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Uncovering the hidden relation between air pollution and ischemic heart disease: Experience from Tehran

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Abstract

Nowadays, air pollution is one of pressing environmental issues, and it causes different diseases especially cardiac and respiratory ones. The relation between air pollutants (including PM10, PM2.5, CO, SO2, NO2, and O3) and heart-pulmonary diseases (ischemic, angina, pneumonia and chronic obstructive pulmonary disease (COPD)) is studied in Tehran, the most polluted city of Iran. Air quality data related to all pollutants PM10, PM2.5, CO, SO2, NO2, and O3 have been gathered. The relation between the pollutants and number of admitted heart-pulmonary diseases patients is modeled by using radial basis function (RBF), multilayer perceptron (MLP) networks and ANFIS in terms of MSE and correlation coefficient. In each network, pollutants are assumed as inputs and heart-pulmonary diseases is considered as an output of the network. The experiments show that the ANFIS network has more accuracy than MLP and RBF. Moreover, the obtained results in ANFIS network show that correlation coefficient between ischemic and NO2, angina and CO, pneumonia and PM10 and COPD and (PM10 & PM2.5) respectively are 0.7229, 0.7006, 0.81 and (0.7280 & 0.7249).
Keywords: Air pollution, ischemic heart disease, neural networks, ANFIS

1- Introduction

Dispersed air pollution incidents, such as the historic London fog in 1952 and several short- and long-term epidemiological studies investigated the effects of air quality changes on human health. Different composition of air pollutants, the dose, and duration of exposure, and the fact that humans are usually exposed to pollutant mixtures more than to single substances can lead to diverse impacts on human health. Air pollutant effects on human health cause nausea, breathing difficulty, skin irritation, or even cancer (Naik, and

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Mohanta, 2020). In worst cases, these sorts of pollutants can lead to congenital disabilities, growth retardation in children, and severely reduce the activity of the immune system or other kinds of diseases. Also, the existence of sensitivity factors such as age, nutritional status, and the predisposing condition has leading roles in the incidence of air pollution caused diseases. Hygienic effects split into two categories; acute and chronic such as cancerous and noncancerous. Epidemiological and animal model data indicate that most impressionable systems are cardiovascular and respiratory systems (Kampa et al., 2008).

Air pollution is one of the main threatening factors for human health, which has become a global concern. Air pollution is composed of one or more pollutants that are created from the smoke of vehicles, factories, forest fires, wind, dust, etc. (Xue et al., 2020). In recent years, many studies have exhibited a great deal of interest in the effects of air pollution on human health.

Sokoty .et al (2021) developed research to predict the influence of air pollutants on cardiovascular disease due to air pollutants using conditional logistic regression. The result show that only CO effects on admission in cardiovascular disease, ischemic heart disease, and hypertension.

Camacho .et al (2020) conducted a study to investigate the association between short-term exposure to atmospheric pollution in the occurrence of cardiovascular disease and mortality in Madeira. This study was performed using exploratory and correlation analysis of all variables.

Dastoorpoor .et al (2019) established a study using a quasi-Poisson regression combined with linear distributed lag models; adjusted for trend, seasonality, temperature, relative humidity, weekdays and holidays to investigate the relation between hospital admission for cardiovascular diseases and the average daily air pollution. Cardiovascular hospital admissions among women, elderly and ICD-10 are significantly caused by O3 and NO2; NO, NO2 and CO; and PM10, NO2, CO, and SO2.

Dai .et al (2018) applied conditional logistic regression to study the effect of particulate matter on hospital admissions for ischemic heart disease in China. Results declared that short-term increase in PM2.5 and PM10 is significantly associated with increased risk of ischemic heart disease.

Chen (2017) conducted a Generalized Additive Model (GAM) and Bayesian hierarchical model to study the effect of particulate air pollution on coronary heart disease (CHD) in China. Results of this study showed that 10 μg/m3 increase of PM10 is accompanying an increase of 0.81% in daily CHD mortality in China.

Tam .et al (2015), in Hong Kong, using a generalized additive model, found that there are significant associations between ischemic heart disease and air pollution.

Yan Tao .et al (2014), in Lanzhou, China using Poisson regression, observed a meaningful relation between air pollution and respiratory admitted patients. Also, they reported severer effects for people over 58 years old.

Liang et al. in Thailand using a time series regression model found that carbon monoxide, nitrogen dioxide, sulfur dioxide and particulate matter with 10-micrometer diameter are related to mortality caused by respiratory and cardiovascular diseases especially among the elderly in winter (Liang et al., 2009).

Lin et al. in Hong Kong using time-layer case-crossover analysis observed that exposure to SO_2, NO_2 and polluted air can increase acute myocardial infarction (AMI) mortality (Lin et al., 2013).

Zhang et al. in China using Cox regression model investigated that PM_{10} effects have a meaningful relation with men cardiovascular mortality, the particularly more noticeable impact on the smokers (Zhang et al., 2014).

Hansen et al. in Adelaide, Australia using time-layer case-crossover analysis concluded that concentrations of particulate matter associated with mortality are increasing in Adelaide (Hansen et al., 2012).

Liu et al. in Beijing, China found a relation between high concentrations of matter and increasing cardiovascular complications (Liu et al., 2013).

Guo et al. in Tianjin, China using case-crossover and time series analysis found that air pollutants have a direct relation with cardiovascular mortality (CVM) (Guo et al., 2010).

Frank et al. in Santiago, Chile using time-layer case-crossover analysis showed that there is a relation between the daily concentration of carbon monoxide, nitrogen dioxide and particulate matter (CO, NO_2, PM_{10} and $PM_{2.5}$) and admitted patients (Franck et al., 2015).

Yorifuji et al. used a time-layer and found that exposure to particulate matter from zero to less than six hours before the event is associated with cardiovascular and cerebrovascular diseases (Yorifuji et al., 2014).

Lavigne et al. in Windsor, Canada examine the relation between SO_2, NO_2 and CO with asthma by using logistic regression and found a significant association between the pollution level and asthma (Lavgine et al., 2012).

Goldberg et al. in Montréal, Québec used parametric log-linear Poisson along with nonlinear delay models framework to study the relation between the mortality and CO_2, NO_2, SO_2, O_3 and PM_{10} and concluded that there are positive relations among not-random daily mortality and all air pollutants except O_3. The result is also valid for cardiovascular disease, congestive heart failure, atrial fibrillation and in the warm season for acute and chronic artery, high blood pressure and cancerous patients (Goldberg et al., 2013).

Chen et al. in Anshan, China using time-layer case-crossover analysis obtained a significant relation between air pollution and daily mortality caused by cardiovascular diseases. Also, they achieved a positive relation between total mortality and air pollution (Chen et al., 2010).

Air pollution is the most significant environmental problem that we currently encounter in Iran, especially in Tehran. Moreover, Tehran is one of the most polluted cities in the country caused by traffic and transportation pollution (Khalilzadeh et al., 2009; Shahi et al., 2014). Air pollution has caused many problems for Tehran inhabitants such as outbreaking and intensification of ischemic heart disease. Air pollution and ischemic diseases data have volatility in time duration and are non-linear. Therefore, it is challenging to extract and model the nonlinear pattern using traditional models. Fortunately, the artificial neural network is capable of detecting the complex relations in non-linear phenomena. Multi-layer perceptron (MLP) networks as well as radial basis function (RBF) networks, as famous learners in non-linear environments, are employed to discover the association between air pollution and ischemic diseases.

The remainder of the paper is organized as follows. In section 2, we first explain the area and the period of our study. Then, a short discussion is given about the conversion process of each pollutant concentration to AQI, standardization of data, RBF neural network, MLP neural network, the correlation coefficient measures, and mean square error. In Section 3, the methodology is presented that contains data normalization, modeling the data using aforementioned neural networks and choosing the best model according to the pre-determined measures, and finally, obtaining the correlation between pollutants and diseases using the best-chosen model. Next, we provide experimental results and discussions. Finally, we present the concluding remarks along with the future research directions. The general structure of the proposed approach is shown in figure 1.

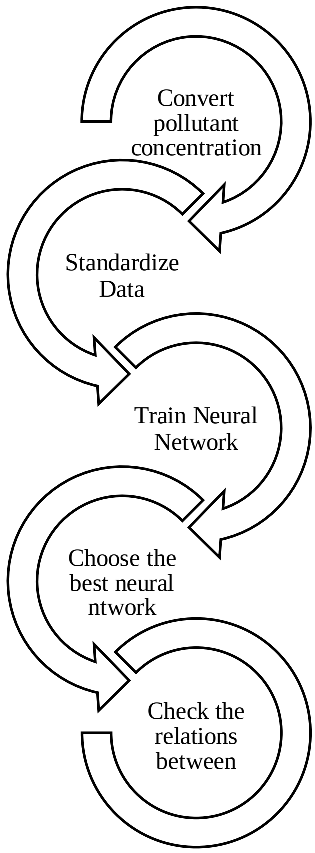

Fig 1. The general structure of the proposed approach

2- Methodology

2-1- Case study

We study the relation between pollutant concentration including PM_{10}, $PM_{2.5}$, CO, SO_2, NO_2 and O_3 and heart-pulmonary diseases in Tehran, Iran. Tehran, the capital city of Iran, contains 11 billion people and its area is about 700 square kilometers and only during 30 percent of days per year it owes clear and healthy air. Air pollution in Tehran is proctored by Air Quality Control Company (AQCC), one of subsidiary companies in Tehran municipality (Saadat et al., 2009; Khalilzadeh et al., 2009; Shahi et al., 2014).

