weather data including air temperature, relative humidity, precipitation, wind speed, wind direction, which was also collected in real-time by sensors in Daegu city and analyzed them along with the air pollution values. In section III, we will show how we used a combination of LSTM and a Neural Network to evaluate the relationship between these factors and predict future air pollution values.

Our contributions have 2 main points:

(1) We apply a CNN algorithm to “image-like” air pollution distribution to predict air pollution values in real-time.

(2) We propose a combination of LSTM algorithm for time series data and Neural Network for other air pollution influential factors. The hybrid architecture is simple but still produces significant future air pollution prediction.

The structure of our paper as follows. In section II, we will introduce some related researches to ours; in section III, we detail our methodologies and solutions; section IV is about experiments and evaluation and we conclude and give some future suggestions in section V.

II. RELATED WORK

In the Introduction section, we already stated that we use some Deep learning algorithms such as CNN, LSTM to build real-time air pollution prediction models. Before that, there are a number of papers which also leveraged the using of Deep learning for air pollution prediction.

The paper in [5] tried to forecast the reading of an air quality monitoring station over the next 48 hours, considers current meteorological data, weather forecasts, air quality data of the station and other stations within 100 km. They used the combination of some machine learning and deep learning algorithms including linear regression-based temporal predictor along with a neural network-based spatial predictor. The authors evaluated their proposal on the collected data of 43 cities in China. Their results were shown on the website http://urbanair.msra.cn/En. Their works were still on predicting hourly pollution values and used very sparse monitoring stations to make the model. After checking on some stations and on consecutive hours (e.g. 17:00 and 20:00), we realized that the prediction values were not good: actually, the pollution (e.g. PM2.5) increased but they predicted decreasing (Fig. 2).

Another paper by Z. Qi et al. [6] stated a unified semi-supervised learning model to interpolate, predict and feature analysis of air quality in Beijing. They used spatiotemporal grid-based data (1 km * 1 km grid), used both labeled (monitoring stations) and unlabeled data to train a neural network (Autoencoder). In their paper, the authors explained which factors have more impact on the air quality model than others. They claimed that wind strength (from the north), temperature, wind strength (from the east) and precipitation have more relevance to the prediction model than barometric pressure, humidity. Their approach was similar to ours by finding the relationship between other factors to air pollution prediction values but their architecture was quite complex with 2 Autoencoders and a Semi-supervised Regression compared to our architecture with an LSTM and a Neural Network along with a weighted combination between them.

To analysis the spatial and temporal information in data, there are also some related papers such as in [7] which used a Deep CNN (CNN and ResNet) for spatiotemporal taxi trajectory data to predict crowded flow.

III. PROPOSED SYSTEM

A. CNN for predicting grid-based real-time air pollution sensor data in Daegu city, Korea

Firstly, we will describe more detail about how real-time sensor data in Daegu are collected. This is a project from Korea Institute of Science and Technology Information (KISTI) and they wanted to create a Mobile Urban Sensing Dataset. They designed a circuit board etching many air pollutants sensors along with weather sensors and then installed on taxis running inside Daegu city (Fig. 3). The 1-minute interval data from sensors of all running taxis are collected and stored in a MySQL database [8,10].

As the collected sensor data is in large-scale, we use Apache Spark (Spark), a big-data computing engine and Apache Zeppelin (Zeppelin), a web-based notebook to pre-process and visualize raw data [13,14]. The procedure is as follows:

- The original dataset is exported to CSV format (e.g. MySQL database has CSV export option to CSV file).
• The CSV files are imported to Spark and stored in memory for next processes. Spark can infer the header information and schema (data types) of the CSV file.

• Thanks to Spark, data is now cached into main memory as a Data Frame (a table-like data structure) and we can use many of Spark functions to clean, filter unused columns or rows, aggregate (group by, sum, average, min, max, ...), add more columns or transform data to appropriate format. We already submitted our work onto GitHub [15] for your reference.

