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Forecasting $PM_{2.5}$ and PM_{10} Air Quality Index using Artificial Neural Network

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Abstract

The Air Quality Index (AQI) was established in response to the Clean Air Act of the Philippines. A complex correlation exists between air pollution levels and exposure, as indicated by the AQI. Manila is one of the cities with severe air pollution-related environmental problems. The impacts of air pollution exposure are detrimental. Therefore, it is essential to forecast air quality indicators and pollution levels to inform the public, particularly sensitive groups, whether or not air quality is safe and healthy. The study's objective is to construct an air quality forecasting model using an Artificial Neural Network (ANN), which, to date, is the only air quality forecasting model in the Philippines. A feed-forward neural network is utilized to make the model. The PM2.5 and PM10 pollutant concentration time series are provided from the real-time monitoring station in Mehan garden station in Manila. The best forecasting performance of the model was observed with having minimum values of MSE. MAPE and MAE have a value of R2 nearer to 1 from expected and predicted values.

Keywords— Air Quality Index, Artificial Neural Networks, Forecasting, Python.

INTRODUCTION

Human health worldwide is at risk due to air pollution [1] and it kills millions of people every year. Today 92% of our world is exposed to polluted air; fine particle pollution caused 32, 019 deaths in the Philippines in 2019 [2]. Thus, the Clean Air Act is established to help maintain healthy air for all Filipinos [3]. Through the Philippine Clean Air Act, Air Quality Indices were formulated. The Clean Air Act is a comprehensive air quality management policy and program that aims to maintain healthy air for all Filipinos. The air quality indices (AQI) protect public health, safety, and general welfare [4]. The Filipino people are exposed to an average of 19 µg/m3 a year, 1.9 times the World Health Organization (WHO) guidelines. Exposure to air pollution has ill effects. Thus, it is important to forecast the air quality indications and pollution levels to guide the public, especially the sensitive groups, on whether or not the air quality is safe and healthy.

The Philippines Department of Environment and Natural Resources (DENR) monitors the air quality system to ensure that public health is protected from the dangers of air pollution. As of 2020, there are 75 air quality monitoring stations strategically located in 16 regions across the country; 34 are capable of continuous online monitoring, while 41 use a manual sampling method. The Environment Monitoring Bureau (EMB) of the DENR provides real-time and historical data on air pollutant concentrations and air quality index calculations. However, the data collection displayed on the EMB page is merely a report of annual monitoring data for ambient air quality. There is no known air quality forecasting model in the Philippines that utilizes neural networks. It is vital to have accurate air quality forecasts to adequately alert the public of potential illnesses caused by air pollution. Air quality forecasting [5] [6] assists decision-makers in improving air quality and public health and mitigating the incidence of acute air pollution episodes, especially in urban areas. The forecasting of air quality is comparable to weather forecasting. The models generate a forecast, which is then modified by local forecasters based on local knowledge and data. Similarly, an air quality forecasting model would be deployed. Forecasting air quality is predicting air quality based on existing data. It is comparable to weather forecasting, except that the latter informs and warns the public about the likely weather conditions for today or a specified period. While the former predicts air quality and provides the public with a warning about harmful air contaminants, the latter measures air quality. There are a variety of data or observed values for time series, which may inhibit or assess the decision to make of a forecasting method. The [7] type of data may necessarily involve the creation of a new forecasting technique. [8] Forecasting methods, especially those based on statistical models, must be optimized to account for local and regional emission reductions.

In the past few years, researchers have developed artificial intelligence (AI)- based methods for forecasting air pollution, with Artificial Neural Networks (ANN) being one of the most widely used AI-based techniques for air pollution [9]. The development of the complete and effective ANN model requires general and consistent protocols [10]. Air quality forecasts can also be derived through statistical techniques such as regression, and artificial neural networks [11]. ANN structure model can generalize and tolerate error, allowing it to be adaptable and quick at problem-solving. ANN can model highly nonlinear relationships and generalize newly presented data. The application of the neural network in forecasting the air quality index is shown in Table I.

