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Deep learning Feedforward Neural Network in predicting model of Environmental risk factors in the Sohar region

Yasra K. Al-Kharoosi [1,*] and Jabar H. Yousif [2,*]
[1,2] Faculty of Computing and Information technology, Sohar University, Oman
* Corresponding author: Yasra K. Al-Kharoosi [1], Jabar H. Yousif [2] jyousif@su.edu.om

Abstract

AQI (Air Quality Index) is the standard degree that guides us to measure air pollution levels such as PM2.5, O3, NO2, and SO2 to show the state of air quality. Polluted gas causes much damage and problems to people, plants, and the environment because of its negative impact. Data mining successfully examines an enormous cluster of data to recognize associations, determine relations between variables, and predict future values. In this paper, an experimental study was performed on analyzing the previous dataset of (PM2.5 and O3) for accurately predicting AQI using deep learning Feedforward Neural network techniques. The deep learning (Feedforward Neural Network (FFNN) predicting models are employed to evaluate based on R, R^2, MSE, MAE, and RMSE criteria using historical data from (the Ministry of Environment-Oman). Different epochs and a different number of hidden layers are deployed to improve and boost performance. In FFNN, the epochs number increase by 50,100 and 500 while the hidden layer utilized to 1,5 and 10. This optimization technique exceeds the performance from R=0.892 to R=0.992 in predicting the level of (PM2.5) and the (O3) from R=0.864 to R=0.999. The results show that the Sohar Region in a safe level of AQI.

Keywords: Deep learning; Data mining; Air Quality Index; gases Emission; predicting models

1. Introduction

Most countries in the world deal with air pollution as a critical environmental issue. Urban improvement and development are the common reason for air pollution (Yousif J., 2016). That comes because of the vehicle, factory, and power situations increment (Saini & Yousif, 2013). Most governments in the world try to take appropriate action to avoid the impact of air pollution by monitoring the common factors that cause the problem (Ng & Dahari, 2020; Alattar & Yousif, 2019). Following IAMAT, Oman has poor air quality because of Crude oil production, refining, and vehicle. The reading data shows that Muscat and Sohar have an increasing level of pollution than other locations (Alattar et al., 2019; Yousif & Alattar, 2017). Port in industrial cities such as Sohar industrial port is one source of pollution that causes an increase in polluted gas and human health (Yousif et al., 2017). The fuel that burns by ships is RFO (Residual Fuel Oil) which contains sulfur content. The emission of polluted gas will increase because of burning RFO (Wang et al., 2019), so we should use renewable energy to reduce the negative impact of burning RFO (Kazem et al., 2022; Yousif et al., 2022; Yousif J., 2021). However, the number of deaths because of air population was reduced from 214.02 to 129.44 death per 100.000 individuals in 2019, according to Statista.com. The reading data shows Delhi in India as the most polluted city in the world in 2020, with a concentration of PM2.5 (Particulate Matter) 10 times greater than the world health organization sitting at the PM2.5 level in statista.com. The statistics show an increase in death in the country with more populations, such as China and India, as shown in Figure 1. In addition, many organizations such as the World Health Organization and the Annual State of Global Air report, show an increase in death every year around the world, with a level of 9 million in 2019, as shown in Figure 2.