• To have more internal insights of the data, we use Zeppelin charts to show historical trends and parameters correlation (Fig. 4).

To see the spatial distribution of the air pollution values, we split Daegu map into a grid of 32x32 or 1024 cells (the grid size can be chosen flexibly but we think it should not smaller than 1 km in real map size for both edges). After that, we sequentially aggregate by grid and by hour as in Algorithm 1.

Algorithm 1. Split sensor data by grid and aggregate pollution values by grid-cell and time interval (using Spark framework)

1. Find the coordinates of the rectangle covering the city map.
2. Calculate the step size in latitude and longitude.
3. With the original data frame structure, add 1 more column of grid index and 1 column of time interval (1-hour time interval).
4. Use Spark aggregation function to group pollution values by grid index and by time interval.

As in Fig. 1, we represent the distributed pollutant values as a gray-scale image. The point is brighter, the air at that point (region) is more polluted and vice versa. This observation inspires us to use a CNN algorithm to predict air pollution values to be one of some states such as Good (for health), Moderate or Unhealthy. CNN is a well-known Deep learning algorithm that has many succeed in computer vision problems such as Image classification, Object detection, Image segmentation, ... In the Daegu city case, we want to use CNN to predict the image-like pollution distribution by real-time (precisely, 1-minute interval).

At first, we need to get the true labels for training. To achieve this, we considered the hourly monitoring air pollution values from Korea Environment Corporation (한국환경공단) website as true labels [9]. As the data are collected from 13 monitoring stations inside Daegu, we will simply average all monitoring values into 1 target value. This value is then compared to the air quality threshold to get the true labels: Good (value ≤ 15), Moderate (15 < value ≤ 35), Unhealthy (35 < value ≤ 75) or Hazardous (value > 75) [9]. The proposal CNN architecture as in Fig. 5. We use 2 Convolutional layers (Conv) with ‘SAME’ padding and max-pooling is 2 and 2 Fully Connected layers (FC) before using a Soft-max layer to make the output. The loss function is a cross entropy loss:

$$H(y, \hat{y}) = - \sum_i y_i \log \frac{1}{\hat{y}_i} = - \sum_i y_i \log \hat{y}_i$$

with y = output of the CNN network, \(\hat{y}\) = true label. In the next section, we will show how to train this CNN and discuss some experimental results on Daegu real-time sensor dataset.

B. The hybrid model of LSTM and Neural Network to evaluate the relationship of weather factor to future air pollution prediction model

The air pollution values are time series data. Recently, one of the most successful approaches to predict time series data is using Recurrent Neural Network (RNN) or a special and more successful of RNN is LSTM because of its capability to remember longer past sequences [4]. Similarly, we also use an LSTM in making a prediction model for air pollution values in some time period ahead (e.g. 8/12/24 hours). The LSTM model we used was quite common. We aggregated air pollution
values by hour and considered each hourly value as a point in the time series sequence. The formulas for an LSTM unit as follows [4]:

\[ f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \]
\[ i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \]
\[ o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \]
\[ c_t = f_t \odot c_{t-1} + i_t \odot \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \]
\[ h_t = o_t \odot \sigma_h(c_t) \]

\( x_t \) is the input vector to the LSTM unit and it is often called the time step. In here, we choose the time step is 24, 48 or higher. We can hope that if the time step is longer, the LSTM can remember more historical sequences and can predict future values better. The parameters of the LSTM unit can be initialized and learned easily if we use a Deep learning framework that supports LSTM model such as Tensorflow, Theano, Keras, ... The only hyper-parameter we need to consider is the number of LSTM unit for training process. In this case, we tried some values of LSTM unit in the range from 128 to 512. In section IV, we will present experiments with these hyper-parameters.