Combination of natural and artificial causes make Tehran one of most polluted cities in the world similar to the cities such as Mexico City, Beijing, Cairo, Sao Paulo, Jakarta, and Bangkok. Tehran's geographical situation generates more air pollution problems. Tehran's high altitude, range of 3300 to 5000 feet, leads to inefficient fuel combustion added to air pollution problems. Since Tehran is restricted to the mountains from the north and east, then the pollution will be stuck in (Khalilzadeh et al., 2009).

Air pollution data are collected from Aqdasieh and Shahid Beheshti University stations for Shohadaieh Tajrish and Taleqani hospitals and Piroozi station for Imam Hossein hospital. This study is conducted in Shoahadaieh Tajrish, Ayatollah Taleqani, and Imam Hossein hospital and during this study number ischemic, pneumonia, angina, and COPD patients respectively are 4799, 650, 2313 and 460 with age average of 61.54, 43.39, 58.33 and 42.92.

Data gathering is composed of two steps; the first step is gathering data related to PM_{10}, $PM_{2.5}$, CO, SO_2, NO_2 and O_3 from Air Quality Control; in the second step, the number of admitted heart-pulmonary diseases patients has been gathered in the aforementioned hospitals in 351 days.

2-2- The conversion process of each pollutant concentration to AQI

Air Quality Index (AQI) is an index to report air quality during a day (Li et al., 2019). AQI indicates that the air is clean or polluted and what can concern us regarding its effects on human health. AQI alters from 0 to 500. AQI is calculated as follows:

$$AQI = \frac{P_i * 100}{P_s} \tag{1}$$

where P_i and P_s refer to pollutant concentration amount and standard concentration amount of pollutant, respectively (Pan et al., 2020). Table 1 shows AQI amount and the concerning level of healthy condition.

Table 1. AQI values and the level of health concerns (Pan et al., 2020)

Value	Level
0 to 50	Good
51 to 100	Average
101 to 50	Unhealthy for sensitive groups
151 to 200	Unhealthy
201 to 300	Very Unhealthy
301 to 500	Dangerous

2-3- Standardization of data

The standardization procedure in the interval of [0,1] is as follows:

$$x_{sn} = \frac{x - b_l}{b_u - b_l} \tag{2}$$

where b_u and b_l are respectively the upper and lower bound of data (Alam et al., 2011).

2-4- Cross-Validation

The cross-validation assures that each observation of the dataset D appears the same number of times in the training sets and precisely once in the test sets. The cross-validation is based on a division of the dataset D into r disjoint subsets $L_1, L_2 \dots and\ L_k$ and necessitates r iterations. At the kth iteration of the process, subset L_k is designated as the test set and the union of all the other subsets in the partition as the training set that is:

$$\nu_k = L_k\ ,\quad T_k = \bigcup_{l \neq k} L_l$$

When the partition has been done, the classification algorithm AF is exploited r times, using each of the r training sets sequentially and evaluating the accuracy each time on the corresponding test set. Finally, the arithmetic mean of the r individual accuracies is considered as the total accuracy. Assigned percent for the test set is 1/r times of all data.

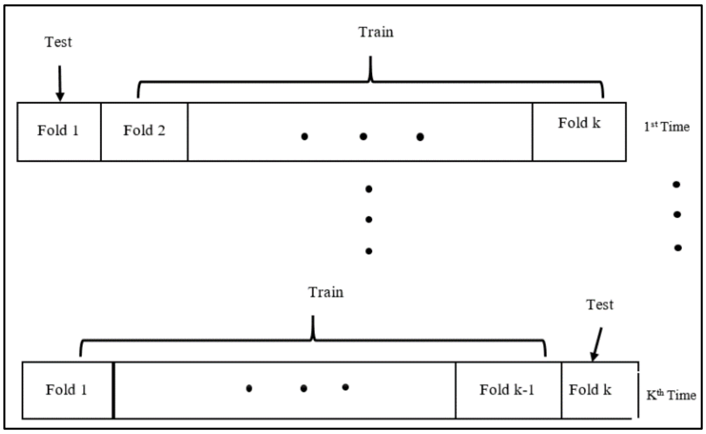

Fig 2. Evaluating the accuracy using k-partition cross-validation

2-5- RBF neural network

RBF networks display a specific class of progressive neural networks structure. RBFN basic structure consists of an input layer, the hidden layer by a radial activation function and an output layer as shown in figure 2 (Amini et al., 2020; Karray et al., 2004).

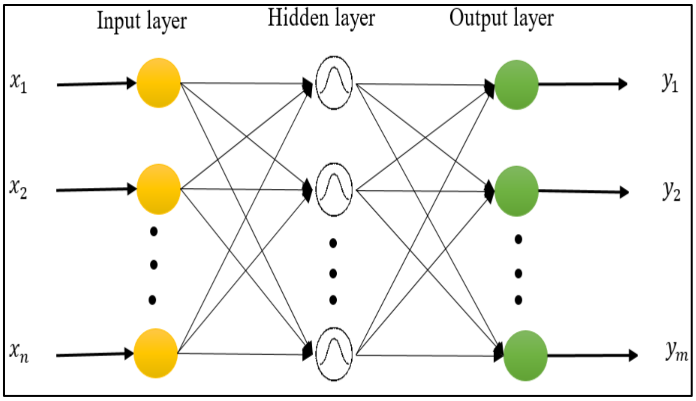

Fig 3. General view of RBF network

As its name implies the symmetrical radial basis functions are used as the activation function of hidden nodes. Conversion of input nodes to hidden nodes is a non-linear conversion, and training of this part is conducted by an unsupervised learning method. Training the connection weights between the hidden layer and output occurs in a supervised learning method based on the desired output (Amini et al., 2020; Karray et al., 2004).

2-6- MLP Neural Network

Multilayer Perceptron (MLP) belongs to the class of feedforward networks, which means that the flows of information among network nodes are exclusively forward. Network is formed of an input layer, a hidden layer, and an output layer. For the first time in 1960, this structure has been suggested to overcome the separability problem of old models such as perceptron and Adaline. The number of required hidden layer in an MLP depends on issues (Bahiraei et al., 2020; Karray et al., 2004). Figure 4 shows a multilayer perceptron network by an input layer, a hidden layer, and an output layer.

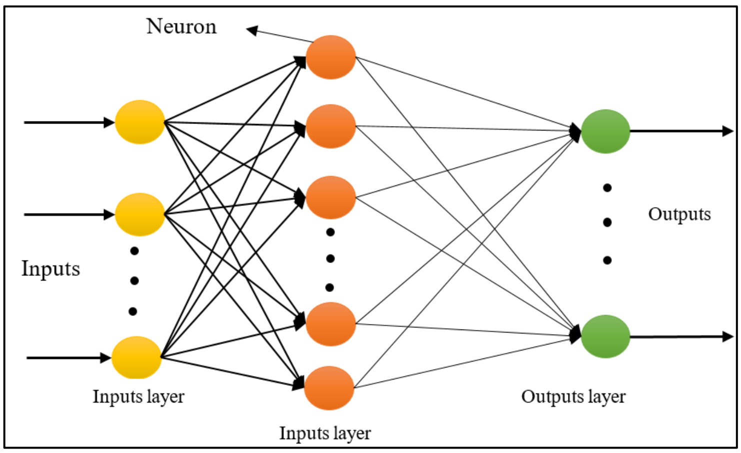

Fig 4. General view of the MLP network (Bahiraei et al., 2020).

Equation 3 shows the calculation procedure of the MLP neural network in any neuron.

$$y = f\left(\sum_{i=1}^{n} w_i x_i - \theta\right) \quad (3)$$

where y is the output for a given input x_i, w_i is adaptive weights, θ indicates bias and f is an activation function. The sigmoid activation function is used in neurons of the hidden layer as equation 4:

$$y = \frac{1}{1 + e^{x}} \quad (4)$$

Moreover, the back-propagation learning algorithm is used to train the weights and biases of the MLP network (Aramesh et al., 2014).

2-7- ANFIS model

Zadeh was the forerunner of fuzzy logic in 1965. A fuzzy logic system is unique in that it can simultaneously handle numerical data and linguistic knowledge (Mosallanezhad, and Ahmadi, 2018). Adopting Neural-Fuzzy Inference System (ANFIS) is a combination of preeminent properties of fuzzy systems and neural networks defined by Jang (1992). ANFIS is a method to simulate complex non-linear mapping using neural network learning and fuzzy inference method. ANFIS structure is formed of IF-ELSE rules, fuzzy input-output pairs, and neural network learning algorithm. ANFIS learning algorithm is a combined learning algorithm including least square error and back-propagation algorithm.