Table I
Different air quality forecasting with neural network

Location	Air Pollutants examine	References
Amman, Jordan	SO_2, O_2, CO_2, NO_2 and PM_{10}	[12]
Tehran, Iran	SO_2	[13]
Fuzhou, Fujian, China	$PM_{2.5}$, and auxiliary data	[14]
Delhi, India	PM_{10}, $PM_{2.5}$, NO_2, and O_3	[15]
Queretaro, Mexico	PM_{10}	[16]
Taipei, Taiwan	$PM_{2.5}$	[17]
Athens, Greece	$PM_{2.5}$, PM_{10}	[18]
Kolkata and Kattankulathur India	$PM_{2.5}$, PM_{10}, SO_2, CO_2, NO_2, and O_3	[19]
Zhengzhou and Shanghai, China	$PM_{2.5}$, PM_{10}, SO_2, CO_2, NO_2 and O_3	[20]
Shenzhen, China	$PM_{2.5}$, PM_{10}, SO_2, CO_2, NO_2 and O_3	[21]

As shown in Table I, the proposed study, to date, is the only ANN-based air quality index forecasting developed in the Philippines to forecast air quality as concerns about air pollution harm public health & welfare. It can be noticed that air pollutants were monitored and forecasted according to emission inventories of the air quality monitoring station. The motivation of this study is to enhance the traditional air quality monitoring and reporting of the DENR-EMB and forecast the air quality index accurately and efficiently. Thus, this paper has developed an AQI forecasting using the ANN model for particulate matter (PM) concentration - PM_{10} and $PM_{2.5}$ in atmospheric air. PM with a diameter of fewer than 10 micrometers is called PM_{10} and while $PM_{2.5}$ if its diameter is less than 2.5 micrometers. Depending on the specific size, properties, and environmental conditions, the heavy concentration of particulate matter seriously causes adverse health effects [22]. Particulate matter (PM) may remain suspended for a few seconds or indefinitely and travel from hundreds to thousands of kilometers. The data recorded at the DENR-EMB Air quality monitoring Manila station were considered. Manila station is one of the emission stations with a real-time recording of pollutants concentration. The performance of the model is evaluated using statistical measurement MSE, MAE, MAPE, and coefficient of determination (R^2)

Materials and Methods

Study Area

Manila, as the capital of the Philippines and the most urbanized city in the area of National Capital Region, the station in Mehan garden as shown in fig 1, was chosen for this paper's study area for forecasting AQI of the air pollutants concentrations. Since then, not only the city’s residents, but also its students, tenants, and their families [23] have been affected. High risk exists for exposure to toxic pollutants and adverse health symptoms. Since 2020, the Mehan garden station has monitored real-time air quality; this station monitors and records Particulate Matter pollutants, which pose a threat to human health and the environment.

Source: DENR-EMB website Emission Inventory page

Fig 1
The location of Mehan Garden air quality station in Manila - Philippines

Air quality index forecasting architecture using ANN

Fig 2. shows the architecture used in this study. It consists of four major phases, Data Preprocessing, ANN modeling, Forecasting, and Analysis.

