Air Quality Forecasting Using Deep Learning Framework

Apurva Sharma [1], Sakshi Mahadik [2], Priya Pawar [2], Komal Rayrikar [2], Siddhi Argade [2]

[1] *Assistant Professor, Department of Computer Engineering, Savitribai Phule Pune University, Pune, India.*

[2]*Student, Zeal College of Engineering and Research (ZCOER), Pune, Maharashtra, India.*

Corresponding Author: priyapawar1377@gmail.com

Abstract: - Air pollution represents an issue that raises many concerns nowadays, as it has various negative effects on the environment and the economy worldwide. Because of the rapid urbanization, cities are suffering from polluted air, so it is important to predict future air quality. For this purpose, new applications of artificial intelligence should be employed. In this paper, we will present several Machine Learning algorithms, the possible software that can be used for them and the applications used in the field of air quality. Based on the research in the field, we propose CNN and LSTM, Machine Learning models, which can be used to predict air pollution. These algorithms have been tested using time-series for PM_{10} and $PM_{2.5}$ particles. The results showed that and algorithms are the most suitable in forecasting air pollutant concentrations.

Key Words: ***Machine Learning, Air Pollution, Forecasting, Time Series.***

I. Introduction

With the acceleration of industrialization and the rapid development of urbanization, the problem of urban air pollution has become more and more serious. Which has badly affected our living environment and physical health. Therefore, research on air quality forecasting is very important and has always been regarded as a key issue in environmental protection. Deep learning is currently the most popular data driven method, which can extract and learn the inherent features of various air quality data automatically Air pollution is an issue that concerns a lot of people nowadays and has a significant influence on human health worldwide. It has a great impact on human well-being, the environment and the economic advancement around the world. Recent studies have shown that in 2015, 6.5 million premature deaths worldwide were caused by air pollution.

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Its impact on health depends on the concentration of the pollutant and the exposure levels. Particulate Matter (PM) represents one of the most important pollutants in regard to the effects on health. Among the best-known PMs are the PM_{10} (PM with a diameter lower than 10 m) and $PM_{2.5}$ (PM with a diameter lower than 2.5 m). Even in small concentrations, these PMs can have many adverse effects on human health. Besides the type of pollutant and its concentration, the duration and the frequency of the exposure are also important factors in the negative impact on human's well-being Considering that traditional air quality prediction methods require more computational power for the estimation of pollutant concentration, many people are trying to apply Artificial Intelligence (AI) algorithms (machine learning, deep learning), which can lead to better results. There is an increased interest in the machine learning methods for forecasting nonlinear time series information, such as meteorological and pollution data. Machine Learning (ML) is a data technique which teaches a computer to create a model using training data. It is a subfield of artificial intelligence and enables software applications to be increasingly precise in predicting results. ML can review a wide range of data and discover patterns and specific trends.

II. Related Work

2.1 System Architecture

This architecture shows how CNN & LSTM models works. First provide the dataset then next step is data pre-processing which convert raw data into suitable form. After that models train and test data and predict the air quality forecasting and result shows the number of pollutants present in air.

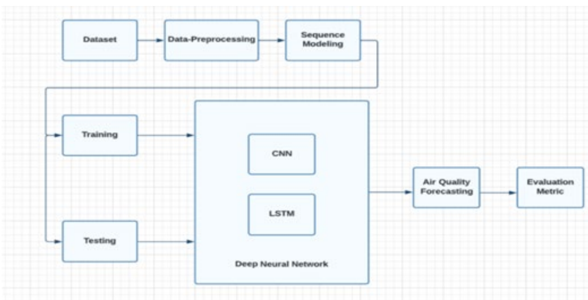

Fig.1. System Architecture

2.2 Deep learning models

In this work, our goal is to investigate the performances of several deep learning models to forecast the concentration of PM2.5. Thus, we decided to use the LSTM, Bi-LSTM, CNN, CNN-LSTM previously mentioned. Next, we briefly describe each network:

2.3 LSTM

LSTM is a type of recurrent neural network (RNN) that was developed in 1980 [39, 40]. RNNs are a powerful type of artificial neural network and are most likely used for time-series forecasting problems. RNN can internally maintain memory to remember things from past occurrences that can predict future events. However, RNNs frequently suffer from vanishing and exploding gradients, which leads the model learning to become too slow or stopped altogether. LSTMs were created in 1997 [41] to solve these problems.