Supposed that targeted FIS has two input (x,y) and an output (f) and rules set is showed by two IF-THEN Takagi and Sugeno rules as below:

$$Rule\ 1: if\ x\ is\ A_1 and\ y\ is\ B_1, then\ f_1 = p_1x + q_1y + r_1$$
$$Rule\ 2: if\ x\ is\ A_2 and\ y\ is\ B_2, then\ f_2 = p_2x + q_2y + r_2$$

As figure 5, five layers are applied to form the ANFIS structure. Each layer function is summarized as following (Riahi-Madvar et al., 2019):

Layer 1: input node

The relation between input and output is described by the following equation:

$$O_i^1 = \mu_{Ai}(x) \quad (5)$$

where O_i^1 is i-th output from layer 1, $\mu_{Ai}(x)$ is x membership degree in Ai fuzzy set as Gaussian membership function as:

$$\mu_{Ai}(x) = exp(-(\frac{x - c_i}{a_i})^2) \quad (6)$$

a_i and c_i in this layer are called hypothesis parameters.

Layer 2: rules nodes

The output of this layer is obtained from the input signal as:

$$O_i^2 = w_i = \mu_{Ai}(x) * \mu_{Bi}(x) \quad (7)$$

Layer 3: Normalized nodes

This layer is used to normalized weight function and defined as:

$$O_i^3 = \underline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1,2. \quad (8)$$

Layer 4: result nodes

Layer 4 is the defuzzification layer. In this layer, the output of the previous layer is multiplied by Sugeno fuzzy rule function and described as:

$$O_i^4 = \underline{w}_i f_i = \underline{w}_i (p_i x + q_i y + r_i) \tag{9}$$

where $\underline{w_i}$ is layer 3 output and (p_i, q_i, r_i) in this layer are result parameters.

Layer 5: outputs nodes

There is only a labeled node in this layer. This node is calculated using summation of all previous layers results.

$$Overall\ output = O_i^5 = \sum_i \underline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{10}$$

Here, a hybrid learning algorithm contains least square error, and the descent gradient is exploited to estimate parameters (Riahi-Madvar et al., 2019; Moayedi et al., 2019).

2-8- Evaluation measures of the model

Two measures of model evaluation (model order) are as follows: correlation coefficient (r) and mean square error (MSE). The correlation coefficient is used to investigate the relation between variables and is defined as equation (11).

$$r = \frac{\sum_{i=1}^{N} (x_i - \underline{x})(y_i - \underline{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \underline{x})^2}\sqrt{\sum_{i=1}^{N} (y_i - \underline{y})^2}} \tag{11}$$

R measures any linear trend between the variables. Its value is always between -1 and 1. Zero value for *r* means that there is no relation between the variables. If the associated value situates between 0 and 1, it means that the sample components are scattered around the line with a positive slope. If the value is one, there is a positive relation between variables, and all sample components are on the line with a positive slope. If the associated value for *r* is between -1 and 0, sample components are scattered around the line with a negative slope. If the corresponding value for *r* is -1, there is a reverse relation between variables and all sample components are on the line with a negative slope (Puth et al., 2014).

The second measure is written as equation (12):

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 \tag{12}$$

where *N* is the number of data and e_i is error value (Khashei et al., 2012).

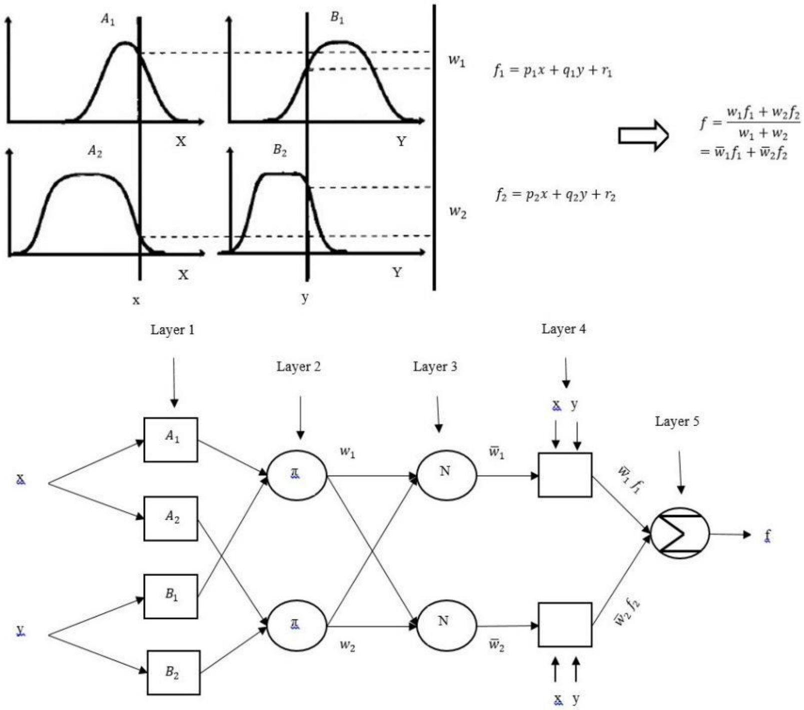

Fig 5. ANFIS structure

3- Results and discussion

3-1- Neural network training

Matlab neural network and ANFIS toolbox are used to run the models. At first; for training the networks, diseases and pollutants are respectively accounted as output variables and input variables. Then after obtaining the optimum network; all pollutants and diseases are compared to show the relation between them using correlation coefficient criteria. RBF and MLP optimum neuron numbers respectively are 18 and 45. Different action functions are tested for MLP and RBF, which respectively Sigmoid and Gaussian functions have more significant results than others. Epoch numbers for RBF and MLP are 3600 and 5800 that shows convergence in RBF is faster than MLP. A hybrid approach is used for training in the ANFIS method, which is a combination of least square error and descent gradient. Random method and cross-validation are used for data classification which paramount cross-validation results belong to five-fold cross-validation 20% and 80% for training and test data and random method, obtained by test and error, is 30% and 70% training and test data. Training parameters options are empirically selected as table 2.

Table 2. ANFIS Optimum Parameters

ANFIS parameters	value
Fuzzy rules number	64
Linear parameters number	24
Non-linear parameters number	448
All parameters number	472
Training percent and number	70% and 246
Test percent and number	30% and 105
Output membership function	Linear
Output membership function	Gaussian
Training method	Hybrid
Epoch number	800

Accuracy of RBF, MLP, and ANFIS is assessed by minimum square error (MSE) and epoch number. Between networks, ANFIS has less MSE and number of epochs than RBF and MLP. See table 3.

Table 3. Network comparison

Network	Epoch number	MSE
RBF	3600	0.0124
MLP	5800	0.0895
ANFIS	800	0.01013

3-2- Comparison of Pollutants and AQI Levels

Using equation (1), we convert the concentration of PM_{10}, $PM_{2.5}$, CO, SO_2, NO_2 and O_3 which were at ($\frac{\mu g}{m^3}$, $\frac{\mu g}{m^3}$, ppm, ppm, ppm and ppm) to AQI and using table 4 we categorize each pollutant. According to figures 6 (a), (b) and (c) the value of each pollutant during study period is the gathered which PM_{10} and $PM_{2.5}$ are more than the other pollutants. Sometimes, these two pollutants are placed in an unhealthy air zone, but the other pollutants are placed in good and average air zones. Thus, the main factors of Tehran air pollution are PM_{10} and $PM_{2.5}$.

3-3- Pollutant effects on heart-pulmonary diseases

According to table 4, PM10 and PM2.5, NO2 and CO, SO2 and NO2 and PM2.5 and NO2 have the most relation with each other. However, the relation between pollutants and diseases is insignificant. As figure 7 shows, the relation between Angina and PM10, PM2.5 and O3 have a negative slope, and other pollutants have insignificant positive slope. The most association is between CO and Angina with 0.21 correlation coefficient. Figure 8 represents the relation between Pneumonia pollutants and O3, PM10, CO, and PM2.5 have a negative slope, and NO2 and SO2 have an insignificant positive slope. Figure 9 shows that COPD and O3 and PM10 have a negative slope and CO, NO2, PM2.5, and SO2 have insignificant positive slopes. Figure 10 displays that Ischemic and

O3 have a negative slope and the other pollutants have insignificant slope. Therefore results explain that linear approaches are inappropriate for reviewing the relation between variables. Pearson correlation between variables shows that non-linear models are optimum for studying the relation between variables