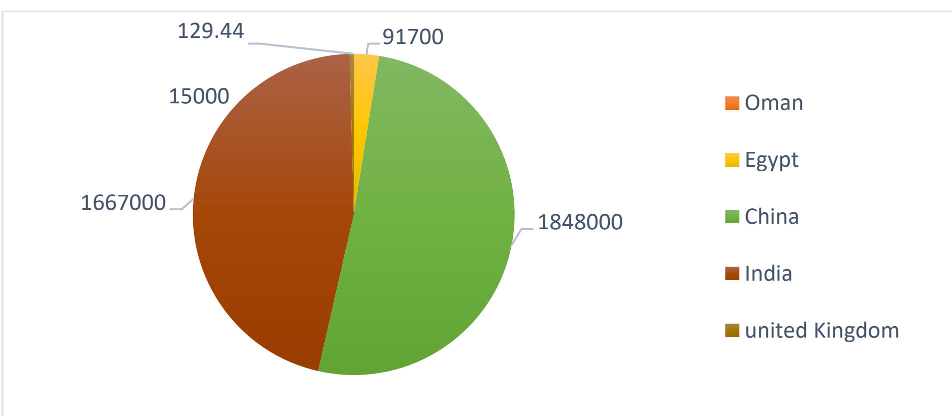

Figure 1: Number of death due to air pollution in 2019 depends on statista.com

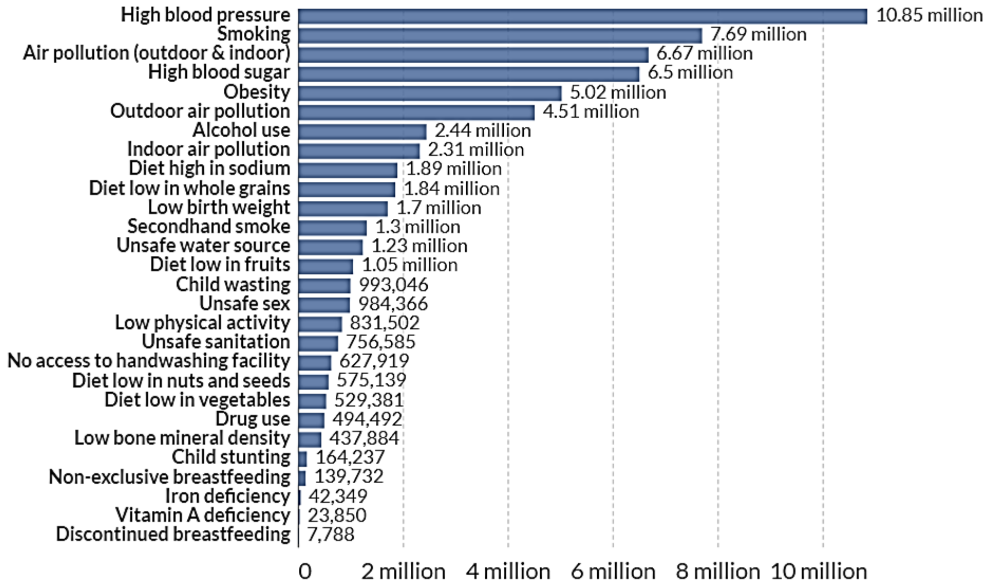

Figure 2: Number of deaths by risk factor, World, 2019 (GBD, 2019)

The motor vehicle is one of the primary sources of air pollution that consume 30% of the world's energy. The first step in reducing air pollution is minimizing vehicle traffic and reducing fuel consumption (Saremi P, 2020). In most Gulf countries, such as Oman, the Kingdom of Saudi Arabia, Kuwait, Qatar, Bahrain, and UAE (United Arab Emirates), distribution pollution is mainly affected by sandstorms. A study in Kuwait shows that continuous exposure to dust storms impacts respiratory and asthma admission (Farahat A, 2016).

This work aims to deploy the Deep Learning Neural Network model for predicting Environmental risk factors in the Sohar region, Sultanate of Oman. Sohar is a city in Oman's south and the second most important city after the capital Muscat. It is between 24˚21'00" N and 56˚42'27" E, as shown in Figure 3. Sohar faces the most industrial and vehicle pollution. According to AccuWeather, the common factor that causes air pollution in Sohar, Al Batinah North is Ozone O_3 which reaches 27, which means people may experience minor to moderate symptoms from long-term exposure and PM_2.5 with 192 that consider very unhealthy depending on Accuweather.com.

In this work, Deep learning is utilized, a type of AI (Artificial Intelligence) that gives an application the ability to learn by mimicking the human brain. It is used to deal with unstructured data and improve performance (Mathew et al., 2021). ANN (Artificial Neural Network) key feature consists of the number of hidden layers, neurons, and input variables that determine network structure. The network's topology used an algorithm and activation function to give the output.

