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Predicting air pollution in Almaty city using Deep Learning Techniques

*[1]Assel Nurlybayeva, [2]Ali Abd Almisreb, [3]Nooritawati Md Tahir

[1,2]Department of Computer Engineering and Information Security, International Information Technology University, Almaty, Kazakhstan
[3]College of Engineering Universiti Teknologi MARA Shah Alam, Selangor, Malaysia Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Universiti Teknologi MARA Selangor, Malaysia

**Corresponding Author*: nurlybayevaassel@gmail.com

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ABSTRACT: Nowadays, in the era of urbanization and the growth of the social welfare of the population, megacities such as Almaty suffers from environmental problems such as air pollution. Air pollution adversely affects people's health, which leads to various harmful diseases. By predicting Particle Matter 2.5 (PM2.5) according to data of pollution particles and physical parameters we will reveal the effectiveness of measures taken by local authorities to meet the standards of the safety threshold for living beings. The paper's main goal is to create a predictive model for particle matter 2.5 using a 3-layered sequential neural network model and gain the highest accuracy to simulate the continuation of the ecological situation in the city. The proposed model consists of four stages: data collection (from 6 stations), data pre-processing by treating missing values we deleted them and data normalization with function MinMaxScaller, building 3-layered sequential neural network and model evaluation using Mean squared error (MSE) metric, supported with a platform - Colab notebook and implemented using Python language. Based on experimental results, the forecast was defined as reliable - the strength of the model was proved using the MSE evaluation metric and equals 1e-5.

1. INTRODUCTION

Urbanization level in Almaty city is in first place among other cities of Kazakhstan, it displays rapid growth from 0.48 index till 0.72 for 1992-2018 years. (Huang et al., 2020). However, it also leads to the inclusion of Almaty into the list of cities with "high" levels of Air Pollution Index in 2019. (Assanov et al., 2020). Polluted city negatively affects live organisms, particularly humans, from a social perspective proven that it causes cardiovascular and respiratory diseases, found associations with diseases like diabetes, mumps, and epilepsy, on the economical side it has adversely impacted human well-being, productivity, and working hours. (Almetwally et al., 2020). To contribute to preventing the above issues, this paper focuses on studying the air pollution problem in Almaty using the TensorFlow predicting model to provide information on future ecological situations to the public, urban planners, and decision-makers. From 2010 to 2018, about 10 research works every year were conducted in forecasting and predicting ambient air pollution variables using artificial neural networks. (Cabaneros et al., 2019). The research declared in work Al-Janabi et al. (2020) created a smart air quality prediction model (SAQPM) using a recurrent neural network (RNN), long short-term memory (LSTM) model, and particle swarm optimization algorithm (PSO) to create a predictor for 6 pollution indicators for the next 2-days. Also, a hybrid model as a neural network and Nonlinear Auto-Regressive Moving Average with Exogenous

