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Application of machine learning and time-series analysis for air pollution prediction

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***Abstract*—Medical research studies show that low air quality can have a direct effect on the increased number of diseases, especially respiratory defects, but also on the increased mortality rate in people. Luckily, harmful particles and substances in the air can easily be detected and measured by using affordable sensors. The number of this type of sensors deployed in the city of Skopje, Macedonia continuously grows. The increased coverage of monitored regions, and the elevated public interest in solving this problem for obvious reasons, make the prediction of high levels of air pollution extremely beneficial. According to the available historical data, the problem of low air quality is proving to be more serious during the winter, that is during the heating season. If weather forecast is available, there is an opportunity to predict the air quality. This work reviews recent advances in air quality predictions using time-series analysis techniques, machine learning and deep learning. We proposes and evaluate two approaches for air quality prediction: combination of LSTM and convolutional neural networks and one-dimensional convolutional neural networks. The results show a promising accuracy of about 78% in predicting the level of air pollution.**

***Index Terms*—air pollution, prediction systems, deep learning, time-series analysis**

I. Introduction

After several key scientific man-made discoveries in the first half of the eighteenth century, a period of industrialization followed. Apart from the technological advances associated with this time, the period of the industrial revolution is also known as the first wave of global aero-pollution caused by man himself [1]. Except for the increased mortality rate to serve as an indicator, the instruments that were at mans disposal were not progressive enough to be able to determine the presence of pollutants, or measure their quantity in the air. Since then, the problem with pollution has only gotten worse.

After several key scientific man-made discoveries in the first half of the eighteenth century, a period of industrialization followed. Apart from the technological advances associated with this time, the period of the industrial revolution is also known as the first wave of global aero-pollution caused by man himself [1]. Except for the increased mortality rate to serve as an indicator, the instruments that were at mans disposal were not progressive enough to be able to determine the presence of pollutants, or measure their quantity in the air. Since then, the problem with pollution has only gotten worse.

As the human population rises, the need for food, clothing, medicine, as well as many other materials and goods consequently grows. This dependence has a direct impact over the reduced storage capacity of warehouses and garbage dumps. In order to cope with the increased demand for goods, the industrial facilities are always up and running. Factories, furnaces, mines, smelters, waste disposal units and similar plants that do not have appropriate filters installed, release a significant amount of particles and gases which may pose a threat to humans health. In addition, densely populated areas and cities are always accompanied by a vast number of vehicles, as well as a high percentage of housings that use non-ecological energetic resources as a fuel for heating. These also play a major role in the air pollution of the inhabited areas. Medical research studies show that low air quality can have a direct effect on the increased number of diseases, especially respiratory defects, but also over the increased mortality rate in humans [2], [3]. At the same time, this global issue indirectly impacts the economy in a negative manner [4].

The number of installed sensors able to detect harmful particles and substances continuously grows in the city of Skopje, Macedonia. Thanks to this increased coverage of monitored regions, as well as the few mobile and web applications which citizens use to keep up with the status of the air quality, the topic of air pollution has been drastically actualized in the last few years [5]. The geological characteristics of the city of Skopje, Macedonia, which is situated in a valley, influence the meteorological conditions in a way that they prevent the movement of air in periods with zephyr or no wind at all. According to the available historical data, the problem of low air quality is proving to be more serious during the winter, that is during the heating season [6]. Most of the sensors that are spread throughout Skopje, are capable of detecting the presence of PM10 and PM2.5 particles, as well as the presence of $NO2$, CO, $O3$, and $SO2$ gases. These types of particles and substances are most commonly present in the air, and are identified as damaging to human health.

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It is a fact that the level of pollution depends on the present weather conditions that can be predicted using firmly established scientific methods that are constantly being improved by meteorologists and scientists of related scientific fields. Therefore, there is an opportunity to design and build an air quality prediction model, with the help of air quality historical data and the results from measurements of meteorological parameters and weather phenomena for the same time period. The meteorological parameters that are monitored and recorded by the National Hydrometeorological Service of Macedonia are: precipitation, air temperature, relative humidity, air pressure, direction and speed of wind. At the same time, changes in weather phenomena are also recorded, which may be: sunshine, cloudiness, fog, rain, hail or frost.