Figure 3: Sohar map (https://www.google.com/maps)

A study in Surat city shows that the efficiency of using ANN in predicting is 79.4% (Kapadia & Jariwala, 2021). Many studies focus on predicting ozone and ground-level gas depending on the Neural Network statistical model. Statistical models provide a more accurate and structured way to predict ozone levels than the traditional model, which mainly shows uncertain results (S. Abdul-Wahab & Al-Alawi, 2008).

2. Materials and Methods

This research focuses on predicting the environmental risk factor of ozone and PM2.5 in the Sohar region. It deploys a quantitative research methodology for predicting PM2.5 and ozone. An experimental methodology was followed by taking actual data from the ministry of environment and deploying a deep learning model to predict and evaluate performance. RapidMiner and Data's mining was implemented, and pre-processed model was used to clean and organize our data before processing by removing all missing values, removing an unnecessary column, and making normalization. In implementation feedforward, the neural network method used to test performance depends on two criteria: epochs and hidden layer.

2.1. Response Rates

RapidMiner is a free, open-source software for data and text mining. Their software tool can download from their website **www.rapid-i.com**. It is user-friendly, available at any time, and very simple. Also, it provides a huge library for miming any machine learning and algorithm to show how to use it. It is the perfect choice in the education process by simplifying the learning purpose. In addition, this application comes with an extension feature that allows the user to download any algorithm that is unavailable to your library. However, Rapid Miner is an application for data analyses and mining that simplifies any code written in it and works on every platform and operating system. (Burget et al., 2010).

2.2. Data Mining

Data mining is a technique that deals with a huge database to analyze input data. The main objective of data mining is to prepare data for predicting dependent variables such as ozone and PM2.5 by using an independent variable (Gosavi & Gawde, 2022). In RapidMiner, data mining is utilized on the structure and relational data, while textual mining (tasks of data mining) works with all unstructured and semi-structural data (Kalra & Aggarwal, 2018). Classification and Regression in prediction models with data mining help to extract meaningful information and deeply analyze data. The classification model predicts categorical class labels, while the regression technique deals with continuous value function (Berrar, 2019). There are two main classes of data mining: supervised and unsupervised learning models. In supervised data mining, the output is predicted by using input data. In unsupervised data mining, there is no output, and the model classifies input data. In addition, data mining tasks include many fields, such as Clustering, classification, Regression, text mining, association, anomaly detection, time series forecasting, and feature selection (Kotu & Deshpande, 2015).

2.3. Deep Learning

Deep learning is a type of Machine learning which conserved as a field of AI (Artificial Intelligence), as shown in Figure 4, that gives an application the ability to learn by mimicking the human brain. It is used to deal with unstructured data and improve performance. There are three fields of Machine Learning: supervised, Unsupervised, and reinforcement. In supervisor input, data have weight, and there are algorithms to give output. In Un-supervisor, there is no output, and you have the observed data. A hybrid shows a combination of supervised and Unsupervised (Mathew et al., 2021). There are many deep learning applications, such as big data, Google’s Deep Dream, and Facebook

(Shinde & Shah, 2018). Since Big data deals with different kinds of data from different sources, such as web and mobile, the data can be text, image, voice, sound, audio, structure or unstructured, and animation. In deep learning, a suitable classification method is used to deal with and learn by providing supervised, unsupervised, and a hybrid of both learnings. Microsoft Speech recognition (MAVIS) is a concern as a deep learning method that gives the strength to search for video and audio using human sounds (Shinde & Shah, 2018). Google's deep dream is an application to classify images and create a painting based on its knowledge.