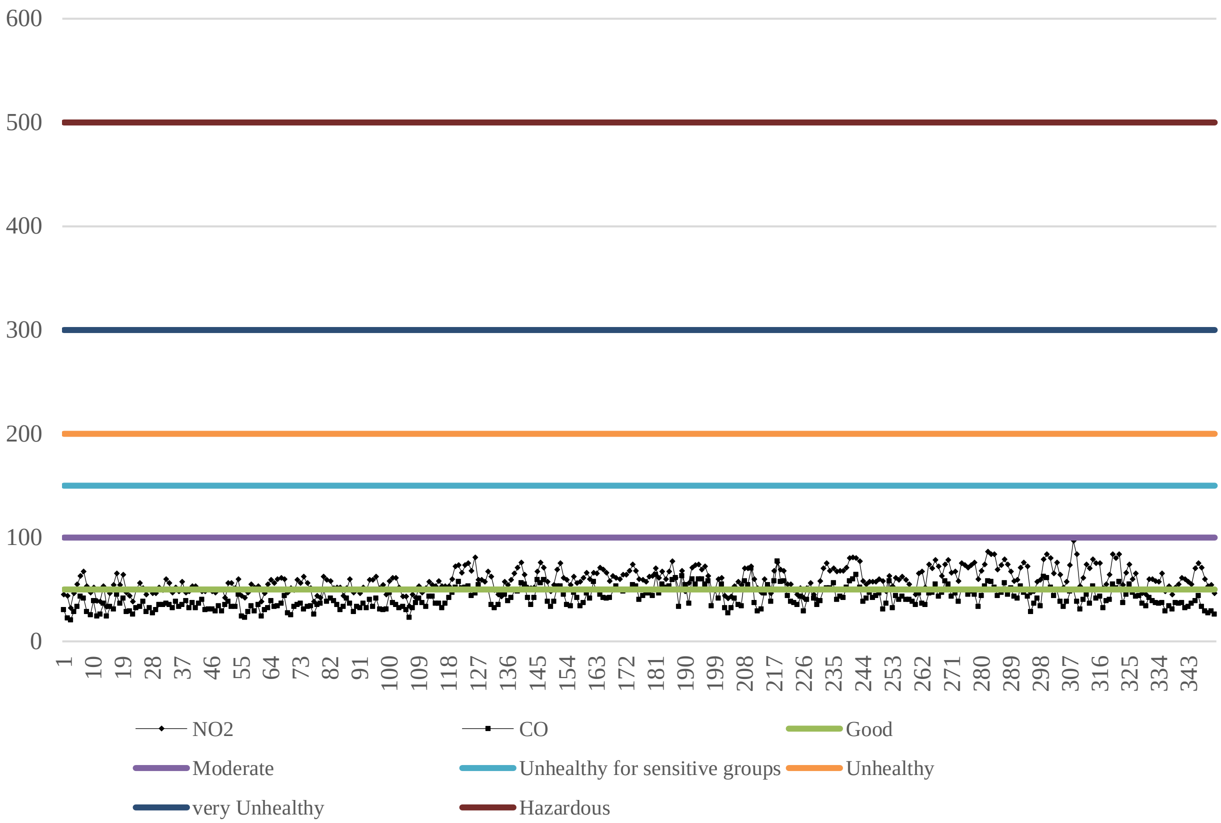

Fig 6 (a). Classification of air pollutants ($PM_{2.5}$ and PM_{10})

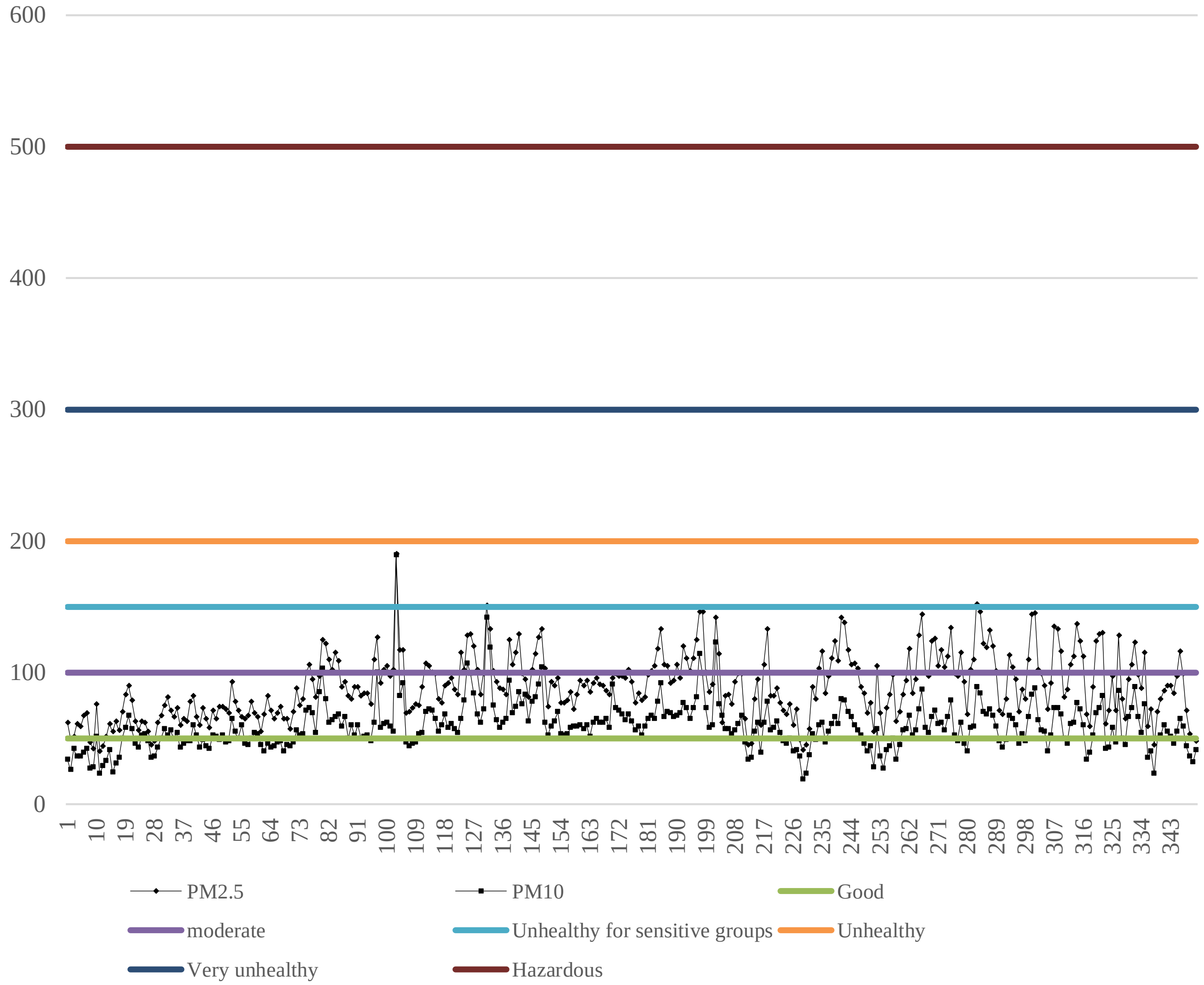

Fig 6 (b). Classification of air pollutants (NO_2 and CO)

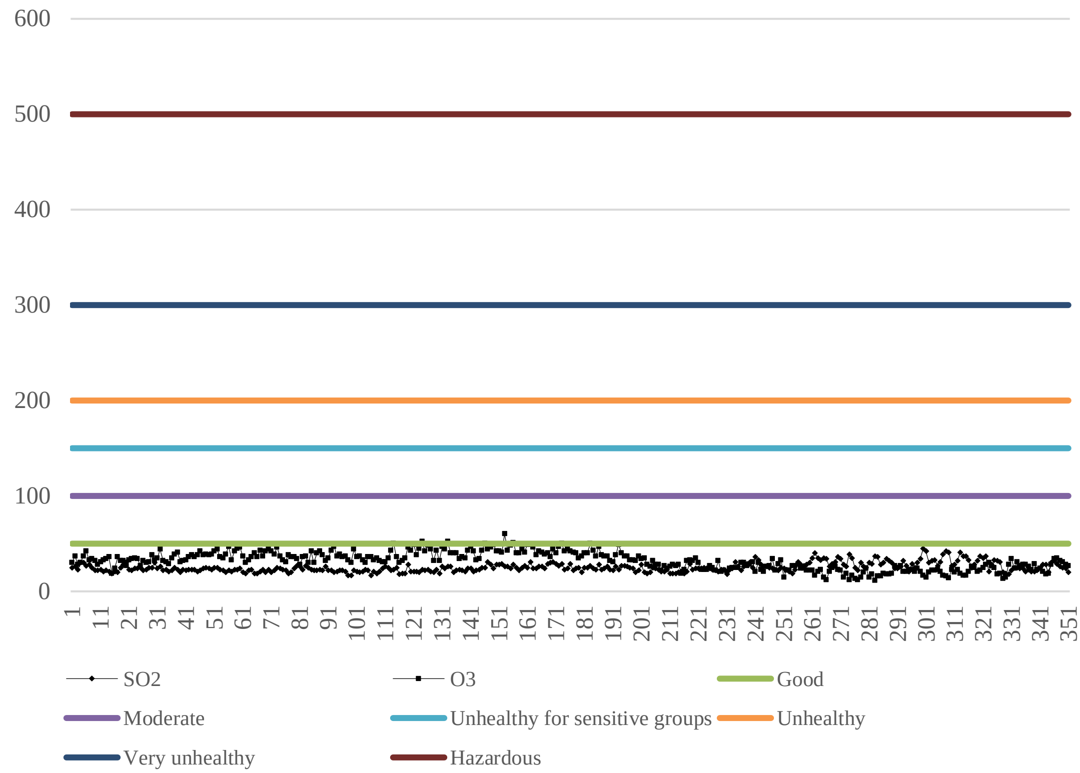

Fig 6 (c). Classification of air pollutants (SO_2 and O_3)

Table 4. Pearson correlation analysis between pollutants and diseases during the study

