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Analysis of Air Quality Index Pre and Post Covid using Machine Learning Technique

Mainka Saharan, Dr. Vishal Bharti
MMDU
"Maharishi markendeswar university ,ambala , Harayana

Abstract - Air is one of the most crucial anticipated assets for the endurance and sustenance of all species on the planet. Air quality sensor devices increase the attention and focus of particles that have an anthropogenic source and cause hazardous consequences during or after a human being's gulp of air. Particles such as PM2.5, PM10, CO, O3, NO2, NO, and others degrade air quality. As technology progresses, researchers and environmental agencies have developed novel methods for combating and managing air pollution.Covid-19 is an epidemic that will influence people' lives and activities in unprecedented ways through the year 2020. This lockout led in a great recovery in ecosystem quality, with much lower levels of air contaminants. Air pollution and the COVID-19 pandemic are connected in two distinct phases— before the outbreak and after its emergence. In the pre-pandemic phase, many regions were already facing severe air quality issues, largely due to dense populations, heavy traffic, and industrial emissions. Aerosol could help to promote the virus at a faster rate, and air pollutants could adversely impact people's lungs, allowing the virus to attack patients more brutally. Public authorities utilize a standardized scale to inform citizens about present and forecasted air pollution conditions. A higher reading on this scale reflects increased health hazards. Many countries have developed their own air monitoring systems, each aligned with their specific environmental safety benchmarks.In this study I have focused on the levels of air quality index pre-covid and post covid and tried to analyze what future outcomes could be possible with either of the situations. Data of 5 cities of India has been processed (Agra, Anand Vihar ,Delhi,Faridabad,Gurgaon),missing value treatments, data validation, and data cleaning/preparation and have been used to predict future outcomes by following a pattern of consecutive years. There is no doubt that this problem has to be addressed with utmost focus.

Keywords - Keywords: PM2.5, PM10, CO, NO2, SO2, O3, AQI,AI, ML

I. INTRODUCTION

In accordance to WHO, air pollution is a primary cause of premature death, accounting for around 4.2 million deaths globally each year owing to lung cancer, heart disease, respiratory disorders, and other causes [1]. Environmental pollution issues such as water, noise, and air pollution are increasing as cities develop economically and technologically. Air pollution, in particular, has a significant influence on human health due to prolonged degradation of pollutants and particles, which has piqued the scientific community's interest in air pollution and its consequences [2]. On the other hand, the COVID-19 epidemic has triggered a global health emergency.

COVID-19 infection has spread to almost every country on the planet. However, some areas have been hit harder than others in terms of infection and mortality rates.

The possibility that air pollution may have contributed to the global spread and death toll of COVID-19 has sparked widespread concern. However, the underlying factors remain uncertain, highlighting the need for more focused and detailed research in this area. [3].

Particulate matter with a size of 2.5 m, is regarded one of Key environmental contributors to health risks, inflicting deaths of millions of people globally each and every year [4]. PM10 levels have been linked to an increase in Breathing-related illnesses, along with admissions due to long-term lung conditions and infections like pneumonia. [4]. Nitrogen dioxide (NO_2) is hazardous to human respiratory systems and enters the atmosphere through both natural and manmade sources. As an example of an external anthropogenic source, NO_2 is mostly released via fuel burning and transportation; in general, they enter the atmosphere via vehicle flue gas and residential heating [5][6]. It is linked to a variety of serious

conditions, including hypertension, diabetes, and cardiovascular disease, and it can even lead to death [4]. When keenly observed bad air quality was directly proportional to increase in Covid [7] also contributing to increased cases of influenza.[8]. Findings indicate the first confirmation that SARS-CoV-2 RNA may be detected on outdoor PM under particular circumstances of atmospheric stability and high amounts of PM10, implying that it might be used as an indication of epidemic recurrence [9].

