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Development of Machine Learning Model for Climatic Impact Prediction on Health Using AQI Dataset in Africa

*[1,2]Oduah Oluwaseun A., [1]Ogunsola Oluseyi E. and [3]Adeleke Oludele

[1]Department of Physics, University of Ibadan, Oyo State, Nigeria.
[2]Federal College of Forestry, Ibadan. Oyo State, Nigeria.
[3]Faculty of Computing, University of Ibadan, Oyo State, Nigeria.

*Corresponding Author's Email: oduahseun123@gmail.com

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ABSTRACT

Air pollution remains one of the major concerns of health crisis in most developing countries with Africa facing a silent health crisis as air pollution worsens, yet predictive tools remain scarce. Pollutants such as PM2.5, NO_2, CO, and O_3 increase the risk of respiratory and cardiovascular diseases. This study develops a Machine Learning (ML) model to predict the Air Quality Index (AQI) and assess health risks across urbanized, industrialized, and rural regions using climatic parameters. A quantitative approach was applied to 23,463 AQI datasets obtained from Kaggle World AQI database. The data was pre-processed and feature engineering was used to remove null values and outliners then splitted into ratio 70:30 for training and testing. Four algorithms namely; Linear Regression, k-Nearest Neighbours, Decision Tree and Random Forest were evaluated using metrics such as R-Squared (R^2), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The result shows that Random forest model (R^2 = 0.997316, RMSE = 2.865823, MAE = 0.2955499) demonstrated superior predictive performance followed by KNN (R^2 = 0.996820, RMSE = 3.119500, MAE = 0.588252) while Decision Trees (R^2 = 0.995046, RMSE = 3.893819, MAE = 0.302845) produced high accuracy with slightly higher error. SVR (R^2 = 0.980160, RMSE = 7.792268, MAE = 1.301302) and Linear Regression (R^2 = 0.975279, RMSE = 8.968122, MAE = 4.831951) showed moderate accuracy. This research confirms that Machine Learning models are valuable tools for predicting Air quality thus offering a powerful tool for mitigating the impact of deteriorating Air Quality in Africa.

INTRODUCTION

Despite the growing evidence of the health risks posed by air pollution, Africa remains one of the least studied regions because there is no sufficient information in terms of pollution–health interactions. Current research is limited by inadequate monitoring infrastructure with fragmented datasets, and the use of linear statistical approaches that often fail to capture the nonlinear dynamics of air pollutants and climate variables (Ogunsola *et al*., 2011; Njoku *et al*., 2019). As a result, health systems remain ill-prepared to anticipate pollution-related health crises. Hence, there is a critical need for predictive models that can analyse Air Quality Index (AQI) datasets and generate health risk forecasts in Africa.

Air Quality Index (AQI) datasets provide an integrated framework for measuring pollutants such as Carbon monoxide (CO), Ozone (O_3), Particulate Matter (PM2.5), and Nitrogen dioxide (NO_2). These pollutants interact with climatic variables, including temperature and humidity, to influence human health. Poor AQI values are strongly associated with increased incidence of respiratory diseases (such as asthma and chronic obstructive pulmonary disease), cardiovascular disorders and even neurological conditions (Manisalidis *et al*., 2020).

However, Machine learning provides the opportunity to close this gap by using existing AQI data (CO, O_3, PM2.5, and NO2) to predict regional health outcomes across Africa with the corresponding value of health impacts associated with pollution exposure in the AQI guideline.

Air pollution has emerged as one of the most significant global environmental and health challenges (Ogunsola *et al* 2023; Fuller *et al.,* 2023) The World Health Organisation (WHO, 2021) estimates that air pollution contributes to over seven million premature deaths annually, with Africa being disproportionately affected due to rapid urbanisation, poor enforcement of emission controls, and limited health infrastructure. However, Climate change is not just a global challenge; it poses a serious threat to human health and represents one of the greatest injustices of our time (IPCC, 2021). Likewise, the increase in global temperatures causing changes in rainfall patterns, and more frequent extreme weather events have significant effects on climate change and its variability with greater consequence on mankind (Ogunsola 2012; Yaya *et al*., 2023). However, pollutants enter the environment through both natural and anthropogenic activities (Akhtar *et al*., 2021)