	CO	O_3	NO_2	PM_{10}	$PM_{2.5}$	SO_2	**Angina**	**Pneu.**	**COPD**	**Isch.**
CO	1									
O_3	-0.49	1								
NO_2	0.774	-0.193	1							
PM_{10}	0.368	0.149	0.348	1						
$PM_{2.5}$	0.549	-0.097	0.607	0.87	1					
SO_2	0.384	-0.385	0.612	0.233	0.474	1				
Angina	0.21	-0.16	0.062	-0.047	-0.012	0.098	1			
Pneumonia	-0.048	-0.0165	0.033	-0.191	-0.118	0.102	0.013	1		
COPD	0.019	-0.212	0.118	-0.061	0.034	0.193	0.038	0.245	1	
Ischemic	0.198	-0.054	0.202	0.117	0.154	0.17	0.403	-0.006	0.138	1

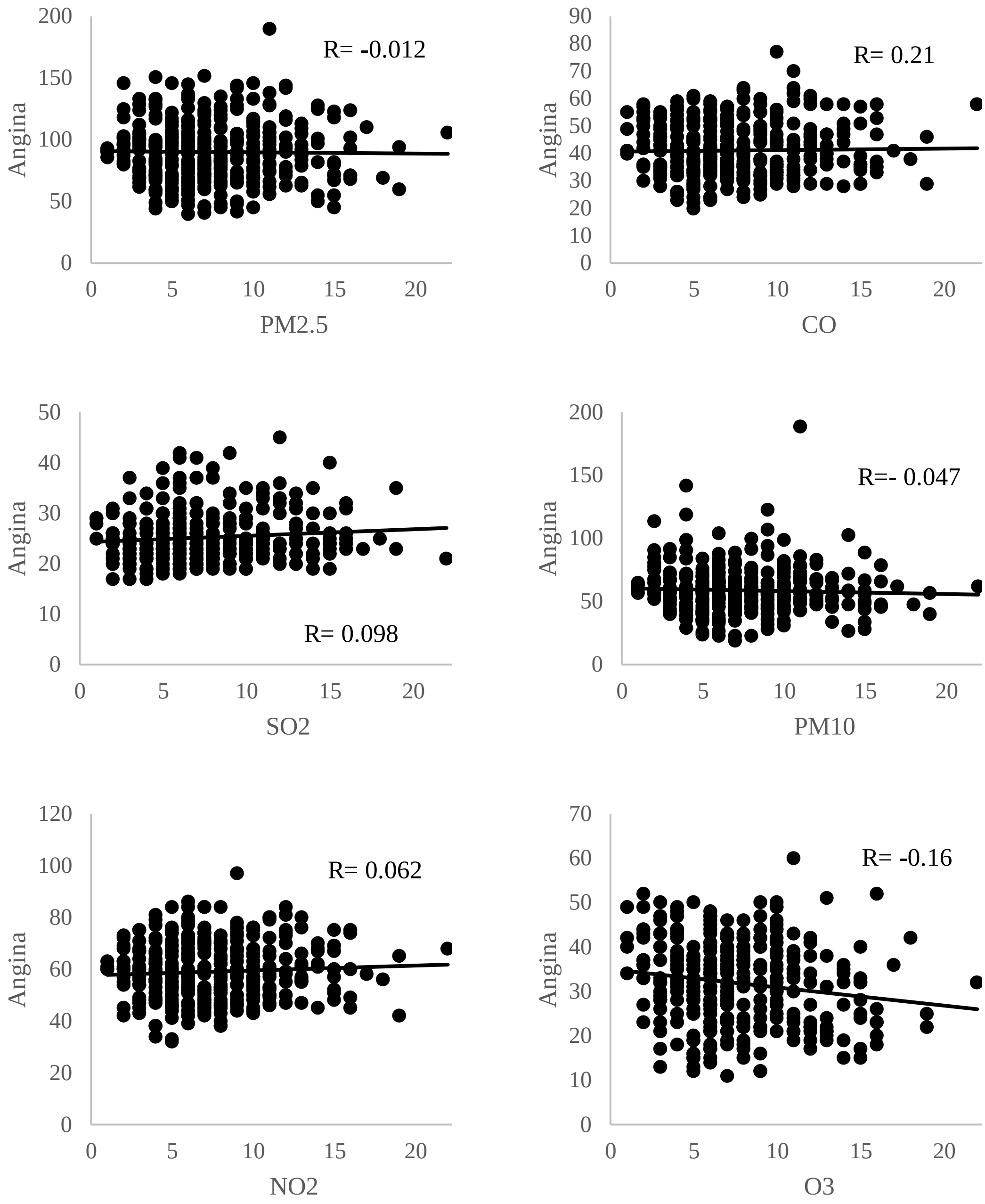

Fig 7. The correlation coefficient between the pollutants and angina

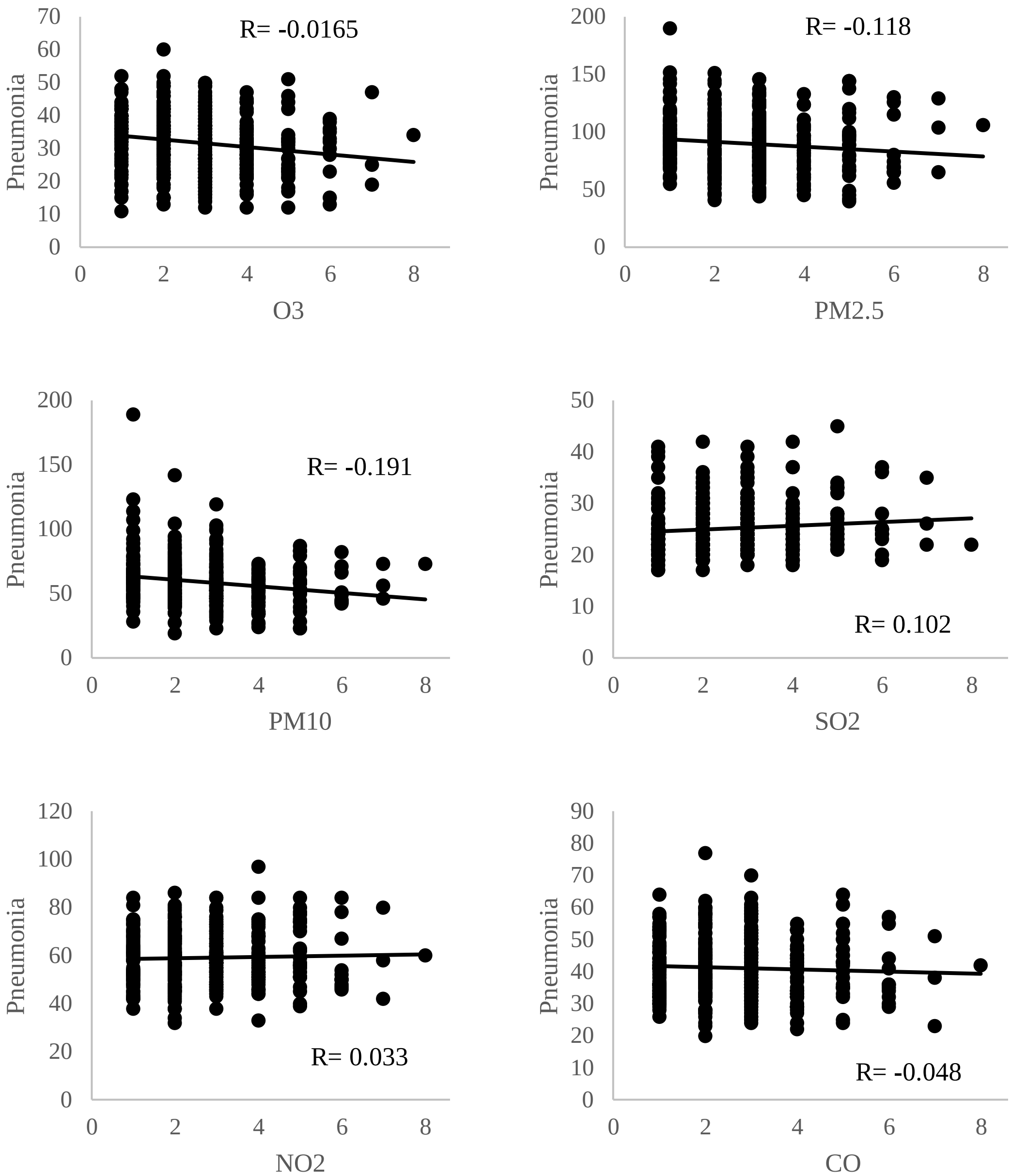

Fig 8. The correlation coefficient between the pollutants and pneumonia

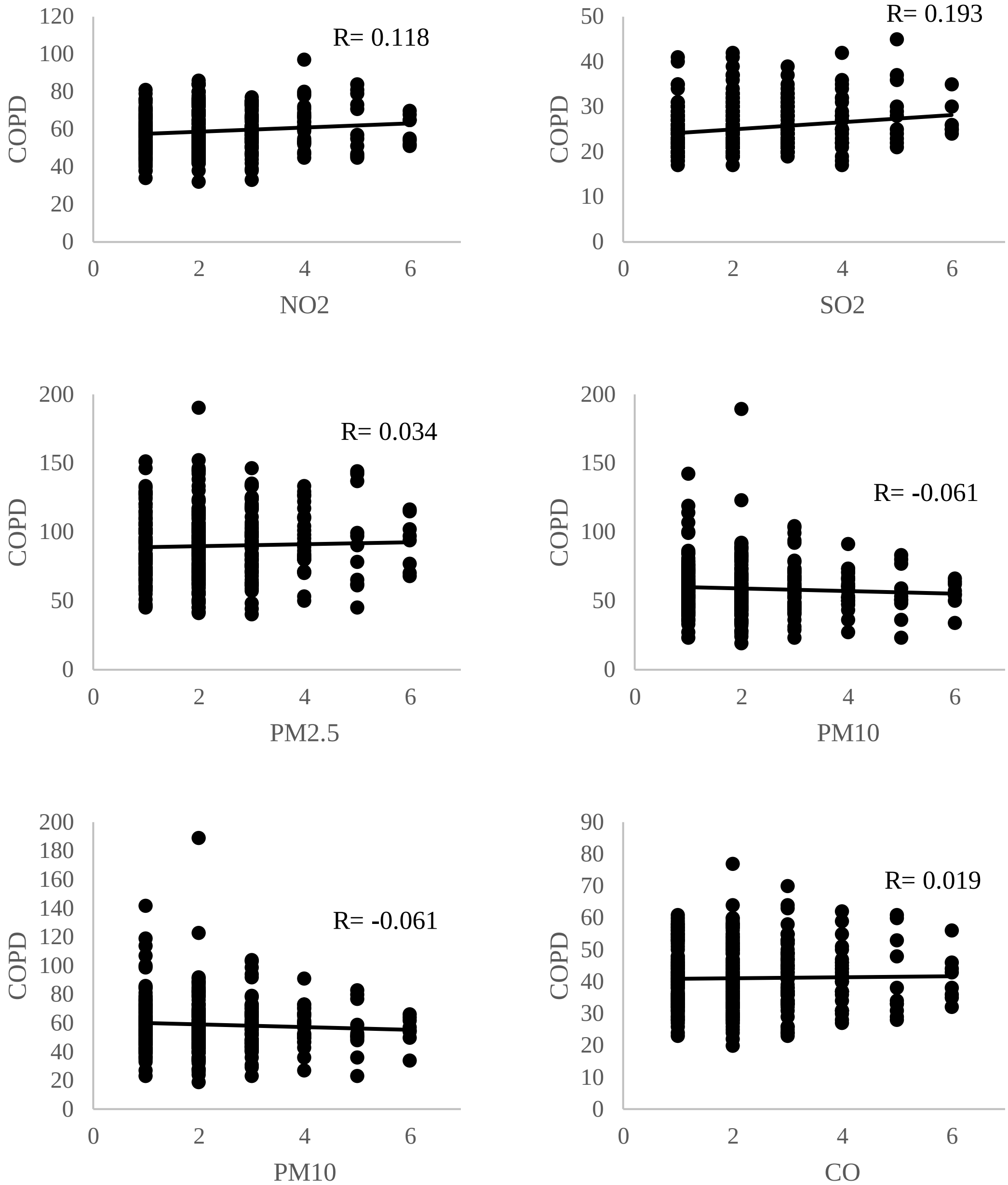

Fig 9. The correlation coefficient between the pollutants and COPD

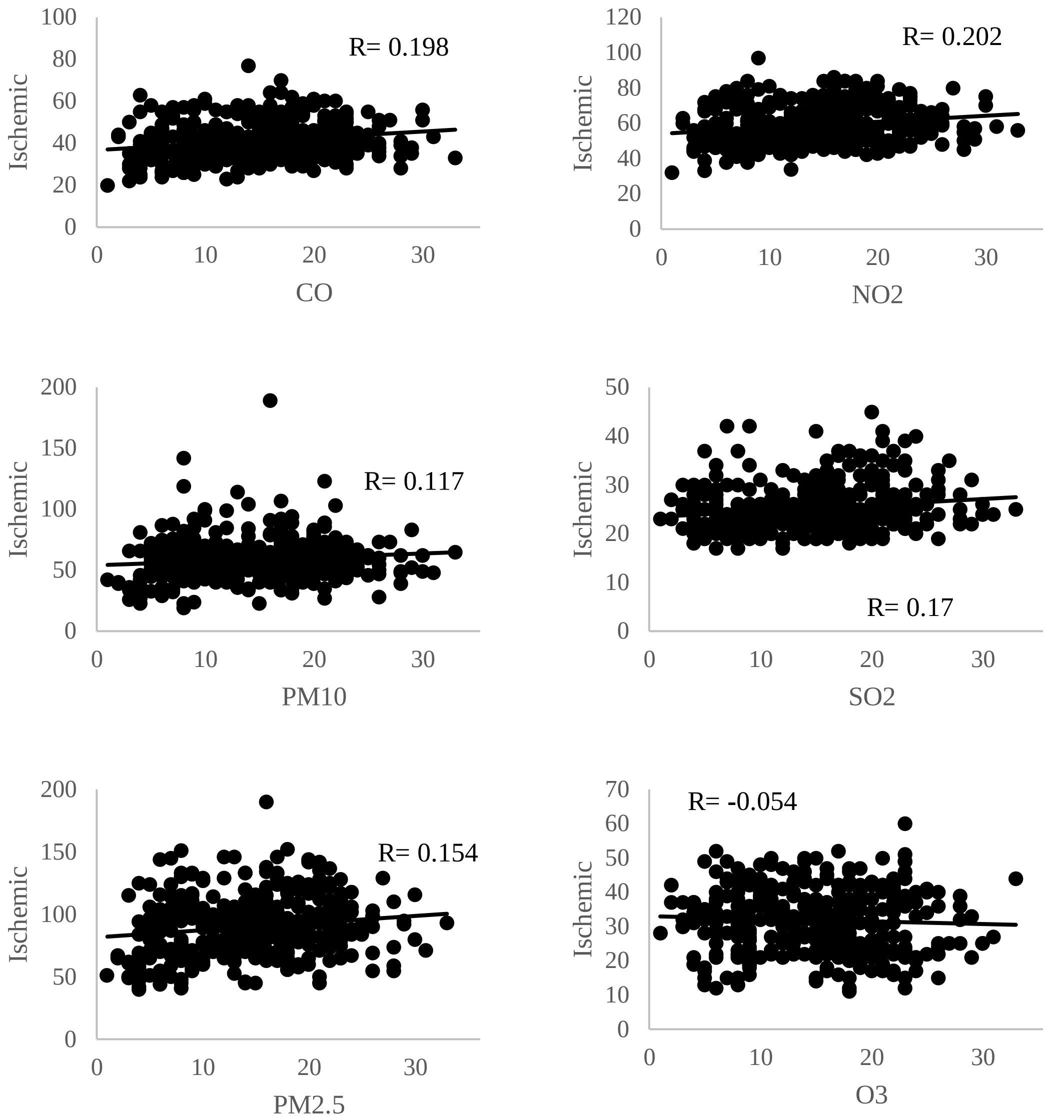

Fig 10. The correlation coefficient between the pollutants and ischemic

Figure 11 presents the obtained results of the network and the desired output. These two curves are approximately fitted, which indicates that the network is excellently trained, and the parameters are accurately retrieved. Figure 12 shows the obtained errors in network performance. In accordance with the optimum network result and correlation coefficient criteria between variables, there is a positive relation between variables. Table 5 shows the correlation coefficient between pollutant and diseases. Figure 13 shows the relation between pollutant and ischemic disease so that most relation is between SO_2 and ischemic disease. Figure 14 contains the relation between pneumonia and pollutants and signifies that PM_{10} and pneumonia have a positive and significant slope. Figure 15 shows the relation between COPD and pollutant so that most relation is between PM_{10} and $PM_{2.5}$

and COPD. Figure 16 demonstrates the correlation between angina and pollutant so that CO has more relation between angina that other pollutants. The aforementioned average age of visited patients for ischemic, pneumonia, angina, and COPD respectively is 61.54, 43.39, 58.33, and 42.92. Hereon, aging is one of the most vital factors of cardiovascular and pulmonary diseases.