Input model was implemented to predict peak values of air pollution as particle matter 2.5 (pm 2.5) according to historical data of pm2.5 connected to data of weather and season (Gu et al., 2022). In the paper of Asha et al. (2022) authors built an Elman neural network (ANN) model based on the Artificial Algae Algorithm (AAA) to make classification of air quality in real-time using data of eight pollutants stored on a cloud server and warn people a case of permissible pollution threshold. A city-wide forecast of air pollution is a difficult issue to solve. The city's air pollution is caused by a variety of spatiotemporal causes. Spatiotemporal datasets from Seoul, Korea, were used in this study to examine the impacts of air pollution on the town. Weather and transport data and mean vehicle velocity and air pollution indices from outside locations are included in databases. With the Convolutional LSTM model, described in the research of Kim and Lee (2021), which is a mix of Convolutional Neural Networks and Long Short-Term Memory, data can be systematically changed in terms of both their spatial and temporal properties. Recent research in Vietnam used single-source data from the US Consulate to construct a daily averaged PM2.5 prediction model for HCM City (Min et al., 2021). However, a daily PM2.5 forecasting model does not give adequate temporal precision for city residents to plan their days ahead of time to mitigate the negative consequences of high air pollution times. Moreover, since PM2.5 levels vary across multiple locations such as transport, commercial, and domestic, a forecasting model for a single area is insufficient to describe the whole city. Work by Shang et al. (2019) proposed a forecasting model that combined the classification and regression tree (CART) methodology with the ensemble extreme learning machine (EELM). The CART technique was used to divide the datasets into divisions using a simple hierarchical tree. EEL models were built at each node of the tree using the node's training data to reduce validation mistakes. Finally, the EEL models for each route to a leaf are evaluated to the root of each leaf, with the shortest possible mistake pathway being chosen to verify the leaf. The CART–EELM strategy outperformed the random forest (RF), v-(SVR), and EELM models, as well as the EELM and k-means EELM seasonality models. Various machine learning models have been suggested for predicting air quality due to the tremendous expansion in data and computing technology. However, in underdeveloped nations, where polluted air is a major problem, the viability of such elaborate techniques has rarely been tested. Three machine learning algorithms were used to predict PM2.5 at various periods: multiple additive regression trees (MART), a deep feedforward neural network (DFNN), and a long short-term memory model (LSTM) in work by Karimian et al. (2019). The LSTM model produced better results as it was able to account for the time-dependent nature of the time series data. More than seventy-five percent of the observed pollutant emissions were forecasted using this strategy, which accounted for and described around eighty percent ($R2 = 0.8$) of PM2.5 variation (R2). Available research approaches have neglected to separate the spatiotemporal aspects of air pollutant concentration data efficiently, resulting in poor accuracy in long-term forecasts and rapid changes in air quality. In the research of Wen et al. (2019), a spatiotemporal convolutional long-term memory neural network extended (C-LSTME) model for forecasting air quality concentration was suggested. The approach included the historic PM2.5 of the current station, as well as that of the adaptable k-nearest nearby stations, into the model to cover the spatiality and temporality of the data. To increase model predictive accuracy, high-level spatiotemporal characteristics were retrieved using a mix of convolutional neural networks (CNN) and long-term memory neural networks (LSTM-NN), as well as climatic and particle data.

Motivated by the importance of works dedicated to air quality problems, the contributions of this paper are summarized as follows:

- check relationships between variables of air quality using Spearman's Correlation.
- normalize data using MinMaxScaller.
- build a TensorFlow neural network model with 3 sequential layers for predicting air quality.

As breathing is an underlying function of existing of all living organisms, air quality is an important component to maintain their health conditions. The main problem is to create a useful tool so that people, government, and decision-makers can reasonably assess the environmental situation of the air soon. However, at present, there is a lack of approaches for considering this objective. Today's methods of predicting air quality do not have high accuracy; hence, it is an ineffective way to solve the problem. To settle the problem productively this research work will be used experiences of TensorFlow neural network models.

The remaining parts of the paper are organized as follows. Section II contains problem identification. Section III includes related works. Section IV describes the proposed plan. Section V is about implementation and results. Section VI contains the discussion of the implantation mentioning its advantages and shortcomings. The last Section VII concludes the paper.

2. PROBLEM IDENTIFICATION

Almaty is the biggest and most economically profitable city in the country, it is attractive for its nature and climate for citizens to work and live. Also, it is dangerous for people by its air quality as it is closed from three sides out of four by mountains and does not have enough ventilation, this leads to anxiety of people for their health and participating in meetings to change the ecological situation of the city or taking decisions of moving to other places. It is necessary to analyse the problem by forecasting the air quality of Almaty in case there will not be any shifts to attract the attention of the government and decision-makers of the industry to change the ecological situation of the city. A forecast of air quality using TensorFlow neural networks was chosen in this research paper as the most beneficial tool.

3. RELATED WORKS

Özkaynak et al. (2013) in a research paper considered the importance of considering monitors except for central-site ambient monitors as they don't take into account, for instance, exposures near localized emissions sources, a demographic-specific human activity which leads to not effective analyses of epidemical situations according to predicted air pollution indicators.