MACHINE LEARNING

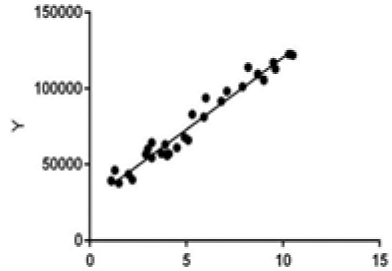
Machine Learning is an ability to teach a computer how to act and function like a human brain by training the machine on variable patterns for ample number of times and expecting desired output. Or, it can be said that machine learning is the ability of a computer to work like a human brain. Machine learning algorithms can increase the accuracy of pollution prediction safety systems, allowing inhabitants, particularly the aged and those with pulmonary difficulties, to avoid outside activities. ML methods differ fundamentally from more traditional modeling of physical systems using conservation laws in the form of partial differential equations (PDEs) [1]. ML algorithms are trained purely on historical data and incorporate no information on the underlying physical laws [1]. It improves through experience.

It is of two types: Supervised and Unsupervised Learning.

In this study we have applied the logics of Linear Regression which is based on Supervised Learning.

LINEAR REGRESSION

Linear Regression tries to establish the link between dependent and the independent variable where in our case dependent variable is the air pollutant concentration as ‘Y’ and the independent variable is the year as ‘X’ because we are considering per year average value of pollutants of all the five cities.



$$y = \theta_1 + \theta_2 . x$$

This is the Hypothesis function of linear regression. Once the model has been trained, it produces a line of best fit that can be used to estimate the value of y for any given x. This line is determined by identifying the most optimal values for the theta parameters that minimize prediction error

$\theta 1$ as intercept

$\theta 2$ as x’s coeeficient

Data of 5 cities of India has been processed. Those five cities include: Agra, Anand Vihar, Delhi, Faridabad, Gurgaon.By analyzing the missing values and coming out with a solution to make it work, validation of data, and data cleaning or preparing the data for processing have been used to predict future outcomes by following a pattern of consecutive years.

Before getting into the practical aspect and calculations, let’s focus on the geographical and meteorological conditions of the above-mentioned citie

AGRA

Also termed as city of Taj, is an exquisite city preserving the footprints of our remarkable history by being the land of various monuments, Mariam’s Tomb, Buland Darwaza, Tomb of Itmad

-Ud-Daula and various other historical monuments. Located approximately 210 kilometers south of New Delhi and 335 km west of Lucknow, the state capital. Agra is the 4th densely populated city in the respective state and ranks 23rd in populous city in the nation, with population of approximately 1.6 million.

Figure 2. Geographical location of Agra (indicated with red mark)

It covers around 121 km square of area with an elevation of 170m.Wind direction is North-West. It’s Latitude and longitude coordinates are: 27.176670, 78.008072 .

Taj Mahal's sensitive inlay and chiselling work in white marble began to deteriorate as Agra's air pollution levels rose. In response, the Supreme Court mandated in the year 2000 that "safe" zone within 50 kilometers around the monument – known as the Taj Trapezium Zone (TTZ) – absence of industries and vehicles will be observed. It had little impact on the city's overall pollution levels.

ANAND VIHAR

It is a Locality in North East Delhi City,India.It is an established area of New Delhi.It’s surrounded by prime locations of east delhi including Sahibabad,Kaushambi,Preet Vihar etc.It also includes Anand Vihar ISBT and Anand Vihar railway station which are important for inter state connectivity

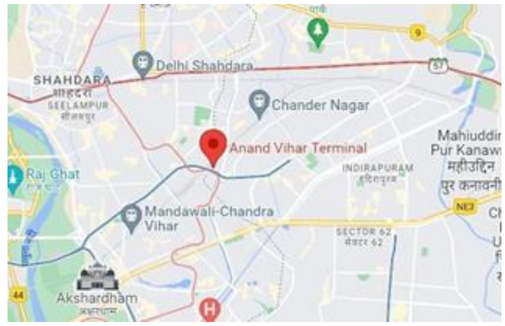


Figure 3. Geographical location of Anand Vihar It is spread over 100 acres and has an elevation of 207.140 m.It’s coordinates are 28° 39′ 2.79″ N, 77° 18′ 54.86″ E.

Emissions from vehicles, industrial waste incineration, residential biomass burning, construction works, and garbage burning are the major sources of pollution. Aside from these sources, climatic factors and seasonal factors also have an impact on the area’s air quality.

