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Short Term AQI Forecasting Jamnagar, Gujarat

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A B S T R A C T :

In this study, we examine the AQI in Jamnagar over the course of 30 days by examining measurements taken both during the day and at night. $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, O_3, temperature, humidity, wind speed and wind pressure were included in the analysis. It was revealed by descriptive statistics that AQI stayed mainly in Satisfactory and Moderate ranges and $PM_{2.5}$ and PM_{10} caused the largest variations. There was a strong positive link between AQI and particulate matter, with the link strongest at nighttime when the air is less dispersed. MLR models were constructed using air pollutant readings (AQI_air) and weather measurements (AQI_met) to study data from day and night. The pollutant-based models had high accuracy, scoring 0.97 for night and 0.98 for day data, against meteorological models. Evaluating the models with RMSE, MSE and MAE measurements demonstrated that AQI_air models worked well. Based on the separation of individual pollutant factors, the PM-related impact was higher than that of other air pollutants. The authors end the study with tips for PM reduction, better nighttime air observation and adding predictive models to air quality control systems. As a result, urban air quality is better controlled and policy choices are made with useful information.

Keywords: AQI, PM 2.5, PM 10, MLR, model.

1. Introduction

1.1. General

The study of air quality in cities requires a comprehensive investigation because it emerges from various human-made activities and weather patterns that affect the environment. The growing air pollution problem requires significant global attention because it threatens human health, environmental stability, and economic stability. Therefore, effective monitoring and mitigation efforts must be developed. Developing nations such as India face significant ecological dangers due to rapid urban growth and industrial development, as they rapidly increase air pollutant emissions despite increasing environmental threats. Research findings from multiple Indian cities have shown that particulate matter, sulfur dioxide levels and nitrogen oxides surpass the standards established by India's national and international governing organisations (Anwar et al., 2021; Gurjar et al., 2016; Guttikunda et al., 2014; Kaur & Pandey, 2021; Wang et al., 2023). The World Health Organisation increases the immediate need for effective air pollution interventions because studies demonstrate that millions of individuals die prematurely each year from their exposure to pollutants (Barnes, 2014; Chen & Kan, 2008; Manisalidis et al., 2020). This academic research aims to analyse Jamnagar City air pollution at an all-encompassing level to predict monthly air quality index changes, alongside examining the negative health consequences of pollution exposure. The study includes using MLR technique for prediction of AQI using the regular AQI parameters and meteorological parameters. The study uses real-time air quality data and advanced statistical analysis with a strong methodology to investigate Jamnagar's complete air pollution patterns.

Nomenclature

1.2. The Air Quality Index: A Critical Tool for Assessing Air Pollution Levels

The AQI transforms complicated pollutant measurements into understandable information for the public through easy-to-grasp presentations. This allows citizens to understand the air quality situation better. The standardised indices demonstrate both the state of total air quality and its health consequences to assist people in taking better actions for protection from airborne pollutants. An adequately designed AQI system converts complex pollutant measurements into straightforward indicators that help people avoid risks to their health by making better decisions (KELLY et al., 2012; Svertoka et al., 2020). The government uses air quality index forecasts to warn citizens, while air purifier manufacturers depend on their sales numbers, and environmentalists conduct deep evaluations using this data. Each region adopts standards when monitoring air quality because it possesses different pollutants and methods to assess pollution levels. The United States Environmental Protection Agency AQI serves alongside the European Union's Common AQI and National AQI from India as standard Air Quality Index systems, which use customised scales and labelling systems to measure air quality levels. Research has been conducted to find appropriate ways of applying these standards in indoor settings. Several pollutant types and distinctive exposure patterns make broad application impossible. Ozone, along with particulate matter, carbon monoxide, and sulfur dioxide, is used by the Environmental Protection Agency to create its AQI measure (Meo et al., 2024). The development of AQI represents a test to determine whether it can deliver complete real-time analysis of indoor air quality levels. People with sensitive health conditions must limit their time outdoors should the AQI enter the unhealthy zone, along with the general public needing to minimise their physical activity intensities.

1.3. Importance of AQI modelling

Air quality assessment and prediction depend heavily on modelling. Human-made learning models serve increasingly as tools for predicting air quality indices alongside pollutant concentration assessments. Cities have few air quality monitoring stations since these instruments are cost-prohibitive. Air quality models are essential tools to analyse how pollution spreads while helping assess pollution reduction strategies and forecast upcoming air quality predictions. The accurate air quality prediction combined with effective implementation allows residents to make beneficial decisions and authorities to execute proper interventions for protecting public health. Spatial estimation improvements for air pollution levels were pivotal in determining health risks and disease frequency. Predicting air quality depends on measurements taken at official locations supported by modelling systems, which show pollution movements along with transformation systems. Air pollution prediction plays a vital role in environmental decision-making because it offers the chance to plan interventions.