An article by Kabir et al. (2020) studied methods to improve the accuracy of prediction of air quality using the Belief Rule Expert System (BRBES). To predict air quality deep learning models are trained by data collected from sensors or images converted with a convolutional neural network (CNN) model to convenient data for further usage. But both of these data can have inaccuracy and subsequently loses accuracy in the final prediction model of air quality. To avoid this problem, data from two sources passes through the BRBES algorithm, which gives weight to each of them and produces unified qualitative data. The researchers' achievement is that they paid attention to the process of collecting data from different sources and found a tool for combining them in the most effective way to improve the accuracy of the forecasting model. However concatenated data wasn't implemented in the final prediction model and accuracies weren't compared with the prediction model of raw data, so there is no information on the significance of the data combination process with BRBES.

Work Janarthanan et al. (2021) implemented a combination of Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) models approach of deep learning to predict air quality in a metropolitan city. In conclusion, was given a recommendation to consider predicted AQI for a committee of city planning to take action in the places of the high index. For Almaty, it would prioritize public transport and electrical cars in the dangerous levels of air pollution according to forecasts.

Tadano et al. (2021) studied connections between Covid-19 and air pollution index using a Multi-layered perceptron model. The correlation between many Covid-19 cases and further lockdown measures to pollution of air was proved. As the part of the public in Almaty have the opinion that vehicles are the main cause of polluting the air it is a great opportunity to analyse the influence of it.

Pak et al. (2020) considered in the paper that the following day's PM2.5 concentration in China's capital Beijing could be accurately predicted using a long short-term memory (LSTM) and spatiotemporal CNN model. For the spatiotemporal correlation analysis, the authors used mutual information (MI), which took the correlation between the goal indicator and analysis parameters into account. They as well accounted for collected air pollutants and weather parameters as well as the entire area of China centered around the target control point. Consequently, a spatiotemporal feature vector (STFV) was generated, which depicts correlations as non-linear and linear among different indicators. For the PM2.5 predictions, CNN effectively extracted the concealed air quality and weather input data's intrinsic properties and completely reflected the long-term historic process of the input time series using LSTM, which resulted in quick and precise prediction accuracy. Air quality and weather data from 384 stations, were utilized to test the suggested method's validity for three years. Finally, it was shown that the suggested technique was more stable and had superior predictive accuracy to MLP and LSTM methods.

There has lately been a surge of attention to quantifying the overall hazardous metal concentrations in heavy-metal polluted air [21]. Toxic chemicals in airborne particles must be separated by chemical separation. Airborne particulate matter (APM) has negative influence on human health. Therefore, to estimate the size of fractional airborne particles, and bound metals, Almalawi et al. (2022) proposed a new arithmetic optimization algorithm (AOA) and multi-head attention-based bidirectional LSTM (MABLSTM). The shape of airborne particulate matter is the focus of the AOA-MABLSTM technology. Using this approach, authors could look at the percentage of PM and APM that have been size fractionated. The suggested model used MABLSTM based on forecasting techniques to identify the temporal trend of heavy metals. When setting MABLSTM variables, the model utilized an AOA-based hyper parameter tuning procedure to get the best results. The research comparing the AOA-MABLSTM technique to more contemporary models demonstrated better results. For AOA-MABLSTM, the RMSE for aluminium metal was 73.200, for Cu metal was 6.747, and for zinc metal 45.250.

PM2.5 ratios can be predicted to enable the authorities to provide warnings to those who are most in danger. PM2.5 predictions were attempted; however, no investigation has been performed into the elements that influence PM2.5 predictions. Using random forest with gradient boosting, and deep learning techniques, in work of Zamani Joharestani et al. (2019) examined variable significance for PM2.5 forecasting in Tehran's metropolitan region. In the simulation analysis, they made use of 23 different variables, such as data from satellites and weather stations, as well as PM2.5 levels collected from the surface. The XGBoost technique, which eliminates unnecessary features, made the highest predictive accuracy, with R2 = 0.81 where R = 0.9, MAE = 9.93 µg/m3, and RMSE = 13.58 µg/m3. Aerosol Optical Depth (AOD) at 3 km resolution was included in all three ML approaches, however, the R2 ranged from 0.63 to 0.67 when it was being used and from 0.77 to 0.81 when it wasn't. The AODs were collected from satellites, in contrast to the PM2.5 data, which did not enhance prediction accuracy.