Numerous industrial plants use a variety of polluting fuels in the Sahibabad & Patparganj, which are close to Anand Vihar. National Highway (NH) 24 runs through the area as well.

DELHI

Figure 4. Geographical location of Delhi

Delhi is the National Capital Territory of Delhi (NCT)it is a humongous urban center in the country's north. The majestic Mughal-era Red Fort, a symbol of India, and the thriving Jama Masjid mosque, it’s courtyard can accommodate 25k people, are both located in Old Delhi.

Delhi is located in northern part of India between the latitudes of 28°-24′-17″ and 28°-53′-00″ N and longitudes of 76°-50′-24″ and 77°-20′-37″ E. The air quality in Delhi, is worse than any other city in the world. It has an impact on the districts surrounding Delhi. On 25 November 2019, the SCI stated that Delhi has become worse than hell after observing the weather conditions and air quality of the city.

GURGAON

Figure 6 . Geographical location of Gurgaon marked as gurugram.

Gurgaon was formally called Gurugram. There are 1,514,432 people living here. It is a district in Haryana's southern region. The district of Faridabad is located at it's east side. The districts of Palwal and Nuh are located to the south of it. Rewari district lies in the west of the district.

Gurgaon has the total area close to 280 square miles so it is a really large urban area. It's latitude and longitude coordinates are: 28.457523 N, 77.026344 E.

Gurugram being the IT hub in the state of Haryana has been one of the busiest cities with crowded and polluted roads. It's not much different from Delhi as surrounded by the same, Delhi has a huge impact on the city in terms of population, transportation and pollution which gives us one of the reasons to monitor the air quality in the city with keen eye.

II. LITERATURE SURVEY

"Research on air quality prediction method in Hangzhou based on machine learning[15]"

Many recent environmental studies have focused on pollution of the air, because quality of air is closely linked to human health and quality of life. The Bayesian network model is employed in this article to forecast Hangzhou air quality. The model's evaluation factors are SO2, NO2 ,O3, CO, PM 2.5 and 10, and the model's output is the AQI value, after which the network model of Bayesian is constructed.

At the end, the model's adopted for forecasting quality of air and comparing the predicted value to actual value. The outputs demonstrate that air quality prediction accuracy is over 80%, and that in most situations, the anticipated number is approximately around actual value[15].

"Song et al. proposed a machine learning framework (Deep-MAPS) to for fine granular PM2.5 inference based on fixed and mobile air quality sensing data[16].

Lana et al.[17][18]"

To forecast levels of various air-pollutants based on traffic data and climatic parameters, whereby an evaluation of the importance of each used component can be obtained via their respective training procedure.

"Research on Machine Learning Prediction of Air Quality Index Based on SPSS[15]"

We can accomplish successful prevention if we can make an accurate forecast, Estimating or assessing the dependent variables seems to be more efficient and reasonable than forecasting or evaluating the independent variables alone.

Multivariate linear regression is regression with two or more factors, and it is more useful in practise than univariate linear regression. The components impacting air quality were observed and assessed through use of a multiple linear regression model. Particulate matter 2.5 ,10,SO2,NO2, CO, and ozone were variables that influenced the air quality index. The prediction model is created using one year regression analysis worth of data samples. It has been established that the prediction approach is worthy of widespread use [15].

Wang et al.[19]

Machine learning outperformed LUR for the same pollutants, suggesting that knowing the way the descriptive factors were stated in models of machine learning might help LUR performance [19].

"Air quality index variation before and after the onset of COVID-19 pandemic: a comprehensive study on 87 capital, industrial and polluted cities of the world[20]."

This study investigates how air quality levels have shifted in key areas across the nation—including industrial hubs, major population centers, and capital cities—by comparing conditions from prior to 2020 with those that followed. [20].

Machine Learning on the COVID-19 Pandemic, Human Mobility and Air Quality

AI and Ml algorithms can be used in upcoming multiscale and non-linear disease modelling to achieve more accurate predictive performance and precisely formulate relevant premises for disease screening and therapeutic measures.