Urbanization across Africa has been closely tied to economic growth, but it has also intensified the production of PM2.5 and CO pollution through industrial activities, energy use, and transportation (Kayode, 2026). Research has shown that air pollution significantly contributes to the region's disease burden (Amegah *et al*., 2017; Brauer *et al.,* 2019). For example, PM2.5 exposure has been strongly linked to higher rates of respiratory illness and premature mortality in major cities such as Lagos, Nairobi, and Johannesburg. Similarly, pollutants like ozone and NO_2 worsen chronic respiratory conditions such as asthma, while carbon monoxide remains a critical risk to maternal and child health. Alarmingly, outdoor air pollution-related deaths in Africa rose from 164,000 in 1990 to 258,000 in 2017, a figure likely to increase further as population growth, industrialization, and consumption patterns intensify pollution (Wiston, 2024). Demographic projections suggest Africa's population will double by 2050, with more than 80% of this growth occurring in cities, thereby exacerbating traffic-related emissions and air quality challenges. In East Africa, for instance, visibility data between 1974 and 2018 indicated that air pollution rose by 62% in Addis Ababa, 162% in Kampala, and 182% in Nairobi (Makoni, 2020).

The scientific framework underpinning this study draws on the physical principles governing air pollution, atmospheric dynamics, and their interactions with human health. Within this framework, a machine learning model was developed and applied to predict air quality variations and their associated health impacts (Essamlali *et a*l., 2024).

This study aligns with Sustainable Development Goals (SDG 3, 11, and 13) contributing to health, sustainable cities and climate action. Moreover, it will also contributes to filling the knowledge gap by focusing specifically on Africa, where empirical research is scarce but where vulnerability to pollution-induced health outcomes is high. The integration of Machine Learning techniques ensures better prediction accuracy, making the study relevant for both scientific advancement and policy action.

MATERIALS AND METHODS

The data for this study was collected from the Kaggle air repository (2025). The obtained dataset contains Air Quality Index for 23,463 observations collected from multiple Cities across different countries including selected African countries. The dataset represents a cross-sectional observation of air quality indicators.

Exploratory Data Analysis

The exploratory data analysis were utilised in investigating the datasets through data visualisation approach and also using Machine Learning techniques to predict health impacts associated with air pollution exposure. The workflow follows the stages in the research design (Figure 1).

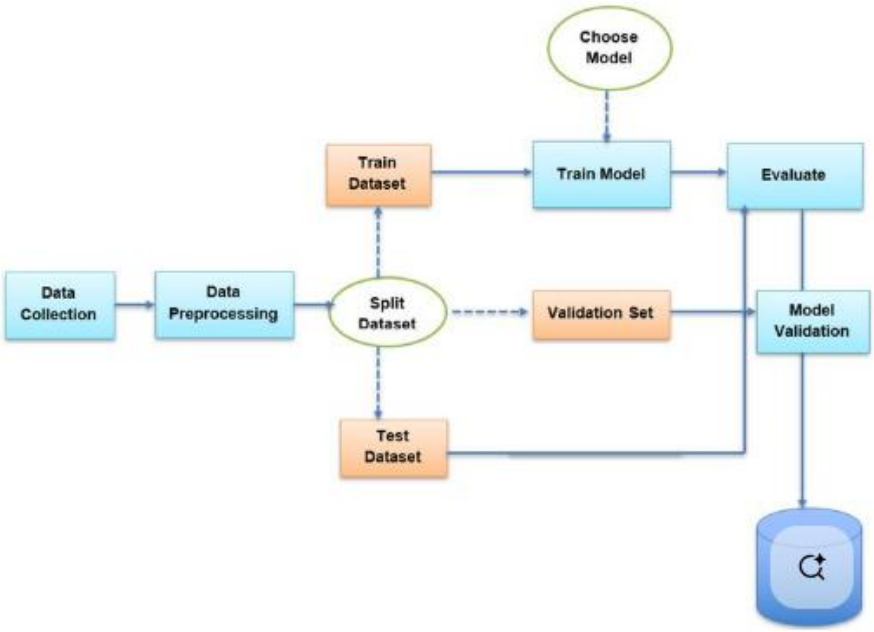

Figure 1: Research Design Workflow

Data Pre-processing
The obtained data were pre-processed so that the quality of data to be fed into the machine learning model can be interpreted correctly. Hence, the collected data undergoes pre-processing steps to ensure quality and suitability for machine learning.

Data Cleaning
Data cleaning was done to remove or eliminate duplicate records, address missing values, standardize data formats and correct inaccurate entries. The duplicated and inconsistent records were eliminated while the cleaned data was used to train the model by enabling it to adjust its internal parameters for improved prediction accuracy. During training, care was taken to prevent over fitting (i.e. where the model excels on training data but fails on unseen data) as well as under fitting, where the model performs poorly on both training and test datasets.

Normalization
Normalization was used to scale the numerical values in the dataset to give a common range without distorting differences in the data. It improves the model performance by ensuring that features contribute equally to the analysis. The data obtained were scaled using Min-Max normalization to ensure all features were within the same range (0 to 1).