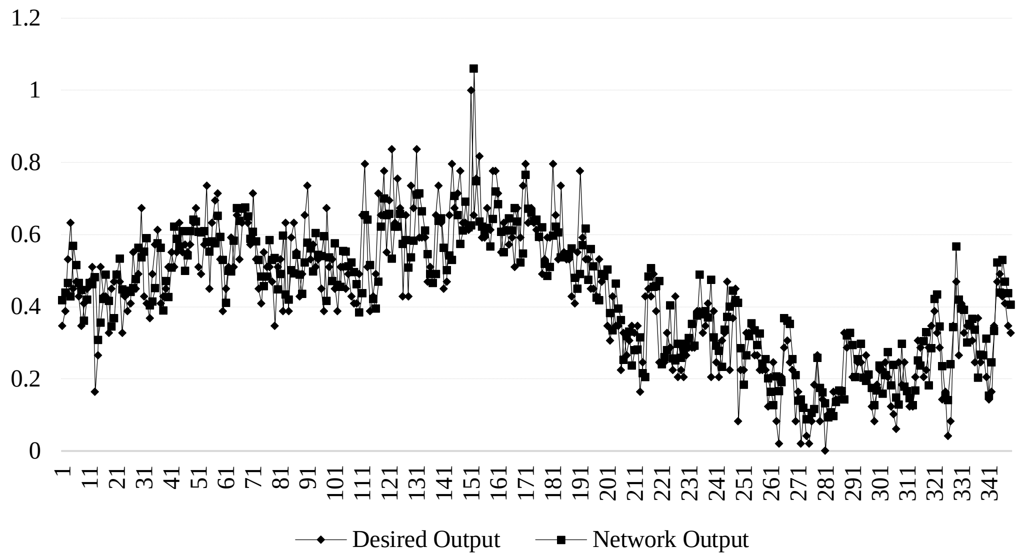

Fig 11. The obtained results of the network and the desired output

Table 5. Correlation coefficient proposal optimum network

	CO	O_3	NO_2	PM_{10}	$PM_{2.5}$	SO_2
Angina	0.7006	0.2335	0.6611	0.6185	0.6761	0.3549
Pneumonia	0.602	0.68	0.741	0.81	0.675	0.613
COPD	0.3596	0.3860	0.6918	0.7249	0.7280	0.6059
Ischemic	0.6312	0.5448	0.7229	0.7003	0.6604	0.8526