III. SYSTEM ANALYSIS

DATASET COLLECTION:

Data was collected for different regions or cities of the country as specified above which were: Gurgaon, Faridabad, Agra, Noida, Delhi. It consisted of pollutant levels on daily basis for required number of years. The pollutants which were worked upon consist of Particulate matter 2.5 and 10,nitrogen dioxide, sulphur dioxide, ozone, carbon monoxide which might differ in the study based on data collected.

DATA PRE-PROCESSING:

Normalization of the dataset was performed. Dirty and raw data was deleted by identifying incomplete of the data and were put into formulas in order to process it and work on it and to evaluate the values that are missing in the dataset using the formula of mean.

DATA ANALYSIS:

The output obtained after applying the validation dataset was analysed that gave us mean and percentage errors which was further put into the regression model and was analysed in order to obtain desired result and predict future values or outcomes.

RANGE OF AQI AND VARIOUS POLLUTANTS AS STATED BY CENTRAL POLLUTION CONTROL BOARD

Reference range for all the pollutants with their units in which they are calculated also including the column of category which describes us about the level of pollution in the air by dividing the range of pollutants and Air Quality Index in six categories as shown below :

AQI Category (Range)	PM_{10} 24-hr	$PM_{2.5}$ 24-hr	NO_2 24-hr	O_3 8-hr	CO 8-hr (mg/m^3)	SO_2 24-hr	NH_3 24-hr	Pb 24-hr
Good (0-50)	0-50	0-30	0-40	0-50	0-1.0	0-40	0-200	0-0.5
Satisfactory (51-100)	51-100	31-60	41-80	51-100	1.1-2.0	41-80	201-400	0.6-1.0
Moderate (101-200)	101-250	61-90	81-180	101-168	2.1-10	81-380	401-800	1.1-2.0
Poor (201-300)	251-350	91-120	181-280	169-208	10.1-17	381-800	801-1200	2.1-3.0
Very poor (301-400)	351-430	121-250	281-400	209-748*	17.1-34	801-1600	1201-1800	3.1-3.5
Severe (401-500)	430+	250+	400+	748+*	34+	1600+	1800+	3.5+

Figure 7. AQI AND CATEGORIZATION

GURGAON

Table 1. To denote the mean concentrations with their standard deviations and range from year 2017-2021 and predicted values from 2022-2023.

Years/Value of.	PM2.5	PM10	NO2	SO2	O3	CO
2017	177.685	-	19.6	6.4	24.07	6.038
2018	183.4776	-	12.582	4.559	30.067	7.824
2019	202.2955	-	8.11	3.792	23.926	6.815
Standard Deviation	12.86	-	5.79	1.34	3.50	0.89
Range	175-199	-	8-19	3-6	22-30	6-7
Category	Very Poor	-	good	good	good	Moderate polluted
2020	168.429	-	8.94	2.309	25.877	8.669
2021	174.735	-	12.804	5.005	25.805	7.057
Standard deviation	4.45	-	2.73	1.90	0.05	1.13
Range	167-176	-	7-13	1-6	25-26	6-9
Category	Very poor	-	good	good	good	Moderate polluted
Predicted value						
2022	181.041	-	16.668	7.701	25.733	5.444
2023	**187.347**	-	**20.532**	**10.397**	**25.661**	**3.833**

ANAND VIHAR

Table 2. To denote the mean concentrations with their standard deviations and range from year 2017-2021 and predicted values from 2022-2023

Years/Value of.	PM2.5	PM10	NO2	SO2	O3	CO
2017	214.822	305.049	41.838	12.180	22.144	20.348
2018	218.249	262.407	43.370	8.974	25.107	23.969
2019	189.695	195.197	39.955	6.296	23.896	19.879
Standard deviation	15.6	55.38	1.71	2.94	1.5	2.23
Range	192-223	199-309	40-44	6-13	21-26	19-24
Category	Very poor	Poor	Satisfactory	Good	Good	Very Poor
2020	169.461	144.365	38.837	3.265	25.469	20.930
2021	182.898	180.439	39.896	6.324	20.345	20.695
Standard deviation	9.5	25.5	0.74	2.16	3.62	0.16
Range	166-186	136-188	38-40	2-7	19-27	20-21
Category	Very poor	Moderate polluted	good	good	good	Very poor
Predicted value						
2022	196.334	216.513	40.954	9.383	15.220	20.460
2023	209.771	252.586	42.014	12.442	10.096	20.225