Feature Engineering
Feature engineering was applied to convert raw data into relevant features that enhance the performance of Machine Learning models. It entails selecting, generating, and modifying the variables to improve the model's capacity to identify patterns. In this study, additional features such as month and season were derived and incorporated.

Data Splitting
Data splitting involves partitioning the dataset into distinct subsets for training and evaluating the Machine Learning models. Its primary purpose is to promote generalization to unseen data while minimizing risks of over fitting or under fitting. In this study, the dataset was divided into a Training Set (70%) used to build the model, and a Test Set (30%) applied to assess its performance on new data.

Model Development
This study employed four algorithms: Linear Regression, Decision Trees, Random Forest, k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM) and the model was evaluated using three key metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Square of one correlation coefficient i.e., Coefficient of Determination (R^2). To assess how well each of the algorithms (i.e. Linear Regression, Decision Trees, Random Forest, k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM) could make predictions, a comparative analysis was conducted. The evaluation employed standard performance metrics such as MAE, RMSE and R^2 across both training and testing datasets.

Mean absolute error
Mean Absolute Error (MAE) quantifies the magnitude of prediction errors in a dataset without considering their direction (Equation 1). It represents the mean of the

absolute differences between actual and predicted values across all test samples (Abdelmalek et al., 2025).

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|x_i - \hat{y}_j\right| \quad (1)$$

Where,
N is Data points Number
x_i is Actual value
$\hat{y}_j$ is Predicted value

Root Mean Square Error

Root Mean Square Error (RMSE) is a valuable metric as it assigns greater weight to larger errors, thereby making it sensitive to outliers. It evaluates the discrepancy between predicted and observed values by taking the square root of the mean of the squared differences. In essence, RMSE reflects how far model predictions deviate from actual outcomes (Chico *et al.*, 2021). It was calculated using equation (2)

$$\sqrt{\frac{\sum_{j=1}^{N}\left(y_j - \hat{y}_j\right)^2}{N}} \quad (2)$$

Where;
y_j is the actual value of the ith observation.
$\widehat{\hat{y}}_j$ is the predicted value for the ith observation
P is the number of the parameter estimated, including the constant
N is the number of observations

R-Squared

The R-squared (R^2) value quantifies how much of the variability in the dependent variable is explained by the model. Its values range from 0 to 1, where higher scores indicate better model performance (Data camp 2025). It essentially indicates the ratio of variance accounted for by the model compared to the overall variance in the dataset. An R^2 value nearing 1 indicates that the predictions made by the model are in strong agreement with the actual data. It can be calculated as shown in equation (3)

$$R^2 = 1 - \frac{\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2}{\sum_{j=1}^{n}\left(y_j - \bar{y}\right)^2} \quad (3)$$

Where,
y_j is the actual value of the dependent
$\widehat{\hat{y}}_j$ is the predicted value for the model
$\bar{y}$ is mean of the actual value
n is the number of observations

Implementation Tools

Programming Language: This study utilises Python Programming Language for its extensive libraries and frameworks and the following Libraries are used for the implementation

i. NumPy adds support for multi-dimensional array in data processing
ii. Pandas is for data pre-processing and descriptive statistics.
iii. Scikit-learn was used to check the accuracy of the model.
iv. Matplotlib and Seaborn was used for graphical visualisation of pollutant distributions and trends.

The Integrated Development Environment (IDE) utilised Google Colab to write and execute the code while for Optimisation Algorithms, GridSearchCV was implemented for hyper parameter tuning to optimize performance.

RESULTS AND DISCUSSION

The results of the Exploratory Data Analysis with the analysis of the AQI dataset utilised as health indicators and their predictive evaluation metrics from Machine Learning models for the selected countries in Africa were used to determine the health impact.

Evaluation Metrics of Model Performance

Table 1 shows that Random Forest exhibited the strongest performance (R^2 = 0.997316, RMSE = 2.865823, MAE = 0.2955499) suggesting highly accurate modelling and low deviation from actual AQI values. K-NN (R^2 = 0.996820, RMSE = 3.119500, MAE = 0.588252) followed with a robust performance indicating excellent variance but had a relatively high MAE highlighting increased individual prediction error. Decision Trees (R^2 = 0.995046, RMSE = 3.893819, MAE = 0.302845) achieved a low MAE (Figure 2) and a high R^2 (Figure 3), indicating an increased individual prediction accuracy. SVR (R^2 = 0.980160, RMSE = 7.792268, MAE = 1.301302) and Linear Regression (R^2 = 0.975279, RMSE = 8.968122, MAE = 4.831951). SVR and Linear Regression showed moderate accuracy in training but higher RMSE (Figure 4) values which suggests over fitting and poor error control.