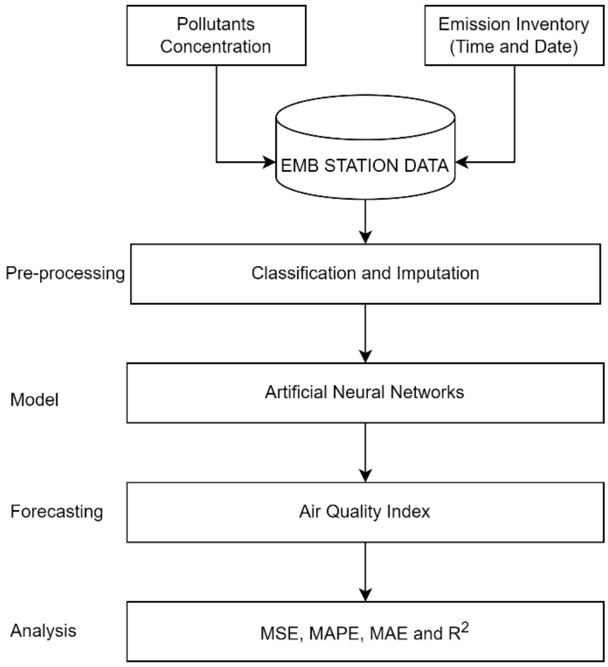

Fig 2
The system architecture of an air quality index forecasting using ANN

Data Collection

The data used in this study is the recorded real-time data on an hourly basis of PM_{10} and $PM_{2.5}$ pollutants from the Mehan garden station. It takes a minimum of forty-five (45) minutes data capture to make a representative hour. The year covered in forecasting AQI is from January 2020 to February 2022. The accuracy of the developed model has been proven by splitting it into two sets – training and testing data.

Data Preprocessing

The data are classified based on the parameter of the pollutants and predict air quality index based on the concertation, date, and time recorded. The error due to missing data has been resolved using Pandas’ DataFrame [24]; this helps the study analyze data. Also used Imputation using the most frequent, zero, or constant to compensate for the missing value.

The AQI Values of the Particulate Matter Concentration

The AQI is by the government agencies to communicate to the public how polluted the air is or how polluted it is forecast to become. [25] stated that the Air Quality Index (AQI) prediction is a useful technique to improve public awareness about air quality. [26] the quality of air and its health effects indicates AQI. To convert concentration values $(\mu g/$

Ncm) to AQI values (unitless) the study used (1).

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}} \left(C_p - BP_{Lo}\right) + I_{Lo} \quad (1)$$

where I_p - *AQI value for the pollutant*
C_p - *Pollutant concentration*

BP_{Hi} - *Breakpoint* $\geq C_p$
BP_{Lo} - *Breakpoint* $\leq C_p$
I_{Hi} - *AQI value corresponding to* BP_{Hi}
I_{Lo} - *AQI value corresponding to* BP_{Lo}

Tables II and III illustrate the AQI range and category of PM_{10} and $PM_{2.5}$ air pollutant concentration [27]. Different ranges of AQI values are analogous d to varying levels of air pollution. For example, the highest level of the AQI value, the worst air quality.

Table II
PM_{10} with range and category and maximum 24-hour average concertation.

AQI value		Category	Breakpoint	
I_{Lo}	I_{Hi}		BP_{Lo}	BP_{Hi}
0	50	GOOD	0	54
51	100	FAIR	55	154
101	150	UNHEALTHY FOR SENSTIVE GROUP	155	254
151	200	VERY UNHEALTHY	255	354
201	300	ACUTELY UNHEALTHY	355	424
301	500	EMERGENCY	425	504

Table III
$PM_{2.5}$ with range and category and maximum 24-hour average concertation.

AQI value		Category	Breakpoint	
I_{Lo}	I_{Hi}		BP_{Lo}	BP_{Hi}
0	50	GOOD	0	25
51	100	FAIR	25.1	35.0
101	150	UNHEALTHY FOR SENSTIVE GROUP	35.1	45.0
151	200	VERY UNHEALTHY	45.1	55
201	300	ACUTELY UNHEALTHY	55.1	90
301	500	EMERGENCY	91	above

Software

Python software [28] was used to conduct data analysis and prediction to develop the AQI forecasting model. Also, TensorFlow 2 works on the open-source artificial intelligence library and builds models using data flow graphs. In addition, TensorFlow allows modelers to create large-scale neural networks with many layers [29].