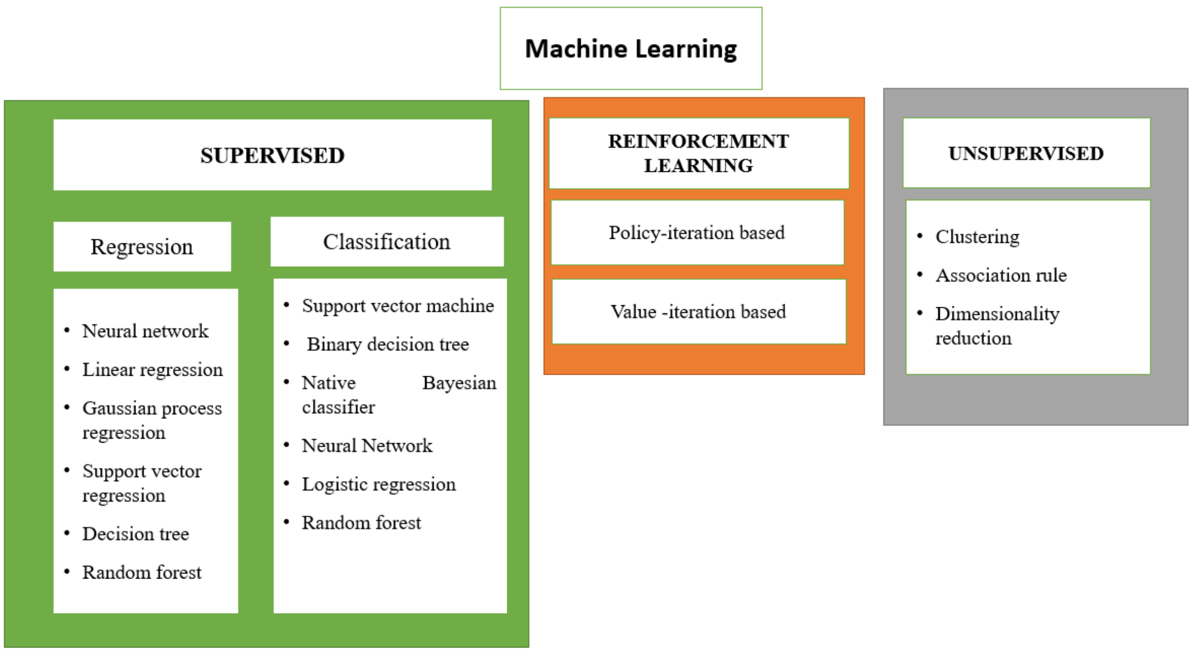

Figure 4: Classification of Machine Learning Techniques (Sarker I., 2021)

However, supervised learning is about using the label in training data to guess tasks for classification and regression. This input is feeding to give output depending on function y=f(x). Function approximation is the core of ML that include different types such as Linear model, Support Vector Machine (SVM), decision tree, deep learning, and the gaussian process (Tien et al., 2022). Unsupervised learning learns from data that does not have any label. It is utilized patterns in data like data compression, which can use encoding and decoding. Encoding happens by minimizing the high dimension to lower dimensions, while decoding does the opposite (Yousif & Al-Risi, 2019). Reinforcement learning is about learning new experiences over trial and error. It is applied to robotics because it allows the policy to control and learn directly from the camera in the real world. It is widely used in decision-making problems and intractable cases. (Li C., 2019). DNN (Deep Neural network) is a type of supervised deep learning that utilizes the same structure as ANN to deploy and implement models with more accuracy. The structure involves a hidden layer between input and output. Neurons are set in each layer and connected. The evaluation starts by calculating the Net and transferring the Net to a Non-linear form, and send to output using the transfer function. Weight and transfer functions dominate the position of the threshold value and the slope of the transfer function. Additional input variables are called bias to make the system more flexible and adjustable (Zhang et al., 2022; Ali et al, 2022).

2.4. Artificial Neural Network

An artificial Neural Network (ANN) is an information processing paradigm that simulates the work of the biological nervous system, such as the brain. It uses in processing information by simulating human behavior and solving problems depending on the experience. ANN is composed of many highly interconnected processing neurons that work together to solve a specific problem in this system. ANN key features consist of the number of the hidden layer, the number of neurons, and the input variable that determines the network structure. The network's topology used an algorithm and activation function to give the output. The system's work starts by receiving the number of input connections with weight and threshold value. It works the same as the input processing system that starts by receiving input from original data or the output of other neurons (Olabi et al., 2022). The neuron weight and bias will be adjusted based on the used neural topology, and the output will be present after it passes to the activation function as shown in Figure 5.