2. Literature Review

"(Guttikunda et al., 2014) Nature of air pollution, emission sources, and management in the Indian cities" A 2014 examination by Guttikunda, Goel, and Pant addresses all aspects of air pollution and its diverse emission sources and management approaches in these urban environments. Many Indian cities appear among the world's most polluted areas above the national air quality standards. The research study details the main pollutants, including particulate matter, sulfur dioxide, nitrogen oxides and ozone, while showcasing an increasing role of vehicular and industrial emission sources in pollution.

"(Gurjar et al., 2016) Air pollution trends over Indian megacities and their local-to-global implications" Gurjar, Ravindra, and Nagpure conducted research that studies air pollution patterns in Delhi, Mumbai, and Kolkata to analyse both local and global pollution effects. Population explosions and fast urbanisation in these massive cities have resulted in higher utilisation of energy as well as atmospheric pollution levels. booting pollution across these cities has passed beyond national standards and threatens human health among their millions of residents. The investigation uncovers the inspection of multiple pollutants, namely PM10 and PM2.5, alongside sulfur dioxide, nitrogen oxides, and carbon monoxide, along with ozone (O_3).

"(Liao et al., 2021) Statistical Approaches for Forecasting Primary Air Pollutants: A Review" Extensive research exists about air pollution prediction methods because of growing pollution concerns. This review explains statistical models that forecast major pollutant reduction trends through an in-depth analysis of recent studies. The research approach based on bibliometrics reveals current conditions of statistical prediction techniques through an evolutionary tree analysis of development directions that Markov chains predict for primary air pollutants. According to the editor, the strategic objective of air pollution prediction involves minimising pollution threats by calculating future air pollutant concentration ranges and their spatial distribution.

"(Bekkar et al., 2021) Air-pollution prediction in smart city, deep learning approach"

The research investigates deep learning approaches to predict air quality in smart cities by focusing on the PM2.5 level forecasting in Beijing, China. Accurate PM2.5 concentration predictions serve as a priority because increasing human activities, industrialisation, and urbanisation create a major global health concern known as air pollution, which leads to respiratory and cardiovascular diseases among citizens. This research develops a hybrid CNN-LSTM predictive system that integrates spatial-temporal data consisting of historical pollutant records and meteorological measures, as well as PM2.5 readings from adjacent stations, and forecasts the concentrations of PM2.5 at each hour. Despite implementing several deep learning models, including LSTM, Bi-LSTM, GRU, Bi-GRU, CNN, and a hybrid CNN-LSTM model, research shows that CNN-LSTM delivers the highest predictive performance.

3. Methodology

The approach used to create an AQI prediction model for Jamnagar, Gujarat, India is described in this chapter. The key features included in the current methodology include:

Data collecting,

Statistical analysis,

Model construction,

Validation and

AQI classifications

A summarised flow chart is made in Figure 1 to show the steps involved in the current investigation.