Artificial Neural Network

Artificial neurons, or simply neurons or nodes, are the fundamental processing elements of neural networks. In the simplest model, synaptic effects are represented by weights that capture the influence of the various input signals, and learning happens by modifying the weights according to the learning algorithm. For example, a typical ANN model employs a multilayered structure, as presented in Figure 3. If the number of nodes in the hidden layer is either too high or too low, the network will encounter over-fitting and under-fitting issues [30].

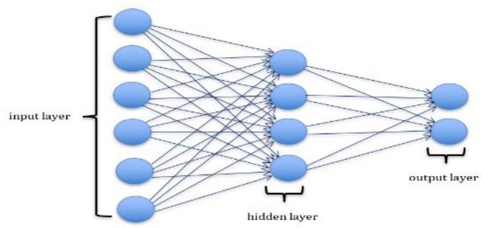

Fig 3
A sample of multilayer feed-forwards network.

This study utilized a feed-forward neural network with a three-layer perceptron model. The ANN structure 4-3-4 was considered since it has good performance with the least value of MSE and the high value of R^2. The input variables -$PM_{2.5}$, PM_{10}, time, and date are contained in the first input layer. Different numbers of neurons and hidden layers were selected to optimize the ANN's performance. In addition, the model made advantage of Rectified Linear Units (ReLU) [31] to reduce computational complexity and accelerate training, as well as Adaptive moment estimation (Adam) [14] to update weights for greater precision. The third layer of the forecasting model is the output layer, which primarily consists of pollutants and AQI. All data were partitioned into 70% for training and 30% for testing.

Evaluation Metrics

Scikit-learn metrics [32] are utilized to implement several losses, scores, and functions to measure the regression model. The study used the following regression metrics to measure the performance of the ANN model.

Mean Absolute Error (MAE):

$$MAE\ (y,\hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} |y_i - \hat{y}_i| \quad (2)$$

Mean Absolute Percentage Error

$$MAPE\ (y,\hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} \frac{|y_i - \hat{y}_i|}{max\ (\epsilon, |y_i|)} \quad (3)$$

Mean Squared Error (MSE):

$$MSE\ (y,\hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} (y_i - \hat{y}_i)^2 \quad (4)$$

Coefficient of Determination (R^2):

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (5)$$

where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ and $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} \epsilon_i^2$

The best-fitted model has the lowest MSE, MAE, and MAPE values. The greater R^2 value indicates a stronger correlation for the model [33].

An autocorrelation Plot is also used for checking randomness in a data set and error. [34] Autocorrelation plots are formed by

Vertical axis: Autocorrelation coefficient

$$R_h = C_h / C_0 \quad (6)$$

where C_h is the autocovariance function

$$C_h = \frac{1}{N} \sum_{t=1}^{N-h} (Y_t - \bar{Y})\ (Y_{t+1} - \bar{Y})$$

where C_0 is variance function

$$C_0 = \frac{\sum_{t=1}^{N}(Y_t - \bar{Y})^2}{N}$$

Note that the $\boldsymbol{R_h}$ is between -1 and +1

Results and Discussion

The input and output values were normalized in this study using the range [-1, 1] in data pre-processing. In fig. 4, the air pollutants concentration value of $PM_{2.5}$ and PM_{10} with the corresponding date were presented using the learning algorithm of the model. Fig 5 shows the air quality index computed from the concertation value per date. It can be noticed that some concentration values depending on the collection date, have increased to the range of good, fair, and unhealthy air quality categories based on National Ambient Air Quality Guideline Values (NAAQGVs).