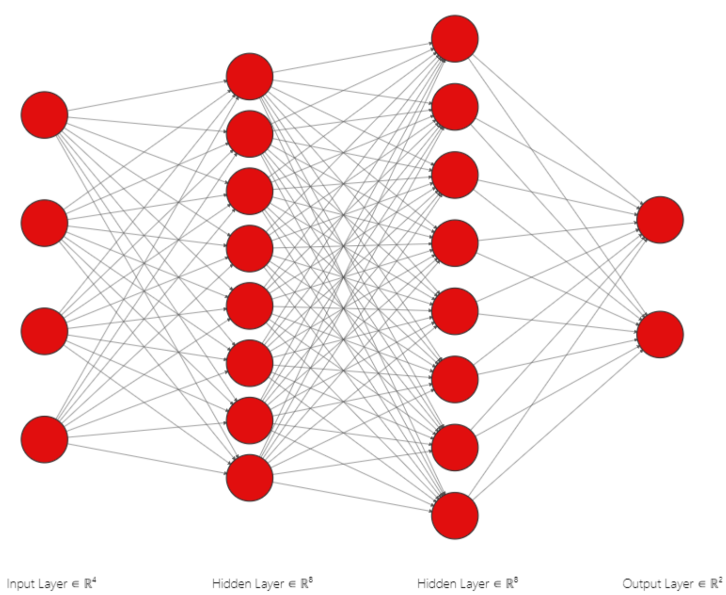

Figure 5: Artificial Neural network Architecture

Feedforward Neural Network is one direction Neural Network that runs from input through a set of hidden layers to give output and does not follow any loopback (Shrestha & Mahmood, 2019). MLP (Multilayer perceptron) is a Feedforward Neural Network that can be trained using the error backpropagation algorithm. The optimizing number of hidden layers and number of neurons causes a huge challenge to choose a better to improve network performance. However, an increasing number of hidden layers and several neurons improve the network's performance, but sometimes overfitting occurs (François-lavet et al., 2018). There are two periods for NN (Neural Network): the training and application period. During the training, the network prepares input by removing, controlling parameters and applying a learning algorithm to improve performance. The network starts its process in the application period and shows the result (Londhe M., 2021). The BP (Backpropagation) algorithm is utilized for training Feed Forward Neural Networks by calculating errors. It is considered a Supervised Learning method where forward propagation passes for the signal, and the reverse propagation of error follows. Forward propagation of input passes through the layer to give the output. The error is entered if the output exception does not match the forward process. However, modification and minimization of error happen by updating the weight and the threshold value (Kang & Qu, 2017). BP (Backpropagation) network work based on gradient descent and causes problems such as slowly learning convergent velocity and quickly converging where the minimum error is not ignored (Wen Jin et al., 2002). However, to overcome this problem, a study by (Wen Jin et al., 2002) tries to improve the BP network to give better execution by automatic the learning rate and inertia factor to give a faster convergence rate.

3. Results and Discussion

In our study, two datasets are collected: the PM2.5 and O3 historical data. It is collected from the ministry of environment as an Excel file for two years, from Jun 2019 to Dec 2020. Our data were collected from four stations. The station is Al Zafran, Agdat Al Mawani, Ghadfan North, and Ghadfan South. Also, two data sets were calculated from Mobile1 and mobile2. The O3 data was collected three times in the day in each station at 8:00, 16:00, and 24:00 from 1/1/2019 to 31/12/2020, while PM2.5 data were collected once every day at 24:00 from 1/1/2020 to 31/12/2020. Data set import in RapidMiner and set the first column of PM2.5 in Al Zofran as a label for prediction while another column keeps the same and removes unnecessary ones. So, there are 1 particular attribute and 5 common attributes with 371 examples, the missing value removes, and Normalization applies. The second data set related to ozone contains 2197 example sets with 1 particular attribute and 4 common attributes whereover all missing value removes and Normalization utilized. We deployed a Feedforward NN with a different number of epochs and hidden layers in a three-stage to enhance the model accuracy, as depicted in Table 1. The output of proposed neural model is demonstrated in Table 2.