In addition to the dependency of air quality on weather conditions, another key characteristic is that all these data records are marked with a timestamp, or time interval. This greatly helps in data fusion of the two types of records. Furthermore, it can facilitate air quality prediction, provided that the weather forecast for the future period is known.

If the authorities in charge have relevant information of this type a few days in advance, they would have enough time to plan and enforce appropriate actions. This plan may include increased level of control over the industrial capacities or even a temporary work halt, more frequent public transport timetables, or timely alert so that the citizens can be prepared accordingly for the upcoming period [7]. Such measures would have a significant effect on those groups of citizens who are most affected by the decline in air quality, such as infants, senior citizens and those people with chronic respiratory diseases. Furthermore, the social network impact on the involvement of the authorities in charge is quite significant [8] and for the case of Skopje is one of the main channels for increasing awareness of the problem.

One of the goals of this research is to analyze several existing prediction models and to compare the level of success of their application in prediction of data that belongs to the domain being studied, such as seismic events prediction [9], [10]. Another aim is to build an architecture model that incorporates several already established prediction models, which should be able to make accurate air quality predictions based on the corresponding meteorological input data.

This rest of this paper is organized as follows: section II provides an introduction to prediction systems for data series and reviews other relevant approaches. Next, section III describes the methods including the analyzed architecture and section IV describes obtained results. Finally, section V concludes the paper and provides directions for future research.

II. Prediction Systems for Data Series

In some of the research studies done so far, analyzes on similar fields have been conducted already [6], [11]–[14]. Namely, due to the complex nature of the relationship between the meteorological and air quality data, the nonlinearity of the modeling approach is inevitable. Therefore, neural networks come in handy for solving this type of problem [6], [11]. The expectancy of the time-series data used in this survey is that the time interval between any two measurements is nearly a constant value [15], [16]. The task of the model will be to learn to detect similar patterns in the series of data, and to classify them, such as predicting dangerous methane concentration in mines [17]. The work done so far on similar topics involves prediction models based on LSTM neural networks, convolutional neural networks, deep learning algorithms, as well as other methods based on feature extraction and classical machine learning algorithms. The work presented in [18] proposes using histogram-based features calculated from the time-series. Such features are easily interpretable, computationally efficient, but also very robust and possibly useful for the prediction of air pollution. The methods presented in [19], [20] facilitate automation of the process of feature extraction and selection from arbitrary time-series data, and could be useful to come up with lightweight and powerful models with the least possible sensors.

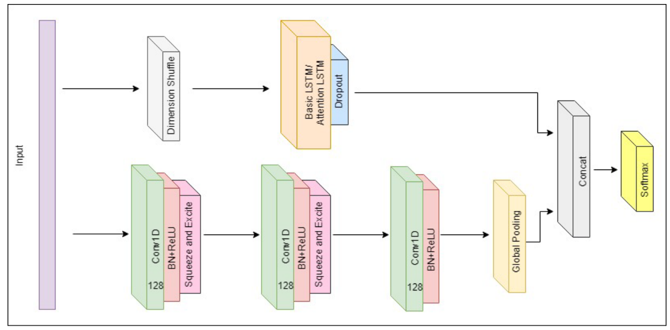

Fig. 1. MLSTM-FCN Architecture. Source: [14].

One of the proposed models in [14] consists of a fully convolutional section constituted of temporal convolutional layers used as feature extractors, in pair with a LSTM section that process the multivariate time-series input, which initially is dimensionally adjusted to enhance performance. The graphic representation of the model is shown in Fig. 1.