Table 1: Analysis of evaluation metrics

	categories	values
	R Squared values	
0	Linear Regression	0.975279
1	Decision Tree	0.995046
2	Random Forest	0.997316
3	K-Nearest Neighbour	0.996820
4	Support Vector Machine	0.980160

	categories	values
	Root Mean squared error	
0	Linear Regression	8.698122
1	Decision Tree	3.893819
2	Random Forest	2.865823
3	K-Nearest Neighbour	3.119500
4	Support Vector Machine	7.792268
	Mean Absolute error	
0	Linear Regression	4.831951
1	Decision Tree	0.302845
2	Random Forest	0.295499
3	K-Nearest Neighbour	0.588252
4	Support Vector Machine	1.301302

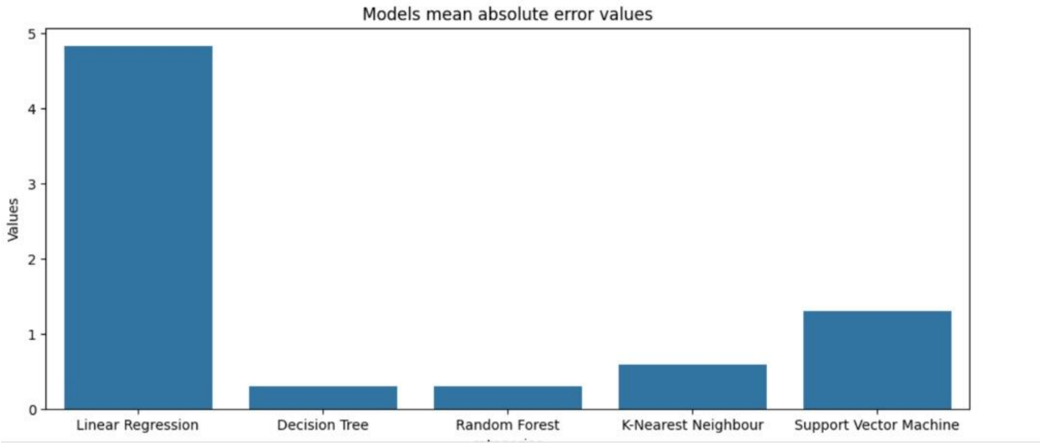

Figure 2: Model of MAE

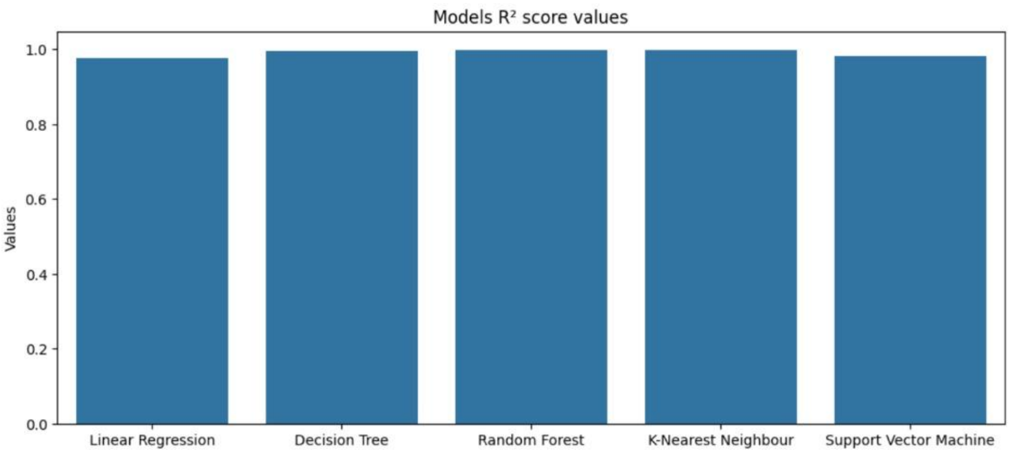

Figure 3: Model of R^2

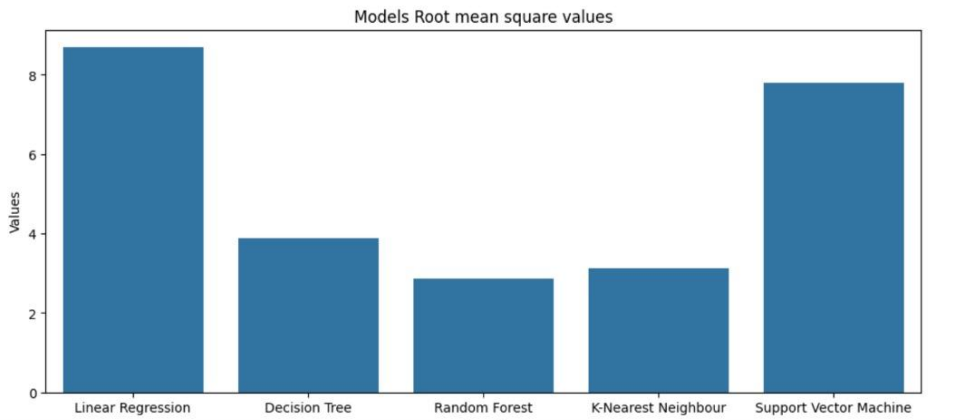

Figure 4: Model of RMSE

Air Quality Index Analysis in Africa

The overall AQI in Africa using the exploratory data analysis (Table 2) shows that the mean is 72.010858, Median is 55.000000 and Standard deviation is 56.055220. The mean is higher than the median indicating right skewness which explains the extreme increase in AQI values.

The AQI range 6.000000 to 500.000000 shows a minimum value of 6.000000 which is good and a higher maximum value of 500.000000 which is hazardous suggesting extreme pollution events. The 25% (i.e., 25th percentile) is 39.000000, while the 75% (that is, 75th percentile) is 79.000000, indicating that half of the data falls around 39.000000 to 79.000000, which ranged from good to moderate levels of health concern according to the US Environmental protection Agency AQI guideline (Table 3).

However, for Carbon Monoxide (CO) the approximate AQI mean is 1.368367, median is 1.000000 while Standard deviation is 1.832064, this shows that the overall values are very low (Table 2). The value range of 0.000000 to 133.000000 reveals that most of the concentration is close to 0.000000 and 1.000000, but with existence of a few extremely high values. The percentiles (25%, 50%, and 75%) are respectively equal to 1.000000. This shows a highly skewed distribution since almost all values are closer to 1.000000 with very few spikes. This means that CO is generally not a major contributor to AQI, except for rare extreme cases since its contribution lies in the good level of health concern (Table 3). Moreover, in the case of Ozone, the approximate AQI mean is 35.193703, median is 31.000000 and standard deviation is 28.098723 (Table 2). These values are moderately spread out. The value range for 0.000000 to 235.000000 indicates