Table 1: FFNN enhancement stages

	#Hidden layers	**#Epoch**
First stage	1	50
		100
		500
Second stage	5	50
		100
		500
Third stage	10	50
		100
		500

Table 2: FFNN implementation and results

		First stage			**Second Stage**			**Third Stage**		
	#Hidden layer	1 hidden layer			5 hidden layers			10 hidden layers		
	#Epochs	50	100	500	50	100	500	50	100	500
$PM_{2.}$	RMSE	0.098	0.069	0.031	0.061	0.054	0.054	0.052	0.036	0.026
	MSE	0.010 +/- 0.014	0.005 +/- 0.008	0.001 +/- 0.002	0.004 +/- 0.008	0.003 +/- 0.006	0.003 +/- 0.007	0.003 +/- 0.006	0.001 +/- 0.003	0.001 +/- 0.002
	MAE	0.077 +/- 0.061	0.054 +/- 0.043	0.023 +/- 0.021	0.045 +/- 0.041	0.038 +/- 0.038	0.037 +/- 0.039	0.036 +/- 0.037	0.025 +/- 0.027	0.017 +/- 0.019
	r	0.892	0.946	0.987	0.952	0.963	0.963	0.965	0.983	0.992
	R^2	0.795	0.895	0.975	0.907	0.927	0.927	0.931	0.966	0.983
O_3	RMSE	0.011	0.011	0.011	0.11	0.010	0.011	0.004	0.003	0.002
	MSE	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000	0.000 +/- 0.000
	MAE	0.007 +/- 0.008	0.007 +/- 0.008	0.007 +/- 0.008	0.007 +/- 0.008	0.007 +/- 0.008	0.007 +/- 0.008	0.003 +/- 0.002	0.003 +/- 0.002	0.002 +/- 0.001
	r	0.864	0.866	0.869	0.869	0.871	0.867	0.988	0.998	0.999
	R^2	0.747	0.749	0.755	0.756	0.759	0.751	0.977	0.997	0.998

In each stage, 1 hidden layer, 5 hidden layers, and 10 hidden layers were used and expressed ass NN1, NN5, and NN10 with 50, 100, and 500 epochs. For performance improvement, the label data convert to Normalize operation to set it is in the range of 0.0 to 1.0. However, a set of technology could increase the performance of the deep learning model, such as input neurons, training cycle, learning rate, momentum, and hidden layer (Fiqha et al., 2022). In our design, input neurons are set to 30, and the epsilon is 1E-8 (like the Learning rate with a typical value between 1E-10 & 1E-4). The training cycle (epochs) is 50, 100, and 500, while the hidden layer is 1, 5, and 10, set as NN1, NN5, and NN10 in the table below. The rho with .99 is used since it has the same momentum functionality and comes in the range of 0.9 to 0.999. In the hidden layer, 30 neurons are set, and ReLU (Rectified Linear Unit) Activation Function utilize in each layer. The output layer adds one neuron, and ReLU (Rectified Linear Unit) Activation Function employ. However, ReLU (Rectified Linear Unit) is linear for positive values and zero for other values since it exceeds accuracy, drives out the need for pre-processing, and makes the DNN model more accurate (Zhang & Woodland, 2015).

Optimization of PM2.5 prediction happens by increasing the hidden layer and epochs value to show a better result for r and R^2. The resulting change from r=0.892 to r=0.992 while R^2 varied from R^2=0.795 to R^2=0.983. In ozone prediction same algorithm and the same step as PM2.5 data are taken. Optimization of O3 prediction happens by increasing the hidden layer and epochs value to show better results for r and R^2. The resulting change from r=0.864 to r=0.999 while R^2 varied from 0.747 to 0.998. Figures 6 and 7 show the result of FFNN model for predicting the PM 2.5 and O3, which indicates the differences in results before and after the enhancement process.