AGRA

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DELHI

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FARIDABAD

Table 5. To denote the mean concentrations with their standard deviations and range from year 2017-2021 and predicted values from 2022-2023

Years/Value of.	PM2.5	PM10	NO2	SO2	O3	CO
2017	214.822	305.049	41.838	12.180	22.144	20.348
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2019	189.695	195.197	39.955	6.296	23.896	19.879
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We have observed all the cities in respect to their pollutants and their mean concentrations.

On plotting the graphs of duration 2017-2019 and 2020-2023 in some regions like Delhi,Anand Vihar ,Gurgaon we observed that there was a sudden increase in the mean concentrations after 2019 ,and the underlying reason of the same was Covid Restriction and the practices during the same. Undoubtedly, restrictions imposed due to covid-19 benefitted the environment but the increased medical dump due to the disease inflated the air which caused an increase PM2.5 and PM10.

Fortunately, Agra can be marked as under control, it experienced a positive decrease in the values of O3, NO2, PM2.5 from 2017-2023 (both trained years and predicted included).

Faridabad might have had variable best fit line for the concentrations of Particulate matter 2.5 , nitrogen dioxide, sulphur dioxide, carbon monoxide and ozone but even these values of mean concentration can be seen increasing in the years after 2019 which again is due to Covid-19 restrictions and it's impact on the environment.

On comparison and keeping future perspective in mind we can predict that pollutants like NO2, SO2, PM2.5, PM10's level might increase with coming years which needs to be checked and important measure need to be taken beforehand. And air pollutants like CO, O3 have shown contrasting behaviors, which might be affected by the meteorological and other weather conditions but remain variable. But their variable nature may prove to be hazardous if ignored, so, it's a hypothetical scenario that it might increase or decrease but definitely can be captured by involving various other parameters.

IV. CONCLUSION

In Gurgaon and Anand Vihar, a relative rise of particulate matter 2.5, SO2, nitrogen dioxide and PM10 was observed and decrease in amounts of CO, O3. Whereas in Agra PM2.5, NO2, O3 amounts were decreasing. Similarly in Faridabad and Delhi, SO2 amounts were found decreasing and particulate matter 2.5 and 10, carbon monoxide, nitrogen dioxide and ozone were relatively increasing.

From above observations it can be concluded that in the half of 2019 and previous years(2018,2017) all the air pollutants which were tested showed contrasting where some pollutants seem to have been obtaining a decrease in their values ,others were reaching at par.It is also noted that during covid i.e. half of 2019 and 2020 ,serious amounts of descend was seen in the values of the air pollutants which depict that following such practices as followed in Covid can be termed advantageous in terms of environment but it was also seen that such amounts are also proving to be a reason for the rise in Covid.

Also, such lockdown practices can be made but under critical observations as it may increase PM2.5 levels and PM10 levels which may increase the atmospheric temperature and vice versa and may cause harmful effects. So it should be done but at checked levels.

Despite the fact that the COVID-19 pandemic had negative effects that were not reversible on people, it contributed in improving air quality throughout most areas with constraints at various places. However, changes from 2020 to 2021 have been reversed, and values for PM2.5, PM10, CO, and NO2 pollutants have risen overall (4–7%) due to a reduction in country restrictions. In broad sense, stringent laws pertaining to COVID-19 restrictions can demonstrate a country's executive power in lowering pollutants in general circumstances.

Lockdown can be enforced depending upon the meteorological conditions, requirements, critical aspect, population and time zone of the specific region which might help in the maintaining a balance in the environment and would prove to be a good practice for ages to come.

It also proved that applying machine learning techniques for analyzing the data and predicting possible outcomes provides promising results.

So,it would be a better step towards becoming efficient in the tech world and beholding an efficient system for future and preparing ourselves in advance in hope of a brighter future.

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