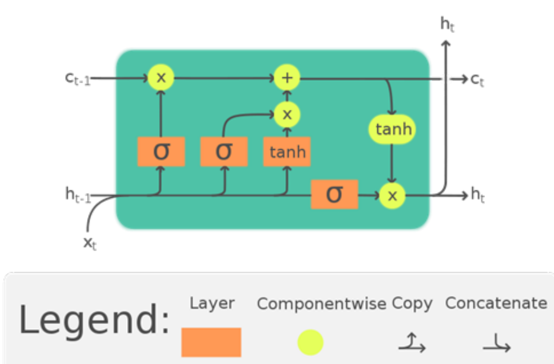

Fig.2. Architecture of LSTM Cell

In order to overcome shortcoming, Long Short-term Memory network (LSTM) is a good option, which is a popular dynamic model for handling sequence tasks. The memory cell of each LSTM block contains four main components. The collaboration of these components enables cells to learn and memory long dependency features. Bidirectional LSTM can process the time series data in two directions simultaneously through two independent hidden layers and these data are concatenated and fed forward to the output layer.

2.4 Bi-LSTM

Standard RNN and LSTM often ignore future information in time-processing, while Bi-LSTM can take advantage of future information. The basic structural idea of Bi-LSTM is that the front and back layers of each training sequence are two LSTM networks, respectively. Moreover, the LSTM networks are both connected to one input and one output layer. The output layer can obtain past information of each point from the input sequence and get future information from each point through this structure. In order to overcome shortcoming, Long Short-term Memory network (LSTM) is a good option, which is a popular dynamic model for handling sequence tasks. The memory cell of each LSTM block contains four main components. The collaboration of these components enables cells to learn and memory long dependency features.

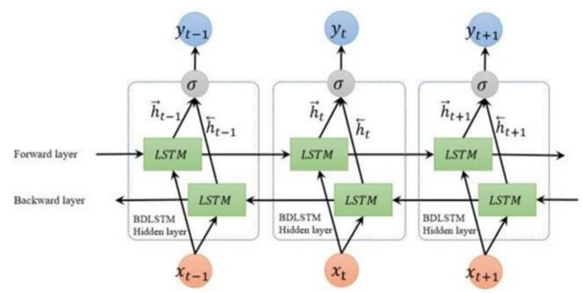

Fig.3. Architecture of Bidirectional LSTM

2.5 CNN

CNN has been successfully applied to computer vision and medical image analysis. Moreover, in this paper auteurs proposes a multiscale fully convolutional neural network (MFCN) for change detection in high-resolution remote sensing images. In our model, the convolutional layers are constructed using one dimensional kernels that move through the sequence (unlike images where 2D convolutions are utilized). These kernels act as filters that are learned during training. As in many CNN architectures, the deeper the layers get, the higher the number of filters. CNN not only has excellent performance in image processing, but also can be effectively applied on time series data mining. A typical CNN has three layers: convolutional layer, activation layer, and pooling layer. Unlike the classical CNN model (also traditional two-dimensional CNN used for images), we propose to use multiple one-dimensional filters convolved (ID-CNNs) over all time steps of air quality time series data.

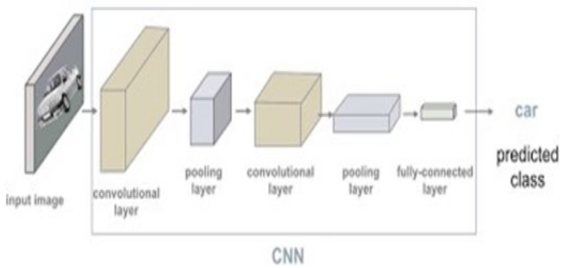

Fig.4. Architecture of CNN

2.6 CNN-LSTM

The use of classical CNN architecture is the best choice when input networks are 2-D or 3-D tensors like images or videos. Since LSTMs architectures are more adapted for 1-D Data, a new variant of LSTM called Convolutional LSTM or ConvLSTM has been designed. In this architecture, the LSTM cell, which contains a convolution operation and input dimension of data, is kept in the output layer instead of just a 1-D vector. A convolution operation replaces matrix multiplication at each gate of classical LSTM. We can say that Conv-LSTM architecture merges the capabilities of CNN and LSTM Network. Another approach to working with Spatio-temporal data is to combine CNN and LSTM layers, one block after another. Such architecture is called Convolutional-LSTM (CNN-LSTM) and was initially named Long-term Recurrent Convolutional Network or LRCN model. In the first part of this model, convolutional layers extract essential features of input data, and the results are fattened in a 1D tensor so that they can be used as input for the second part of the model (LSTM).