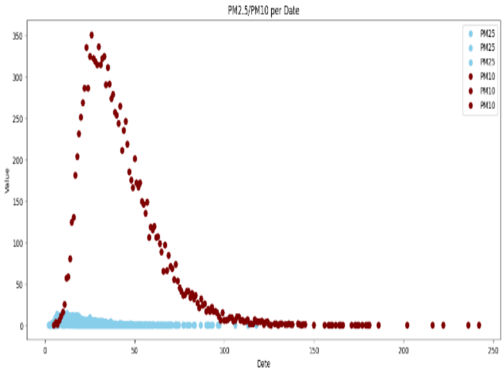

Fig. 4
Concertation values of air pollutants $PM_{2.5}$ and PM_{10}

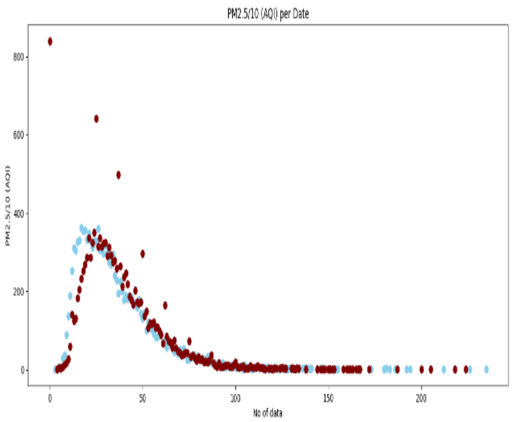

Fig. 5
Air quality index of air pollutants $PM_{2.5}$ and PM_{10}

The network performance begins with a high value during the initial epochs, but as a result of training, the weights are modified to minimize this function, causing it to decrease. The ANN model's validation and regression analysis were performed to investigate the correlation of the expected and predicted AQI based on the testing data (30%). Table IV presented some data that the ANN model's expected and predicted AQI values are closely related.

Table IV
Comparison of the Expected and Predicted Particulate Matter AQI

Index	Concentration		Air Quality Index	
	PM_{10}	$PM_{2.5}$	Expected	Predicted
1	22	10.44	33.33	35.56
2	25	12.02	20.37	20.88
3	40	16.83	23.14	24.04
4	52	20.06	37.03	33.66
5	56	20.78	48.14	40.12
6	45	20.6	51.85	41.56
7	53	24.99	41.66	41.2
8	52	25.5	49.07	49.98
9	36	16.02	48.14	51
10	32	11.38	33.33	32.04

The regression analysis has been performed to understand the relationships of different independent input variables with pollutants concertation from the air quality monitoring station year 2020 to 2022. Fig 6a-d represents the values of how the model fits to forecast the air quality index of the pollutants PM_{10} and $PM_{2.5}$.

With the ANN model's early stopping method, overfitting in training has been eliminated, ensuring that training and testing results are exactly equivalent.