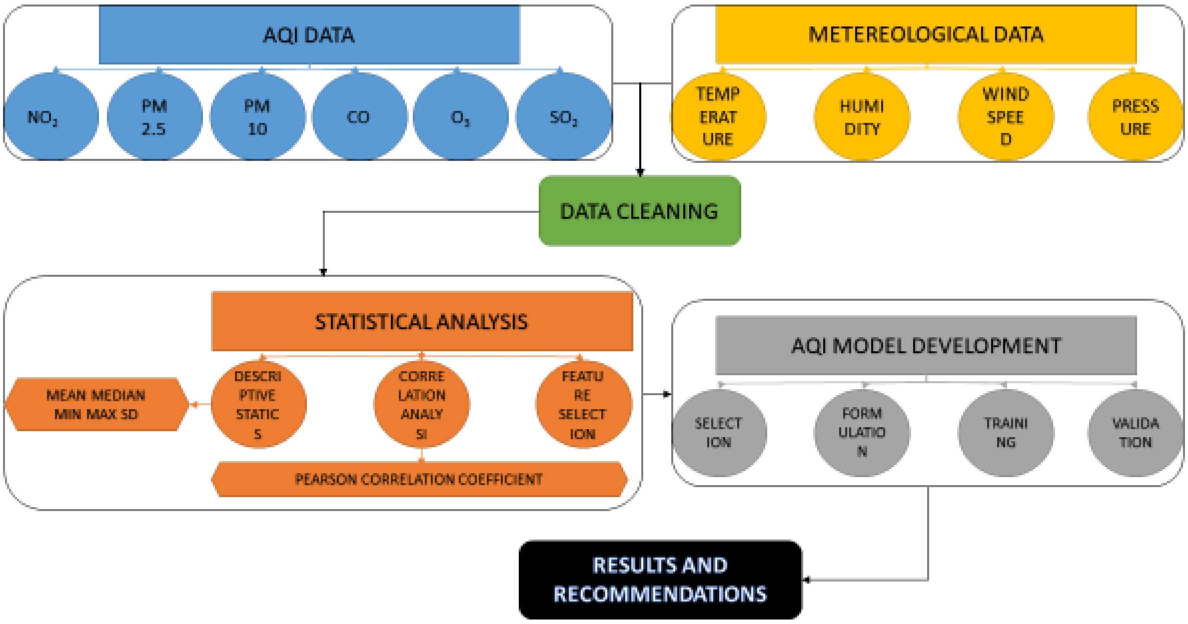

Fig. 1 – Flowchart of current Methodology

4. Results

4.1. Descriptive Statistics

A detailed statistical analysis was carried out on the observed air quality and meteorological data obtained for a period of one month; the daytime and nighttime readings were segregated. The parameters that will be used include AQI, $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, O_3, temperature, humidity, wind pressure, and wind speed. The descriptive statistics (mean, maximum, minimum, median, and standard deviation) were derived

Statistical summary of the collected data for both day and night presents the ground knowledge of variation in air quality and meteorological parameters during the study period. This description analysis is critical in recognising trends, comparing pollutant levels during the day and night and determining the uniformity and extremes in the recorded values. The following table 5.1 shows the mean, maximum, minimum, median, and standard deviation for each parameter.

Table 1 – Descriptive statistics

Descriptive Statistics	AQI	PM 2.5 (μg/m³)	PM 10 (μg/m³)	CO (ppb)	SO_2 (ppb)	NO_2 (ppb)	O_3 (ppb)	Temp (°C)	Hum (%)	Wind Press (mbar)	Wind Speed (kmph)
	NIGHT										
Mean	102.47	35.70	98.80	480.53	6.93	13.10	13.90	25.77	82.20	1006.63	6.20
Max	123.00	46.00	132.00	643.00	10.00	19.00	22.00	29.00	96.00	1011.00	11.00
Min	78.00	23.00	77.00	245.00	4.00	11.00	11.00	24.00	62.00	1002.00	0.00
Median	103.00	36.00	98.00	495.50	7.00	13.00	13.00	26.00	84.50	1007.00	6.00
Std. Dev.	10.85	5.37	11.31	108.58	1.64	1.83	2.11	1.19	9.23	2.06	2.61
Descriptive Statistics	**AQI**	**PM 2.5 (μg/m³)**	**PM 10 (μg/m³)**	**CO (ppb)**	**SO_2 (ppb)**	**NO_2 (ppb)**	**O_3 (ppb)**	**Temp (°C)**	**Hum (%)**	**Wind Press (mbar)**	**Wind Speed (kmph)**
	DAY										
Mean	101.50	35.13	101.53	468.43	6.53	12.77	20.93	40.97	29.43	1005.07	12.93
Max	134.00	51.00	156.00	787.00	10.00	18.00	29.00	45.00	80.00	1009.00	24.00

Min	68.00	18.00	61.00	181.00	4.00	10.00	15.00	27.00	16.00	1002.00	5.00
Median	102.00	36.00	97.00	474.50	6.00	12.50	20.00	42.00	25.00	1005.00	12.50
Std. Dev.	13.98	6.90	17.22	139.36	1.36	1.87	3.48	3.64	14.96	1.60	5.58

4.2. Correlation Matrix

In order to study the relationship between AQI and numerous environmental factors, a Pearson correlation analysis was performed on two datasets, one for daytime and one for nighttime. There were strong links discovered between AQI and the majority of pollutants and weather factors. Particulate matter (PM 2.5 and PM 10) and CO have been found to be the biggest influencers of AQI variation during the study's nighttime. Temperature, humidity and wind play a role in the spread and quantity of pollutant particles in the air. Inspired by these findings, future approaches in air quality management are built. The following tables 2 and 3 show the Pearson correlation coefficient for each parameter.