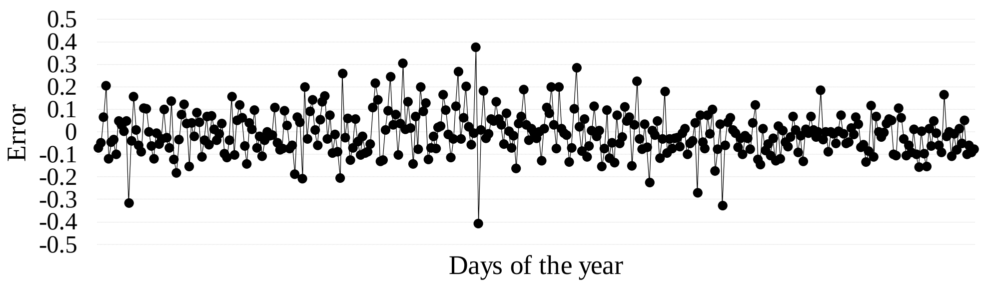

Fig 12. ANFIS network error for all data

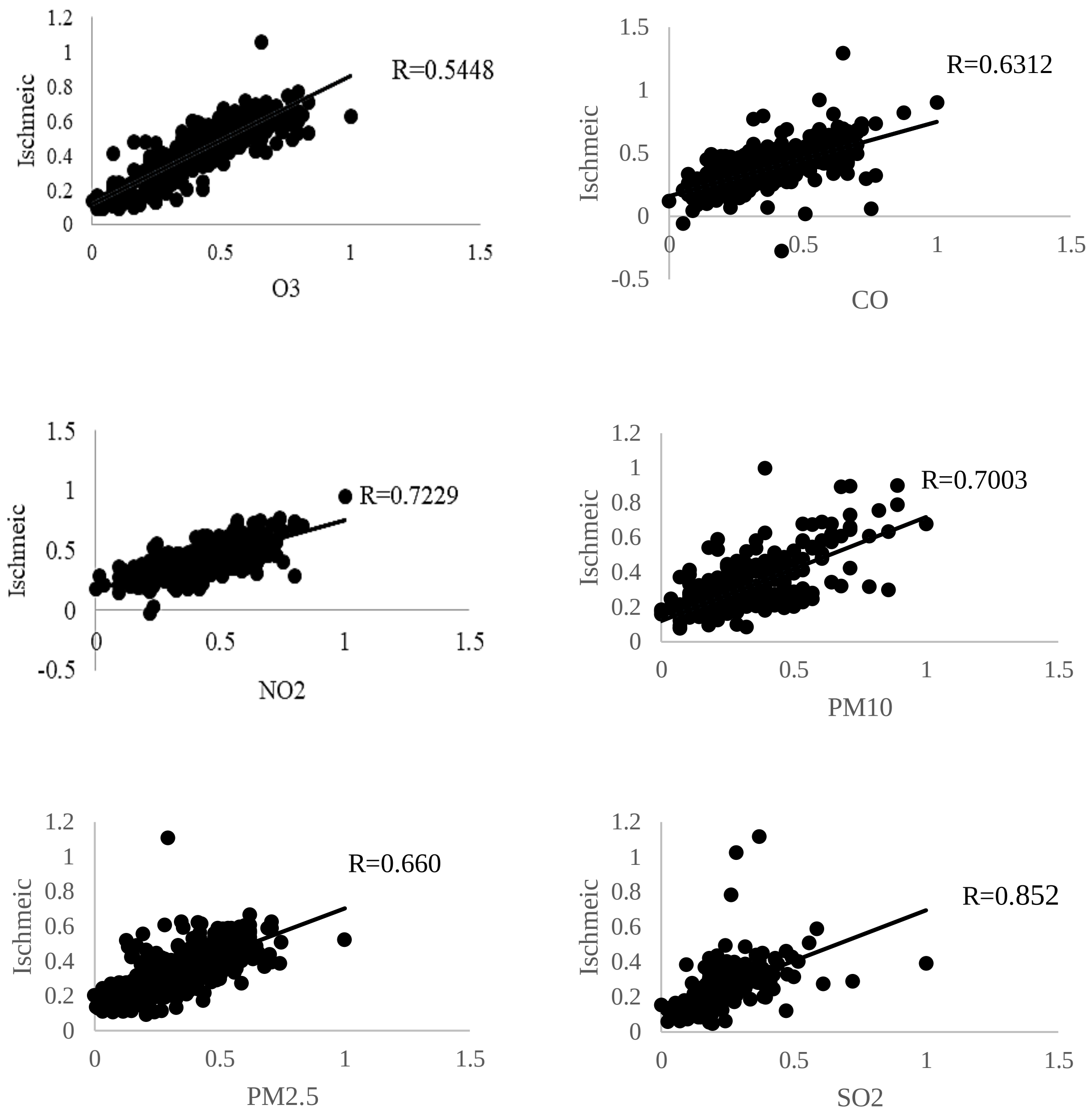

Fig 13. The correlation coefficient between the pollutants and IHD

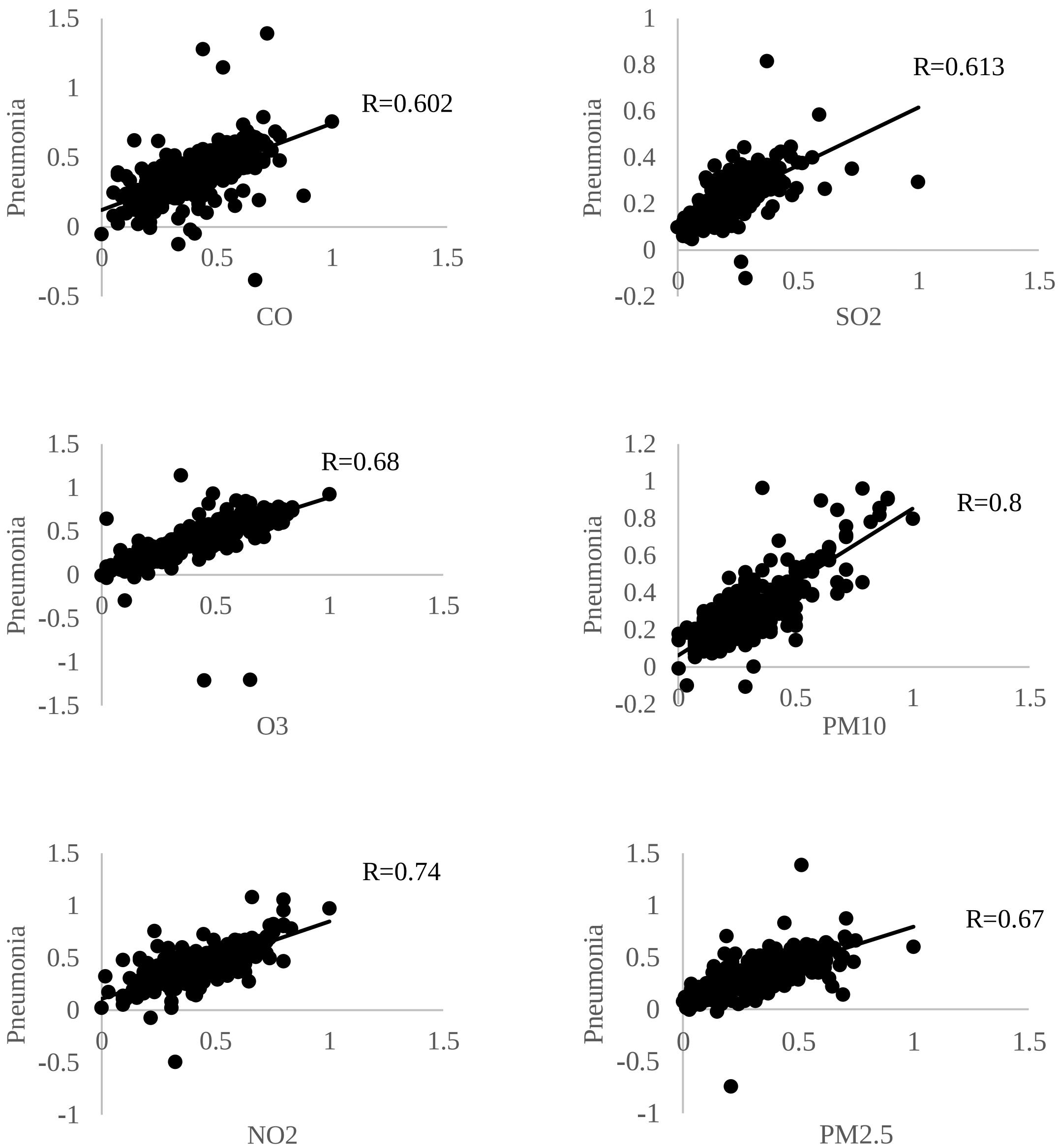

Fig 14. The correlation coefficient between the pollutants and pneumonia

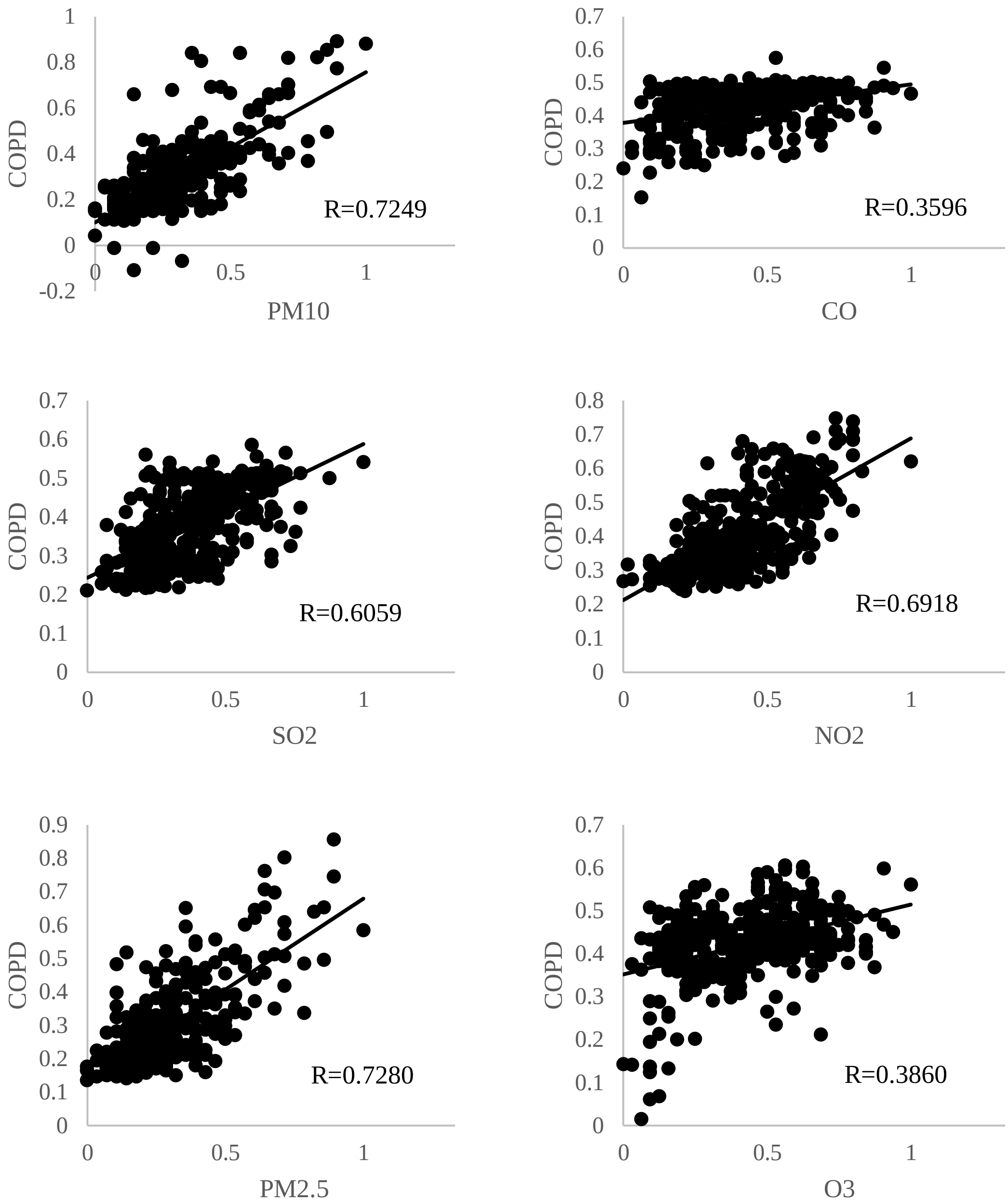

Fig 15. The correlation coefficient between the pollutants and COPD

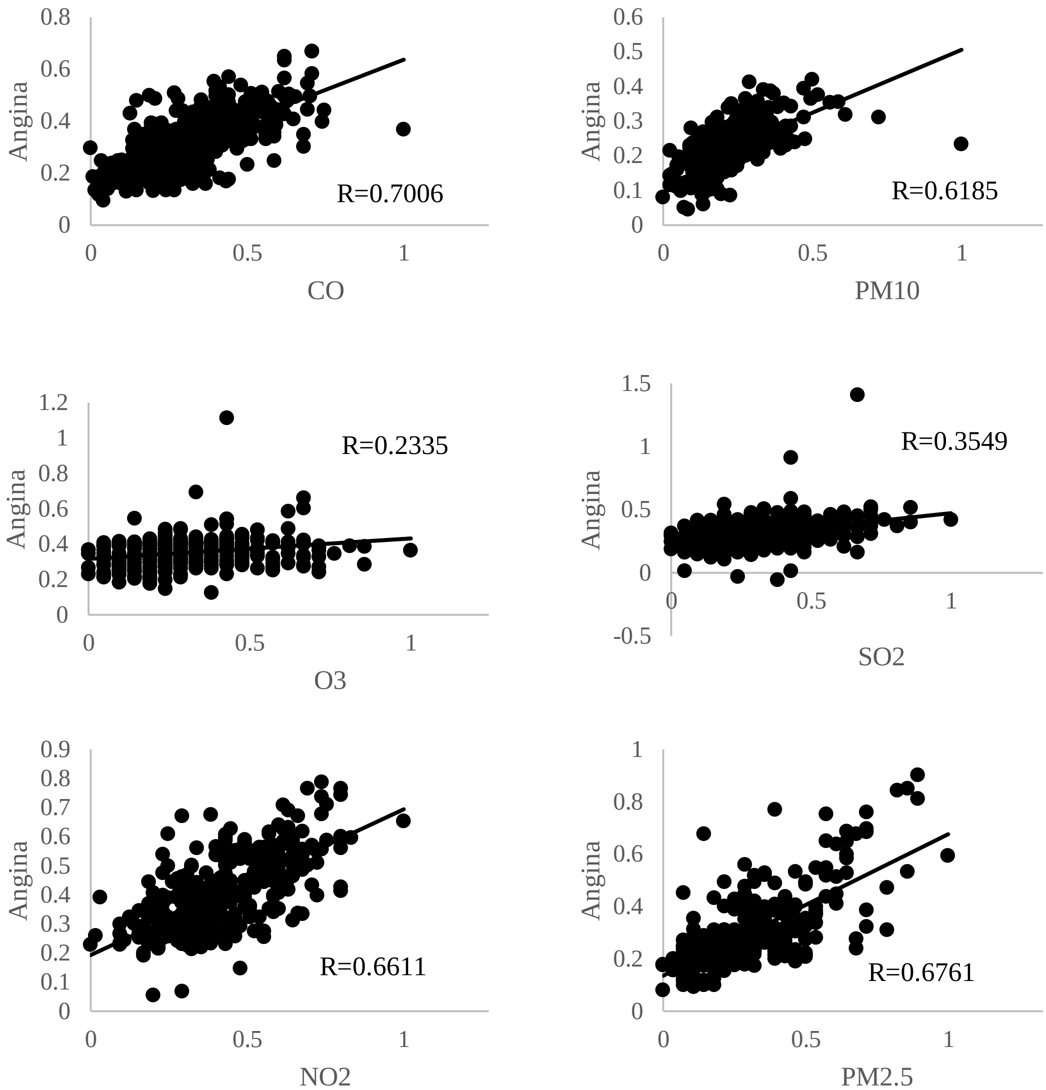

Fig 16. The correlation coefficient between the pollutants and angina

4- Conclusions

This study is the most recent widespread study done in Tehran as the most polluted city of Iran. The effect of all pollutants on heart-pulmonary diseases is investigated in the study by a neural network.

First, we used Pearson correlation to study the relation between pollutants and heart-pulmonary diseases. However, an incompatible relation was observed. Then, we had a clue to use non-linear models instead of linear models. Moreover, the accuracy of ANFIS was more than that of MLP and RBF. This indicates that the ANFIS network can extract the non-linear relation between pollutants and heart-pulmonary diseases according to defined measures.

As for future research, we suggest using other networks such as NARX. Also, one can create patients' age intervals to study the correlation at different intervals.

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