III. Methods

A. Air Pollution Prediction Architectures

This research contains an analysis of the performance and effectiveness of the Long Short-Term Memory (LSTM) neural networks, as a recurrent neural network type suitable for solving this type of prediction problems [21], [22]. The difference between recurrent neural networks and regular feed-forward networks is the concept of time. This concept is introduced by feeding the output of a hidden layer back into itself. The problem with basic recurrent neural networks is that back-propagation gradients for maintaining long-distance connections tend to either vanish or accumulate and explode. Owing to the properties of the architecture, LSTM networks tackle this problem, which causes dissipation of the sensitivity of older input data [23], [24]. The main building block of a LSTM network is the LSTM cell, see Fig. 2. The cell

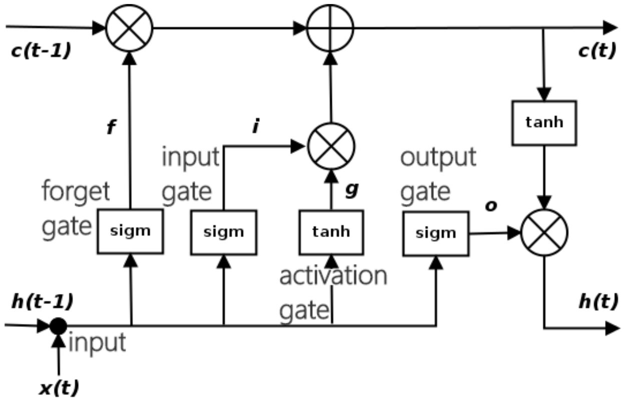

Fig. 2. A single LSTM cell.

maintains an internal memory state over time, backed up by non-linear gates that control the data flow in and out of the cell [25].

This structure facilitates the diminishing effect of the multiplication of tiny gradient values. This is done by first, squashing the input value with a tanh activation function, see 1. The U^g is the weight for the input, V^g is the weight of the previous cell output, and b^g is the input bias. The element x_t is the actual input, and h_{t-1} is the output of the hidden layer.

$$g = tanh(b^g + x_t U^g + h_{t1} V^g) \tag{1}$$

On the new value, element-wise multiplication by the output of the input gate is performed. This acts as an input filter, see 2.

$$i = \sigma(b^i + x_t U^i + h_{t1} V^i) \tag{2}$$

Another specific mechanism that's part of this cell, i.e. the forget gate is responsible for regulating which state is to be forgotten, or memorized, see 3.

$$f = \sigma(b^f + x_t U^f + h_{t1} V^f) \tag{3}$$

The internal state of the cell is named as c_t, see Fig. 4 and it is used to provide a recurrence loop for learning dependencies between time-separated inputs. The output of the forget gate actually determines which previous states should be remembered based on c_{t-1}.

$$c_t = c_{t-1} \circ f + g \circ i \tag{4}$$

The final step of this cell is the output gate, which is expressed in the first part of 5, 6, where the final output value is the second part.

$$o = \sigma(b^o + x_t U^o + h_{t-1} V^o) \tag{5}$$

$$ht = tanh(c_t) \circ o \tag{6}$$

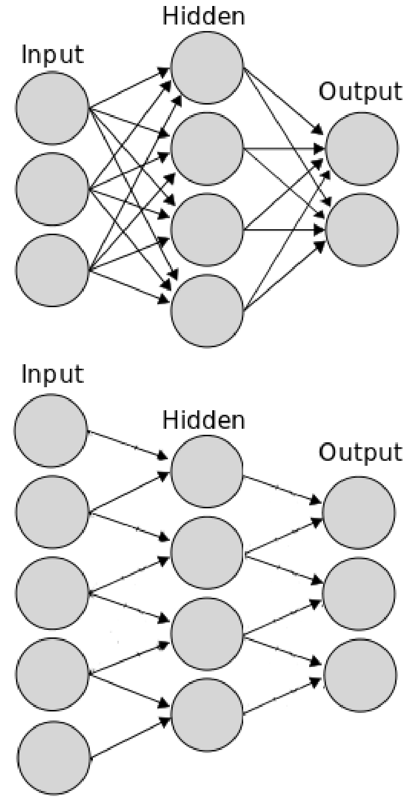

Fig. 3. Fully connected neural network vs. convolutional neural network with filter size [1,2].