For the PM2.5 short-term forecasting, a multivariate linear regression model is presented by Zhao et al. (2018). Data remotely sensed on aerosol optical depth (AOD), climatic elements (wind speed, temperature, humidity), and other gases contaminants were the major indicators for the presented model (CO, O3, SO2 and NO2). As part of the situation, Beijing was chosen as an example. Regression models, the first for yearly data and the second for seasonal data, were built using citywide 2015 data on the mentioned variables indicators. The regression model based on yearly data demonstrated high performance as R2 = 0.766, cross-validity equals R2 = 0.87, according to the findings. Springtime and wintertime data yielded series higher predictive results, with an overall fit of 0.85 and 0.87, respectively. As a starting point for future research, the model's uncertainty levels were provided.

Tracking and regulating pollution levels has become increasingly crucial as a result of lifestyle changes and the increased use of fossil fuels in metropolitan areas. Via time-series modelling, the research of Zeinalnezhad et al. (2020) was able to provide forecasts of the situation of many important contaminants. Time- data has seldom been analysed using Logistic Regression with Adaptive Neuro-Fuzzy Inference System (ANFIS) approach, which are more often utilized by scientists. There are nonlinear and complicated elements in air quality modelling that are not included in normal time series forecasting models. ANFIS modelling was used in work to evaluate the efficiency of everyday pollution predictions using time-series analysis of data. Experimentation and refinement of a nonlinear multivariate regression model yielded the most accurate results. Only one monitoring station in Tehran collects data on emissions comprising CO, NO2, SO2, O3. To start, data is randomly divided into three categories: training, testing, and verification, with an 80/10/10 split between each. The semi-experimental model yielded indices of determination of 0.8445, 0.7602, 0.8001 and 0.7830, for the forecast of CO, NO2, SO2, and O3 at 0.8686, 0.7640, 0.8011 and 0.8350.

4. SYSTEM MODEL

To forecast air pollution with the neural network model of TensorFlow first of all analysed the correlations between variables with the Spearman correlation coefficient. Spearman correlation coefficient has a probability indicator that has measures to define the validity of the following prediction model.

The architecture of work consists of six stages and involves several utilities as depicted in Figure 1

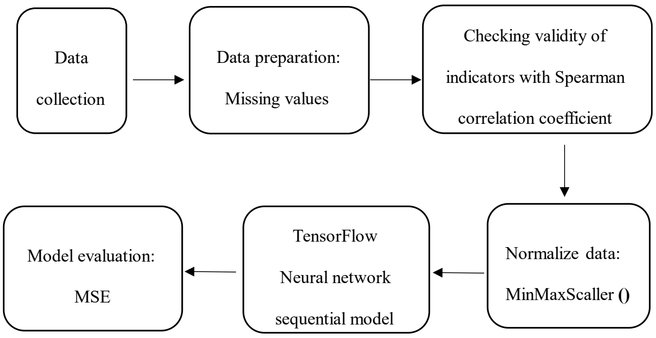

Figure 1: The architecture of model

5. Methodology

5.1 Data collection

Collected data of Almaty city air quality indicators as data to test and train neural networks from the website www.purpleair.com. This website provides air sensors and collects data on hyper-local and real-time air quality and shares it with the public and data scientists. As the “PurpleAir” company also allows users to download a free huge amount of historical air quality data from 6 Almaty sensors, it becomes the most preferred source to collect data. Algorithm 1 explained the data collection process. In step-1 initialization process of given variables is explained. In steps 2-3, input and output are shown respectively. Steps 5-7 show defining air quality data of Almaty sensors with necessary indicators and saving them in a CSV file and then into a folder. Steps 6-7 will process in the cycle of steps 4 -9 until all air quality indicator data of sensors will be checked and saved in a file and folder.