Table 2 – Correlation matrix (day)

PARAMETERS	**AQI**	**PM 2.5 (µg/m³)**	**PM 10 (µg/m³)**	**CO (ppb)**	**SO₂ (ppb)**	**NO₂ (ppb)**	**O₃ (ppb)**	**Temp (°C)**	**Hum (%)**	**Wind Press (mbar)**	**Wind Speed (kmph)**
AQI	1.000										
PM 2.5 (µg/m³)	0.976	1.000									
PM 10 (µg/m³)	0.900	0.878	1.000								
CO (ppb)	0.736	0.752	0.568	1.000							
SO₂ (ppb)	0.441	0.377	0.349	0.454	1.000						
NO₂ (ppb)	0.713	0.642	0.708	0.514	0.591	1.000					
O₃ (ppb)	0.695	0.621	0.697	0.628	0.422	0.566	1.000				
Temp (°C)	0.848	0.769	0.765	0.581	0.531	0.723	0.716	1.000			
Hum (%)	0.017	-0.024	0.127	-0.167	0.302	0.247	-0.017	-0.092	1.000		
Wind Press (mbar)	0.701	0.539	0.591	0.357	0.517	0.680	0.634	0.834	0.156	1.000	
Wind Speed (kmph)	0.156	0.136	0.181	0.099	0.418	0.319	0.243	0.317	0.231	0.215	1.000

Table 3 – Correlation matrix (night)

PARAMETERS	**AQI**	**PM 2.5 (µg/m³)**	**PM 10 (µg/m³)**	**CO (ppb)**	**SO₂ (ppb)**	**NO₂ (ppb)**	**O₃ (ppb)**	**Temp (°C)**	**Hum (%)**	**Wind Press (mbar)**	**Wind Speed (kmph)**
AQI	1.000										
PM 2.5 (µg/m³)	0.977	1.000									
PM 10 (µg/m³)	0.941	0.917	1.000								
CO (ppb)	0.763	0.800	0.649	1.000							
SO₂ (ppb)	0.616	0.600	0.498	0.639	1.000						
NO₂ (ppb)	0.762	0.707	0.754	0.644	0.652	1.000					
O₃ (ppb)	0.714	0.675	0.795	0.534	0.373	0.736	1.000				
Temp (°C)	0.826	0.709	0.786	0.531	0.545	0.747	0.632	1.000			
Hum (%)	0.721	0.645	0.689	0.466	0.340	0.504	0.648	0.735	1.000		
Wind Press (mbar)	0.806	0.670	0.767	0.495	0.475	0.698	0.641	0.956	0.793	1.000	
Wind Speed (kmph)	0.386	0.440	0.365	0.269	0.189	0.110	0.253	0.218	0.359	0.214	1.000

4.3. Model formulation and validation

For distinct groups of parameters, separate Multiple Linear Regression (MLR) models were designed for each dataset at day and night. In both instances, the first model made independent use of PM 2.5, PM 10, CO, SO_2, NO_2 and O_3 and the second considered only temperature, humidity, wind pressure and wind speed. By following this method, we were able to examine how changes in each range of parameters impact AQI at different times. The models are shown below:

Nighttime model

$$\mathrm{AQIair(n)} = 1.75 * \mathrm{PM\,2.5} + 0.234 * \mathrm{PM\,10} + 0 * \mathrm{CO} + 0.9099 * \mathrm{SO_2} + 0.469 * \mathrm{NO_2} + 0.353 * \mathrm{O_3} \quad (1)$$

$$\mathrm{AQImet(n)} = 2.0399 * \mathrm{T} + 0.1052 * \mathrm{H} + 0.0353 * \mathrm{WP} + 0.9120 * \mathrm{WS} \quad (2)$$

Daytime model

$$\mathrm{AQIair(d)} = 1.8787 * \mathrm{PM\,2.5} + 0.1267 * \mathrm{PM\,10} + 0.0010 * \mathrm{CO} + 0.1.1216 * \mathrm{SO_2} + 0.4576 * \mathrm{NO_2} + 0.4179 * \mathrm{O_3} \quad (3)$$

$$\mathrm{AQImet(d)} = 2.1828 * \mathrm{T} - 0.04177 * \mathrm{H} + 0.0233 * \mathrm{WP} - 0.783 * \mathrm{WS} \quad (4)$$

The AQIair(n) model indicates that PM 2.5 had the greatest importance (1.75) in air quality during nighttime, while PM 10, SO_2, NO_2 and O_3 influenced it a little less, and CO was almost absent (0). High particulate matter at night is normal due to reduced mixing in the air, so PM 2.5 becomes the main cause. In the nighttime model of air quality, 2.0399 and 0.9120 were the corresponding positive numbers for AQI and wind speed, respectively. The results suggest that during nighttime, having moderate winds and higher temperatures promotes the trapping of pollutants, which makes the air quality index rise.