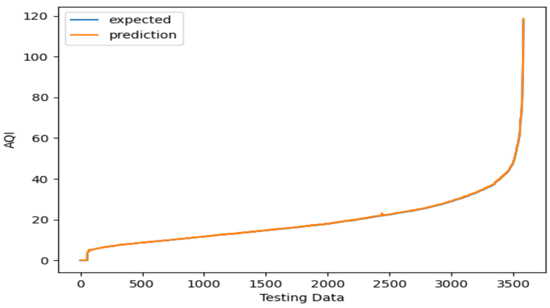

Fig. 6a
Regression analysis from predicted values vs expected values

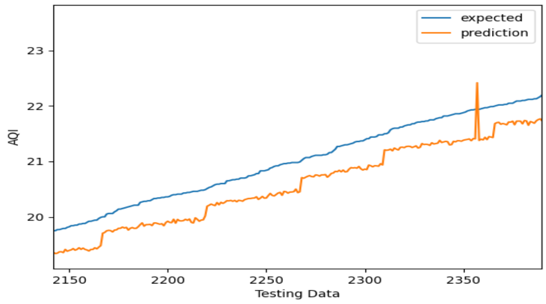

Fig. 6b
Regression analysis from predicted values vs expected values

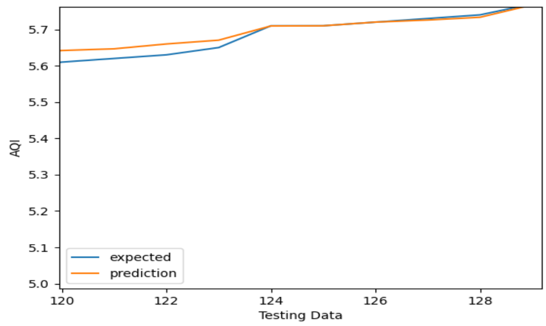

Fig. 6c
Regression analysis from predicted values vs expected values

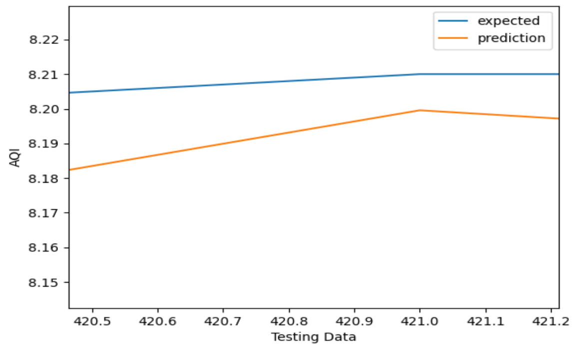

Fig. 6d
Regression analysis from predicted values vs expected values

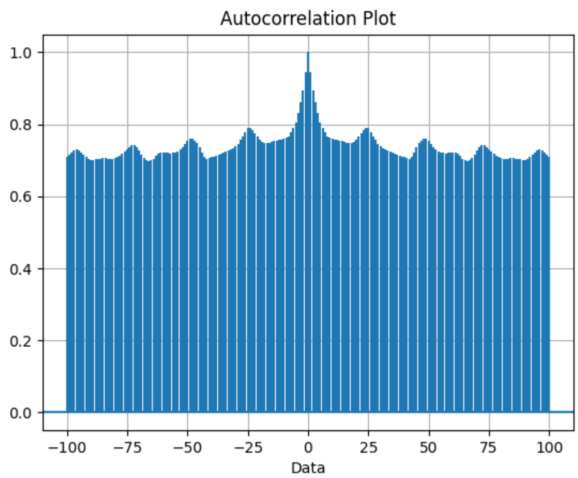

Fig. 7
Autocorrelation Plot of the ANN model with training and testing data.

In the context of model validation checking, fig 7 presented the autocorrelation plot to test the randomness of data and the relationship between each value of errors in the equation. It can be noticed that the values are closer to 0, indicating a greater degree of positive correlation.

Table V
Performance measure of the ANN model for Air Quality Forecasting

Evaluation Metrics	Value
MSE	.086
MAE	.268
MAPE	.145
R^2	.999

Table V shows that the MSE, MAE, and MAPE have very low values, which means the ANN model used is accurate and efficient. On the other hand, the obtained coefficient of determination (R^2) is nearer to 1 from expected and predicted values. Therefore, a highly reliable model for this particular forecasting air quality index.

Conclusion and Recommendation

Based on the initial assessment of an ANN application on air quality forecasting in Manila, the model produces an R^2 of 0.999, and it determines that expected and predicted outputs have a better correlation. Therefore, the outcomes of this study give a strong indication of the applicability of AQI forecasting of air pollutants concentration. The model would become an appropriate tool for forecasting AQI. The ANN model can be simulated using the required setup, optimization, and validation. In addition, the method has significant advantages over real-time or continuous monitoring data.

The data used in the present study for the training model cover only three years and two out of 6 air pollutants; therefore, it is suggested to fine-tune the model using the concentration of the pollutants to other air quality monitoring station which has real time monitoring.

Lastly, the researchers believe that this study will be used as an input to the two of the challenges that the DENR and EMB are addressing right now (a) Assessment of air quality and its health impact at the regional level and (b) Assessment and addressing the needs in air pollution research.

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