5.2 Data preparation

Data requires appropriate preparation before the start of using it for predictive modeling. For instance, data should be checked for missing values and then, at the discretion of data scientists missing values should be replaced with data defined by logic based on whole data. Also, data must be normalized if indicators have different measurement systems. So, the data preparation process concerns the following phases:

- **Partition of data into training and test sets:**

The separation of data into training and test sets aimed to create a system that can predict the value of air quality target value PM2.5. Implied that data in the training set is non-identical to test data and parted as 90% to 10% respectively.

- **Load and clean the data:**

After loading data from 6 sensor files, the cleaning data process was made by deleting missing values.

- **Check data variables - air indicators for Spearman correlation:**

Spearman correlation is used for the collected data on ratios to determine the strength and monotonic relationship between two variables. Instead of working with the data values themselves, it works with the ranks of these values. Observations are first ranked, and then these ranks are used for correlation.

$$\boldsymbol{\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}} \quad (1)$$

Where ρ-Spearman correlation coefficient, d_i-difference in paired ranks of the i^{th} element, n-number of data points of the two variables, i-paired score.

The Spearman Coefficient can take a value between +1 to -1 where,

A ρ value of +1 means a perfect association of rank.

A ρ value of 0 means no association of ranks.

A ρ value of -1 means a perfect negative association between ranks.

Closer the ρ value to 0, the weaker the association between the two ranks.

- **Normalize data using MinMaxScaller() function:**

Every value in the indicator deducts using MinMaxScaler() function by the algorithm of taking the minimum value divided by a range, where the range is the difference between the initial maximum and minimum of the indicator. Function retains the form of the original distribution, so it doesn’t significantly change the information embedded in the source data. It should be noted that MinMaxScaler() function doesn’t reduce the importance of outliers. The default range for the function is from 0 to 1.

- **TensorFlow Neural network sequential model:**

Intended to develop a 3-layered neural network TensorFlow sequential model to predict the quality of air. All nodes in the neural network of layers are connected. Activation functions of dense layers: sigmoid, Relu, linear.

- **Model Evaluation**

In this section mean squared error (MSE) method of evaluating the model is described as MSE (Mean squared error).

Mean squared error (MSE)- a parameter that measures the average value of squared errors, it means the difference between predicted and actual values in the square.

$$\boldsymbol{MSE} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{j}=\mathbf{1}}^{\boldsymbol{N}} (\boldsymbol{predicted} - \boldsymbol{input})^{\mathbf{2}} \qquad (2)$$

where

N- number of items, j- each item in total N items, predicted- predicted values, input- original values.

6. EXPERIMENTAL RESULTS

The model is written using the Colab application based on the Python programming language to validate the performance. To collect data from sensors of physical and PM indicators used cite www.purpleair.com. The laptop configuration, on which the application is executed, is described in Table 1.

Table 1: Used tools for experimenting.

Name	Description
OS	Windows 10
Processor	Intel® Core™ i7-5500U CPU @ 2.40GHz × 8
Processor architecture	x64
Graphics card	GeForce MX150/PCIe/SSE2
Hard drive	256 GiB SSD
RAM	6 GiB

Data collected from purpleair.com, sensors situated in Almaty city, and the appearance of the sensor showed in Figure 2. As input data used 3 million measurements from 6 sensors for the period 2019-2022.