The future air pollution values not only depend on the earlier data but also on current local factors such as weather. For example, the PM2.5 value is affected somewhat by weather factors as well as temperature, humidity, ... To evaluate this coupling, we propose a Neural Network (NN) combined with previously described LSTM model. The NN will try to capture the influence of weather factors and merge with the output of LSTM model by an appropriate weight (chosen by cross-validation). The model is below:

![Combination model](image)

The formula for this combination model as below:

\[ y = \alpha \ast y_{\text{lstm}} + (1 - \alpha) \ast (x \ast w + b) \]  \hspace{1cm} (1)

with \( y \) is the final output, \( y_{\text{lstm}} \) is the output of the LSTM unit, \( x, w, b \) is the input, weight, and bias of the NN model, \( \alpha \) is the combined weight, \( 0 \leq \alpha \leq 1 \). In the experiment section, we will show how different values of this weight reflect the affection of weather conditions to air pollution prediction.

### IV. EXPERIMENTS AND EVALUATION

#### A. CNN for predicting air pollution values in real-time

As previously described, we propose a CNN model for image-like grid-based distribution of air pollution in real-time in Daegu city. The output is to predict air pollution in 1 of 4 states: Good (0), Moderate (1), Unhealthy (2) and Hazardous (3). We use the training set is the data of sensor values in 4 months, from 09/2017 to 12/2017 and the testing set is the data of month 01/2018. In the training phase, we split the training set into training and validation set with the ratio of 0.9. All values are normalized to the range 0-1. The network is built by Tensorflow deep learning framework [12] and trained for 100 epochs with a batch size of 64 and using Adam for gradient optimizing. We got the testing accuracy approximate 74%. Table I below shows the parameters of the CNN training and testing set while Fig. 7 displays the graph of loss value decreasing during the training phase. We also tried with a CNN model similar to MNIST model in Tensorflow guide website ([https://www.tensorflow.org/tutorials/layers](https://www.tensorflow.org/tutorials/layers)) and got the same result as our proposal. It states that the prediction accuracy does not depend much on the CNN model architecture. We will explain for this accuracy in some next few lines.

| TABLE I. CNN MODEL PARAMETERS |
|-----------------------------|
| **Training set**            |
| Size                        | (2875, 32, 32, 1)        |
| #Samples in Good pollution  | 1055                      |
| #Samples in Moderate pollution | 1199                    |
| #Samples in Unhealthy pollution | 616                  |
| #Samples in Hazardous pollution | 5                     |
| **Testing set**             |
| Size                        | (404, 32, 32, 1)         |
| #Samples in Good pollution  | 55                       |
| #Samples in Moderate pollution | 222                    |
| #Samples in Unhealthy pollution | 117                   |
| #Samples in Hazardous pollution | 10                  |
For **real-time air pollution prediction**, one can aggregate data in e.g. 1 minute each but with the interval fixed at 1 hour to get 1-hour data slice. Then we can apply the proposed CNN model to this new 1-hour aggregated data and got prediction value in 1 of 4 states. Fig. 8 shows some of our results on the testing data.

![Graph of loss value](image)

**Fig. 7.** Graph of loss value for CNN training phase.

The accuracy for prediction (~74%) is not very high because of the following reasons:

1. The data is not very big with just 4 months of data samples. We need maybe 1 to 2 years of data to cover all time interval of air pollution values.

2. The testing set is in quite different distribution than the training set (see Table 1 when we showed the distribution in #Samples in each pollution types) because the air pollution can depend on the seasons and months of a year.

3. The image size is just 32x32 which could be quite small for a CNN model to find valuable patterns. However, if we increase the grid size then the real-time samples for each grid cell may be too small to be a good representation.

4. The taxi running paths could be too bias to some popular areas such as the airport, downtown, ... or bias to some common hours. This makes the grid may not reflect accurately the air pollution of the whole city.

**B. The hybrid model of LSTM and Neural Network (NN)**

We also use Tensorflow framework [11] to build a hybrid model of LSTM units and NN model (weather conditions model). The training data is Daegu air pollution sensor data from 09/2017 to 01/2018 with 4 months (09~12/2017) as the training set and 1 month of 01/2018 as testing set.