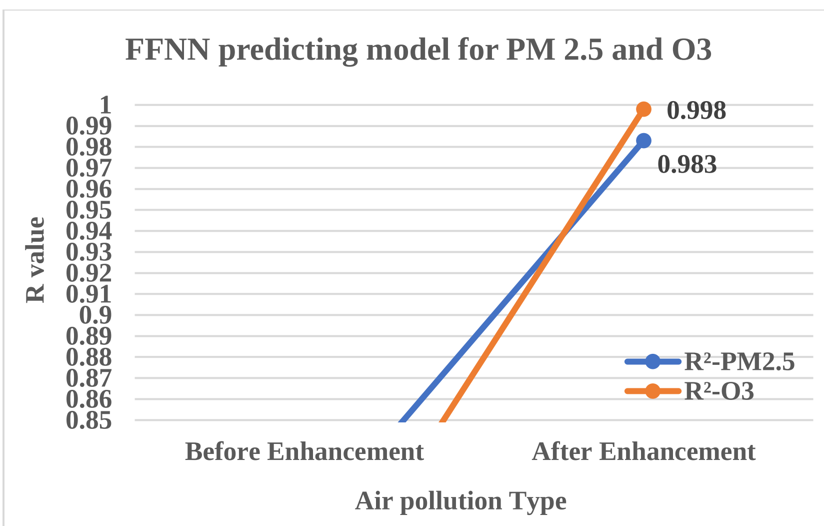

Figure 6: Correlation results (R) of FFNN predicting model for PM 2.5 and O3

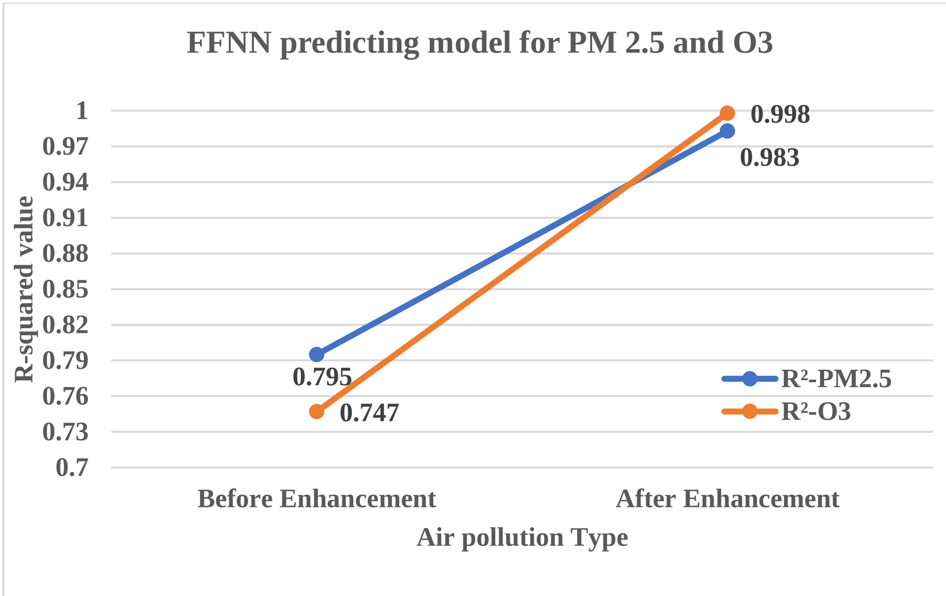

Figure 7: Correlation results (R^2) of FFNN predicting model for PM 2.5 and O3

Data mining and deep learning can be applied by different deep learning techniques and compared with other studies to discover new factors that will increase the forecasting performance of new figures and patterns. Also, new data mining models are utilized to examine and determine the associations and correlations between environmental data, which will help reduce toxic gases.

4. Conclusion

Scientists and engineers developed many prediction methods to help in improving the prediction model. A Deep Learning Feedforward Neural network is employed in this paper to predict PM2.5 and ozone climate in the Sohar sky. DNN-FFNN training in three stages to show their strength in the prediction of ozone and PM2.5. The prediction depends on two criteria that is epochs and hidden layers. As a result, increasing the number of epochs to 5, 100, and 500 improves performance from $r = 0.892$ to $r = 0.992$ in PM2.5, while an increased hidden layer boosts the performance. Before applying Data mining in Rapid Miner, our result was 40% to 50 %. Fortunately, Data mining exceeds the accuracy to 99% since it provides mining prospects to find hidden and effective knowledge from the vast data set.

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