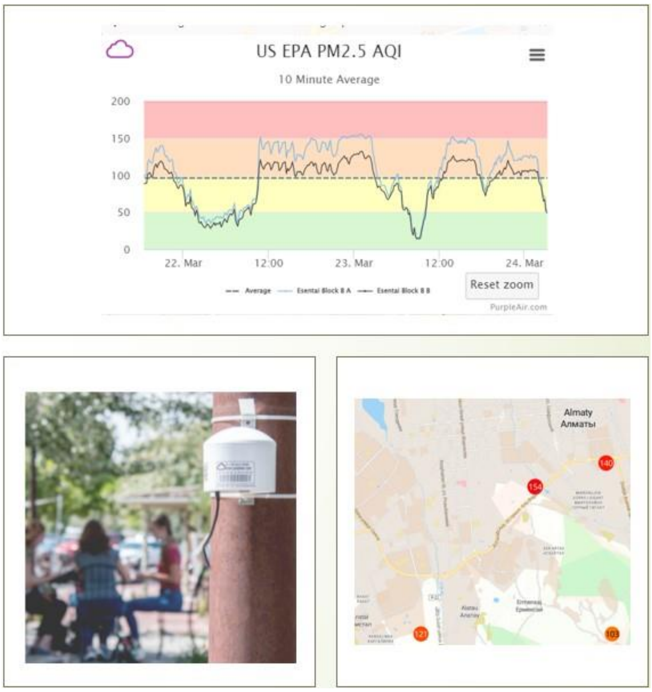

Figure 2: Sensors from purpleir.com.

Below is described the meaning of the indicators used in the prediction model and shown in Table 2.

PM stands for particulate matter (also called particle pollution): the term for a mixture of solid particles and liquid droplets found in the air PM1, PM 2.5, and PM10 inhalable particles, with diameters that are generally 1, 2.5, and 10 micrometers respectively, and smaller.

PM 2.5 ATM – to convert the particle count data (um/dl) to the mass concentration (ug/m3) use an average particle density. There are 2 different mass concentration conversion options; CF_1 uses the "average particle density" for indoor particulate matter and CF_ATM uses the "average particle density" for outdoor particulate matter.

RSSI indicator is Sensor's Wi-Fi signal strength in dBm.

Temperature is a physical indicator of the current temperature in Fahrenheit.

Humidity is a physical indicator of current humidity in percent.

Table 2: Indicators used in the prediction model.

created_at	PM 1	PM 2.5	PM 10	RSSI	Temperature	Humidity	PM2.5 ATM	location
2019-02-21 22:05:25	3.00	3.50	3.50	-54.0	68.0	22.0	3.50	Esental Block
2019-02-21 22:06:45	2.61	4.59	5.34	-50.0	69.0	22.0	4.59	Esental Block
2019-02-21 22:08:05	2.09	3.98	4.49	-47.0	69.0	21.0	3.98	Esental Block
2019-02-21 22:10:11	2.07	3.73	4.13	-50.0	69.0	21.0	3.73	Esental Block
2019-02-21 22:11:25	2.87	5.09	6.50	-52.0	69.0	21.0	5.09	Esental Block

Table 3 shows normalized data using the MinMaxScaler function from the scikit-learn library.

Table 3: Normalized data.

PM 1	PM 2.5	PM 10	RSSI	Temperature	Humidity	PM2.5 ATM
0.004476	0.003444	0.002019	0.552632	0.543689	0.2750	0.005171
0.003894	0.004516	0.003080	0.605263	0.553398	0.2750	0.006782
0.003118	0.003916	0.002590	0.644737	0.553398	0.2625	0.005880
0.003088	0.003670	0.002382	0.605263	0.553398	0.2625	0.005511
0.004282	0.005008	0.003750	0.578947	0.553398	0.2625	0.007520

Figure 3 provides the results of Spearman correlation analyses.