In addition to this network type, we also examine the applicability of convolutional neural networks in the aforementioned domain. This type of neural networks have so far proven to be suitable for dealing with classification tasks which most often involve image recognition. However, this neural network model has also made a breakthrough in solving time-series classification or forecasting problems gross2017predicting, wang2017time. A convolutional neural network is comprised of sequential convolutional layers. Each of these layers is associated only to a single, sub-region of the input, i.e. it represents a convolution between the input and a sliding filter at a certain point, see Fig. 3. The filter is a weight matrix. The core idea behind employing this neural network architecture relies on the capability of the base model to learn filters that are adept in detecting specific patterns present in the input. Consequently, these filters can be used in forecasting future values. Standard convolutional networks contain an activation layer, which is useful for transforming the input into a non-linear value, which allows for learning more complex models. In this paper, one of the activation functions we will use is the sigmoid function, see Fig. 4. An interesting feature of these neural networks is that they are capable to process raw sensor information while generating structured data that may contain the key domain specific properties, and can be used in the process of training the model [26], [27]. This is a result of a structural characteristic, i.e separate channels, one for each

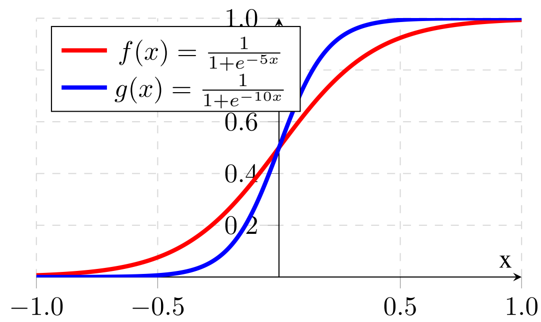

Fig. 4. Sigmoid Activation Function.

key feature. Another positive trait is the possibility to process complex multivariate data [28].

The aim of the research is to achieve a stable model that will reliably generate predictions for air quality based on weather forecast information. In this paper, several approaches for modeling an air quality prediction system will be presented.

B. Evaluated models

The first neural network model that was evaluated is a general model for classification. The results from this evaluation can used for benchmarking and comparison of future models. The key notion supporting this approach is tightly coupled with the nature of convolutional neural networks. Namely, it would be interesting to analyze the applicability of 2-dimensional convolutional layering in the domain of air quality data classification.

The measurements records are scarce at some points, meaning that the distance between two subsequent measurements may be larger than the usual, but the data shows that every measurement contains measurement entries for at least eight continuous hours. This circumstance can be exploited in a constructive manner, i.e. since every eight hour data sequence can be perceived as an image, thus can be used for classification during training. Each image represents a table, or a matrix with 8 rows, and 16 columns of data. Four of these columns contain pollution measurement values, which can be used to produce label sequences required for the supervised fragment of the training task. Every image can be associated with 4 different labels. Each label belongs to one of the four pollution-data columns and is calculated by using a simple categorical activation function, the output of which signals the level of pollution. The model contains two convolutional layers, each characterized by feature maps, and down-sampling sub-layer, see Fig. 5.

C. Data Description

The dataset consists of pollution and meteorological data from the area around and in Skopje, Republic of Macedonia. We took into consideration all of the meteorological and pollution measurement stations. In order to generate data without missing values, we added only the sensors that had