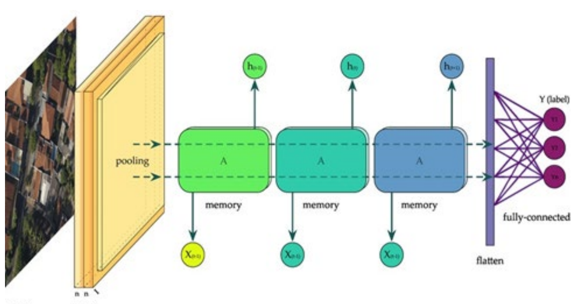

Fig.5. Architecture Of CNN-LSTM

III. RESULT

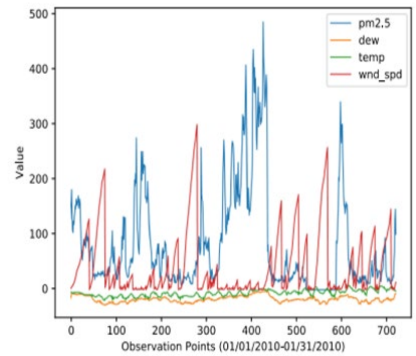

Fig.6. Air quality related time series data in one month (01/01/2010-01/ 31/2010) (include PM2.5 pollution concentration, temperature, pressure, wind speed, wind direction, snow, rain, etc.) of Beijing PM2.5 data set from UCI [31]

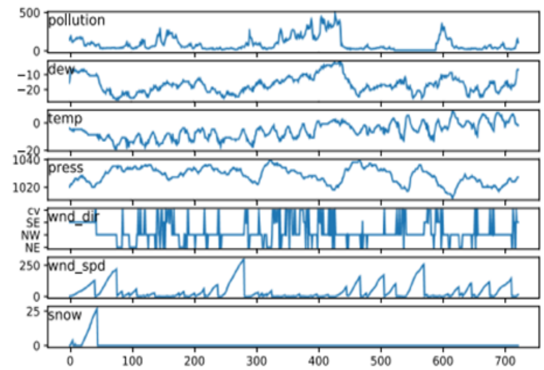

Fig.7. The interdependences and correlations of multivariate air quality time series data (such as PM2.5, dew point, temperature, wind speed, etc.)

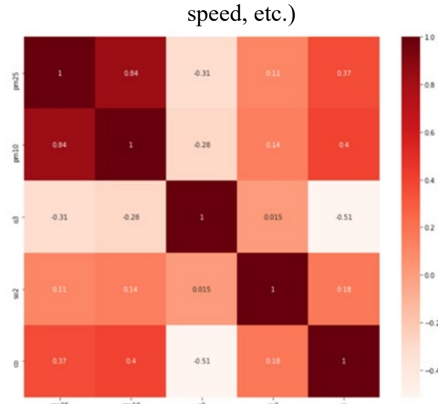

Fig.8. Heatmap

IV. CONCLUSION

This Study will include the New Air Quality Forecasting Framework which will discuss about CNN BI-LSTM levels for PM2.5 single step forward and multi-Step forward Prediction, which is based on Hybrid Deep Learning Model. It demonstrates the Effectiveness of the model and helps to forecast about the contents in the Air to Predict the Air Quality and discusses about the Approach and the applications of Deep Learning with Neural Networks. A new hybrid deep learning framework which can deal with hierarchical feature representation and multi-scale spatial temporal dependency fusion learning in an end-to-end process for air quality forecasting. This study was the first attempt to combine multiple one-dimensional CNNs and bi-directional LSTM for hybrid fusion learning of air quality related multivariate time series data, which can extract spatial-temporal dependency and correlation features for air quality multi-step forecasting modelling.

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