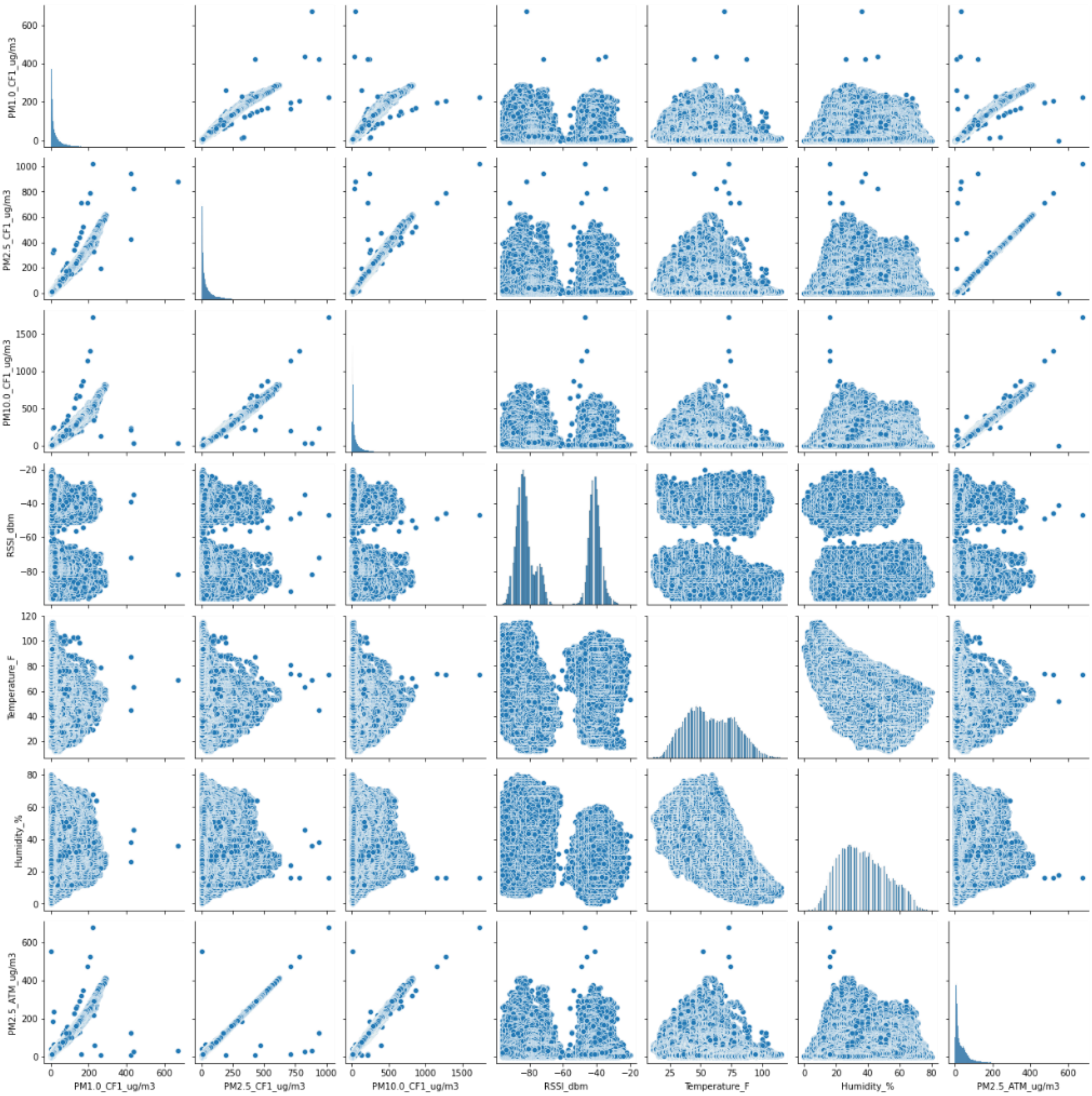

Figure 3: Spearman correlation

Three-layered sequential neural networks with one hidden layer were built-in in Table 4.

Table 4: Sequential neural network model

Model: "Sequential"		
layer (type)	Output Shape	Param #
dense (Dense)	(None, 7)	56
dense_1 (Dense)	(None, 49)	392
dense_2 (Dense)	(None, 7)	200
Total params: 648		
Trainable params:648		
Non-trainable params: 0		

Made predictions for test data showed results of MSE in Figure 4 with neural network TensorFlow model. To train, the model used 100 epochs to gain a 1e-5 MSE value.

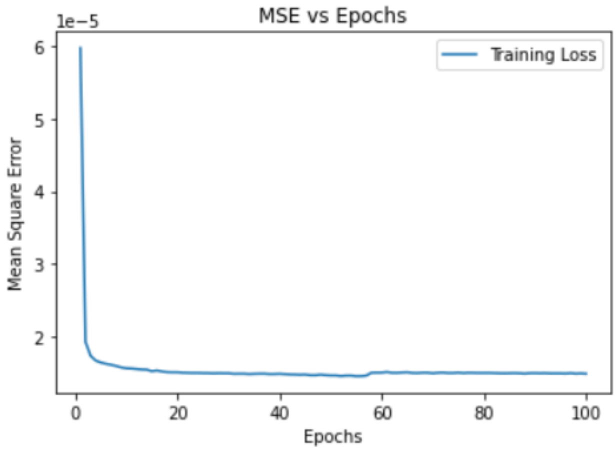

Figure 4: MSE

Figures 5 and 6 show results of actual and predicted values from test data.