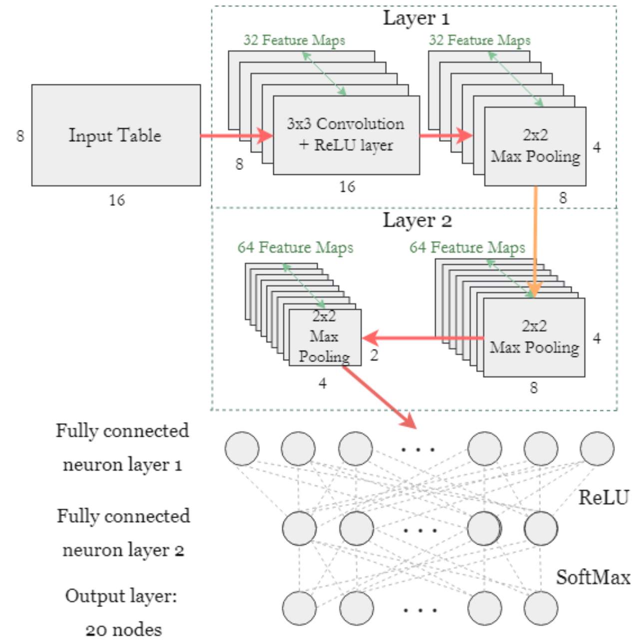

Fig. 5. Neural Network model composed of 2 Convolutional Layers, each with feature maps and sub-sampling.

enough samples measured in continuous intervals of 9 hours. By doing this we obtained data from 21 sensors. Each sample of the data contains measurements for 8 continuous hours and the ninth hour measurements are taken as labels.

D. Prediction Approach

One of the planned approaches involves combination of LSTM and Convolutional neural networks. The main idea behind applying convolutional neural networks is that multivariate time-series can can be viewed as a sequence of space-time images, which is an area where these networks excel. The STaR architecture proposed in [29] builds on this idea as shown in Fig. 10. In the STaR network, a hybrid network model is formed by combining RNN and CNN, streaming a copy of the input to each and concatenating the outputs in the end. Different filters are used on the same input in order to extract and learn different feature representations [29]. In contrast, the effectiveness of the sole LSTM based model shall also be analyzed, in terms of prediction of future values based on the previous N sequential measurement records.

Another method that will be examined is the appliance of one-dimensional convolutional neural networks. The expectation is that this network type is capable of learning how to predict future values based on meteorological and air quality time-series data. The reason for this expectancy is a result of the nature of the strong one-dimensional structure of time-series, which implies the high degree of correlation between spatially nearby variables, and this can be used to extract local features [30].

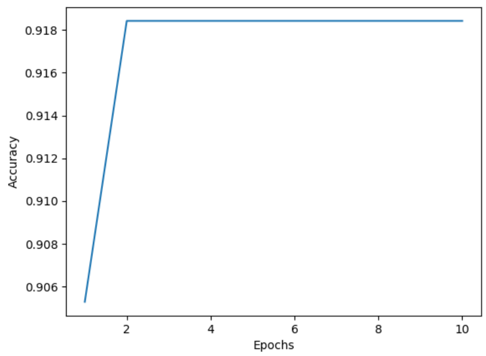

Fig. 6. Convolutional Neural Network model - 10 class labels - Results.

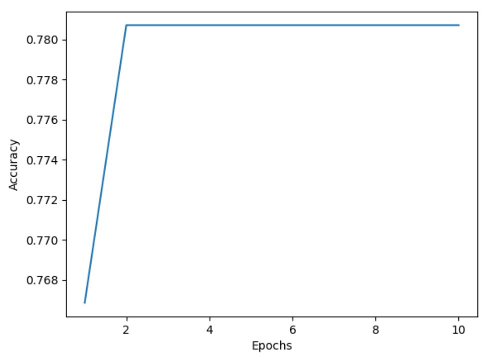

Fig. 7. Convolutional Neural Network model - 20 class labels - Results.