For evaluation, the coefficient of determination (R^2), mean squared error (MSE), root mean square error (RMSE) and mean absolute error (MAE) were used on the developed MLR models. The metrics were determined for each model on both days and nights using information about air pollutants and the atmosphere. The results demonstrate that air pollutants mainly shape the AQI, while variations in weather conditions affect it more during the daytime. The coefficient of determination (R^2), mean squared error (MSE), root mean square error (RMSE) and mean absolute error (MAE) are tabulated below in Table 4.

Table 4 – Metrics for model validation

Metric	$AQI_{air(n)}$	$AQI_{met(n)}$	$AQI_{air(d)}$	$AQI_{met(d)}$
R^2	0.97	0.07	0.98	0.44
MSE	6.45	105.69	6.77	106.32
RMSE	2.54	10.28	2.60	10.31
MAE	1.89	8.56	2.06	8.01

4.4. AQI classification

Over a period of 30 days, the Air Quality Index (AQI) for each pollutant was classified using the standards set by the Indian government. There were no days during the observation period with AQI values ranking as "Good." There were 13 days when air quality was reasonable (AQI between 51 and 100), but the air quality was considered moderate most of the time, staying in the 101-150 AQI range on 17 days.

The same type of inspection was performed during nighttime hours for the same 30-day period. Similar to the trends during the daytime, no day had an AQI rating of "Good." Three-quarters of the nights, 17, were Moderate and only 13 were classified as Satisfactory. There being no "Poor" or worse levels highlights that the air quality is not as bad as it could be.

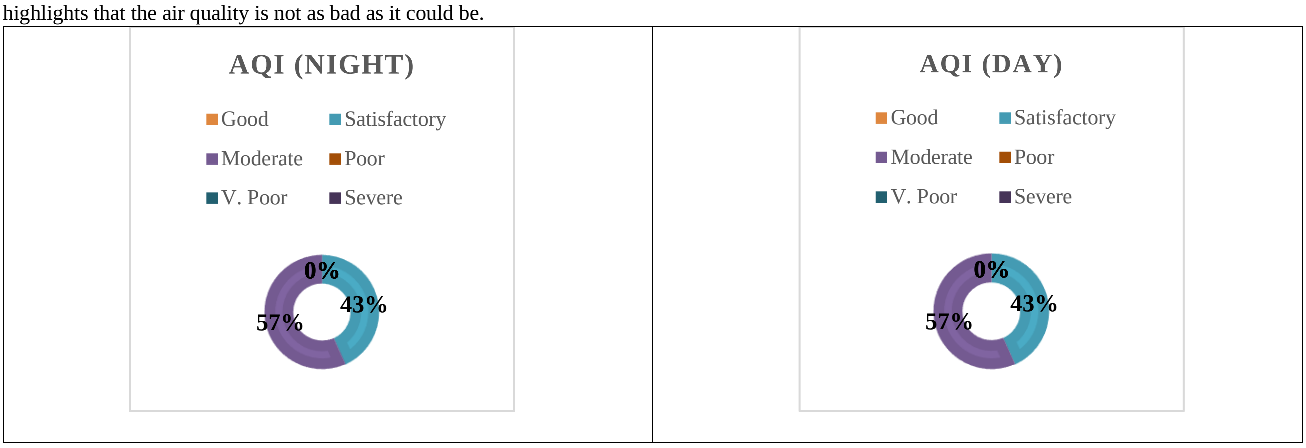

Fig. 2 – AQI classification

5. Conclusions

- AQI Trends: While observing the AQI values for 30 days all the values were found to be under satisfactory or moderate ranges for both daytime and nighttime. There were no instances of "Poor," "Very Poor," or "Severe" air quality, meaning there were no serious health dangers for the public during normal weather.
- Correlation Analysis: It was observed that AQI was strongly linked with both PM 2.5 and PM 10, which means that these pollutants caused most variation in AQI. It was found that temperature, humidity, wind pressure and wind speed also play a significant role in determining how pollutants are spread and accumulated in the air.
- Model Development is done using MLR. Two models were developed using MLR, one for daytime and the other for nighttime. An AQI that measures pollution levels (AQIair). AQI that is determined based on weather patterns (AQImet) R^2 values of 0.97 (night) and 0.98 (day) confirm that pollutant-based models are accurate and produce much lower error metrics than meteorology-based models. This means that air pollutants are directly measured for AQI, yet meteorological variables are still useful for making predictions.
- Model Performance: AQIair(d) was found to be the most accurate, as shown by its high value of R^2 and small RMSE and MAE, indicating that pollutants play a stronger role during the day. The AQI_met for nighttime was less precise, possibly because the weather changes more rapidly at night in nonlinear ways.

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