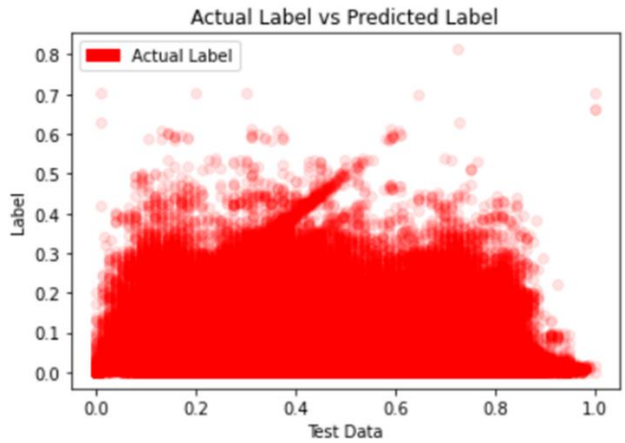

Figure 5: sequential neural network model.

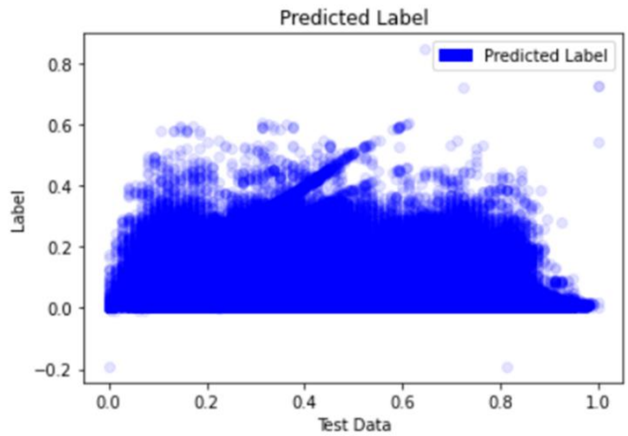

Figure 6: Sequential neural network model.

7. DISCUSSION

Based on Figure 3, Spearman correlation defined that PM particles have a linear correlation between each other and with physical indicators. To understand the not linear relationship of particles between each other and with temperature, and humidity we used the Spearman correlation coefficient. To have better accuracy the data was cleaned by deleting missing values and normalized with the MinMaxscaller function from the scikit–learn library, cleaned and normalized data showed in Tables 2 and 3 respectively. TensorFlow neural network model with 3 sequential layers for predicting air quality shown in Table 4, built with sigmoid, Relu, and linear functions between layers. On Figure 4 using the Mean squared error indicator proved the accuracy of the built model. Figures 5 and 6 depicted tested values in comparison to predicted and actual values and gives a high resemblance.

The advantage of this work is that explored relationship between indicators and their influence on target value

PM2.5 using Spearman correlation analyses before training the model using a neural network model.

A minor disadvantage of this work is that chemical pollutants such as NO2, CO, and SO2 were not considered in the Spearman correlation analysis and neural network model as data on them are not publicly available.

Nowadays, we can see that air quality is monitored in real-time, but the prediction of air pollutants is not available

8. CONCLUSION

Prediction of the PM2.5 concentrations to prevent the citizens from the dangerous impact of air pollution in advance was made in this paper. Analysis of Spearman correlation revealed that the variation of PM2.5 depends on a variety of factors, including physical parameters such as humidity and temperature. This paper implemented a deep learning solution to predict the forecast of PM2.5 concentrations in Almaty, Kazakhstan, based on a neural network model using TensorFlow. Using sigmoid, Relu, and linear functions in 3 layered sequential neural network models showed high accuracy evaluated by the MSE indicator.

In the outlook will be attractive to use chemical pollutants like SO2, NO, and CO in the training dataset to identify the impact of it on predicting PM2.5.

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