IV. Results

The analysis performed after the initial experiments, where the neural network model described in Section **??** is employed, yields somewhat promising results. The accuracy of the current model is highly dependent on the size of the class set that the pollution values belong to. The results from the first experiment with 20 classes are displayed on Fig. 7. The accuracy is around 78%, while on Fig. 6, a model with 10 classes shows increased accuracy of around 92%. In both cases, each class is a discrete interval of the air pollution. However, the dataset is highly imbalanced, i.e. a few classes are represented by a great number of examples, while the rest are represented by a few. To be more specific, in the scenario where 10 classes are used, the majority of examples (65% and 19%) belong to only 2 classes, and on the other hand the rest examples (16% of the total number) belong to 8 classes, see Fig. 8. In the other scenario, with 20 classes, the distribution is still imbalanced, where the most represented classes contribute with around 80% of the total number of examples, and the rest 17 classes are only represented by a 20% of the entries, see Fig. 9. This leads to the conclusion that the general classification accuracy is not the perfect fit for measuring the effectiveness of the model.

V. Conclusion and Future Work

In this work, we have presented recent advances in air quality predictions using time-series analysis techniques, machine learning and deep learning. We proposed a new architecture model for prediction based on the existing discussed frameworks.

The number of air-quality sensors deployed in the urban areas continuously grows. Combining the data from these sensors, with the weather forecast data, provides an opportunity to predict the air quality.

The paper proposes two approaches for air quality prediction: combination of LSTM and convolutional neural networks and one-dimensional convolutional neural networks.

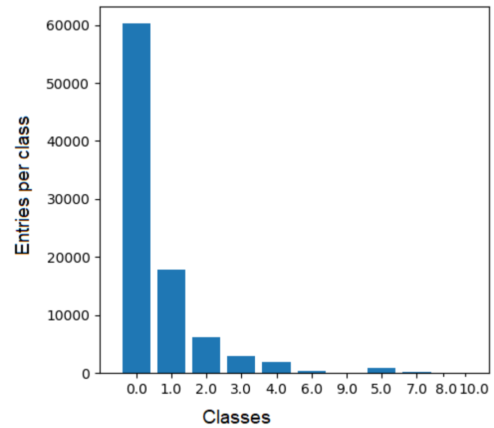

Fig. 8. Measurement entry value distribution by class, with a set of 10 classes.

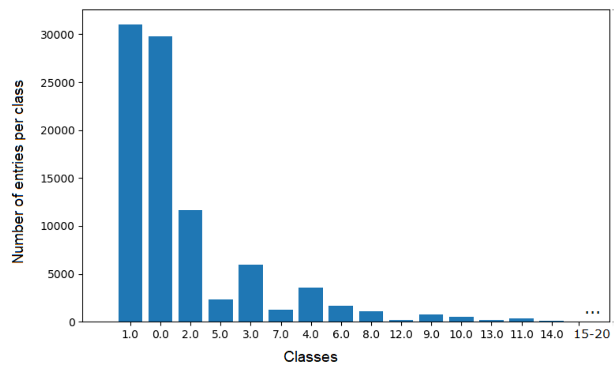

Fig. 9. Measurement entry value distribution by class, with a set of 20 classes.

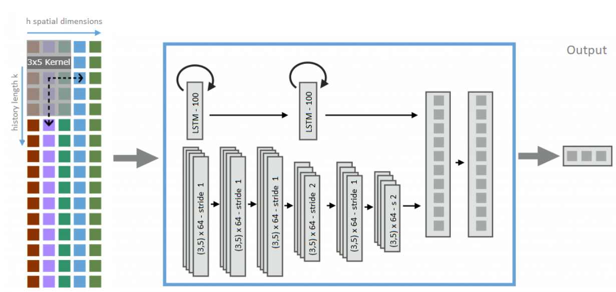

Fig. 10. The Space-Time Convolutional and Recurrent Neural Network (STaR) architecture. Related time-series are arranged in a space-time picture and fed to the input layer of STaR. Source: [29]].

The main idea behind applying convolutional neural networks is that multivariate time-series can can be viewed as a sequence of space-time images, which is an area where these networks excel. In LSTM based approach, LSTM model can be used for prediction of future values based on the previous N sequential measurement records. In one-dimensional convolutional neural networks approach, we rely on the strong one-dimensional structure of time-series, which implies the high correlation of spatially nearby variables, and this can be used to extract local features needed for prediction.

Our initial experiments show that both approaches produce promising results.

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