Recently, Recurrent Neural Network (RNN) and LSTM model begin to be used to predict time series air pollution values [12]. To evaluate our hybrid model with other related works, we make a standalone RNN model, a standalone LSTM model and compare with our hybrid model. The evaluation metric is relative mean absolute error (RMAE):

\[
\text{error} = (1/m) \times \sum [(y - \hat{y})/y]
\]

with \( m \) is number of evaluated examples, \( y \) is real air pollution value and \( \hat{y} \) is prediction pollution value.

Since our hybrid model is the combination of an LSTM model and an NN model with a weighted parameter value \( \alpha (0 < \alpha < 1) \), we will change the \( \alpha \) value between 0.0 and 1.0 and compare the validation error of some baseline models and other weighted models corresponding to each \( \alpha \). The results are shown in Table 1 as follows.

**TABLE II.** VALIDATION ERROR OF BASELINE MODELS AND OUR HYBRID MODEL WITH DIFFERENT \( \alpha \)

| \( \alpha \) | Standalone RNN model | Standalone LSTM model | RNN + NN model | Hybrid model (LSTM + NN) |
|-----------|-------------------|---------------------|---------------|-------------------------|
| 1.0       | 5.010952          | 5.775150            | 5.010952      | 5.775150               |
| 0.9       | 5.207657          | 5.775150            | 5.54787       | 4.656111               |
| 0.8       | 4.574787          | 5.775150            | 4.880526      | 4.895847               |
| 0.7       | 6.302503          | 5.775150            | 4.946835      | 4.705889               |
| 0.6       | 4.946835          | 5.775150            | 4.837472      | 4.257993               |
| 0.5       | 4.837472          | 5.775150            | 4.265581      | 5.341873               |
| 0.4       | 4.265581          | 5.775150            | 6.811509      | 7.887727               |
| 0.3       | 6.811509          | 5.775150            | 5.673909      | 4.966643               |
| 0.2       | 5.673909          | 5.775150            | 5.198360      | 4.546102               |
| 0.1       | 5.198360          | 5.775150            | 6.597609      | 6.476847               |
| 0.0       | 6.597609          | 5.775150            | 6.476847      | 5.775150               |

As in Table II, when \( \alpha = 1.0 \) we will have a standalone RNN or LSTM model for predict time series data, and with \( \alpha = 0.0 \), we have a standalone NN model for only weather condition factors. A smaller error indicates a better model (shown in **bold**).

We can infer from Table II that, a standalone RNN model may be better than a standalone LSTM because its validation error is smaller. However, the number of smaller validation errors of Hybrid model (LSTM+NN) is more than that of RNN+NN model for 11 values of \( \alpha \) from 0.0 to 1.0 (7/11 smaller validation errors compare to 4/11). That means the combination of an LSTM model and an NN model is better than RNN + NN model. We think it is because of an LSTM unit could represent long time series better than an RNN.
Also, as in Table II experiment results, we could state that a combination of a time series model (RNN or LSTM) with an NN model is better than a standalone RNN or LSTM only because the validation errors of the combination model is smaller than a standalone model (see with $\alpha$ is 0.1, 0.2, 0.5–0.9).

V. CONCLUSION

In this paper, we introduced a real-time air pollution sensor data collected in a big city in Korea. The data is massive and in both spatial and temporal format. For spatial distribution air pollution, we proposed to consider the whole city as a grayscale image and applied a CNN model for real-time predicting air pollution values. For temporal information, we present a simple but efficient combination of an LSTM for time series data and a Neural Network model for other impact factors. We think this is just a beginning for the research of real-time air pollution sensor data. The researchers have the plan to extend this project to more cities of Korea and we will also have much bigger real-time data. In the future, we will try to find more accurate prediction models and be able to predict air pollution values for any points of interest in the monitoring city. We will also compare the prediction model based on this real-time sensor dataset to other hourly collected air pollution datasets of other cities in Korea and in the world.

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