ozone can reach dangerous levels in some cases while the percentile values for 25% and 75% are 21.000000 and 40.000000 respectively. Most values lie in the good-to-moderate range for Ozone which indicate that it is a more consistent contributor to AQI than CO since its level of health is in the unhealthy scale (Table 3).While the approximate values for NO_2 shows that the mean is 3.063334, Median is 1.000000 and standard deviation is 5.254108 which are mostly low values (Table 2). The range is 0.000000 to 91.000000 indicating a few high spikes and the percentile for 25%, 50% and 75% are 0.000000, 1.000000 and 4.000000, respectively, indicating that most values are very minimal like CO and NO_2 its contribution to AQI is not dominant since it is in the good and moderate level of health concern (Table 3). Finally, for PM2.5 the approximate AQI mean value is 68.519755, median is 54.000000 and standard deviation is 54.796443. However, these high values of mean and median is an indication that it is a major contributor to AQI. The range is also from 0.000000 to 500.000000 which covers the full AQI scale, indicating extreme pollution events by being hazardous in the extreme level of health concern (i.e. hazardous) (Table3). Similarly, the 25% percentile is 35.000000 while 75% percentile value is 79.000000 which indicates that large portion of data lies in the moderate to unhealthy range making PM2.5 the dominant pollutant influencing AQI in this dataset.

In summary, the dominant Pollutant in this analysis is PM2.5, and it strongly contributes to the overall AQI since its distribution closely matches the whole AQI's value range and spread. However, CO and NO_2 rarely contribute to the AQI by having good and moderate level of health concern, while Ozone moderately contribute with values that sometimes exceed safe thresholds through unhealthy and very unhealthy levels of health concerns. The mean overall AQI value for all the pollutant considered in this study is 72.010868, which is very close to 68.519755 for that of P.M2.5. Thus, supporting the dominance of P.M2.5 in driving AQI levels for this region of the world (Africa) since majority of the pollutants considered have minimum values which could mean clean air periods or sensor detection limits.

Table 2: Exploratory Data Analysis

	aqi_value	co_aqi_value\t	ozone_aqi_value	no2_aqi_value	pm2.5_aqi_value
count	23463.000000	23463.000000	23463.000000	23463.000000	23463.000000
mean	72.010868	1.368367	35.193709	3.063334	68.519755
std	56.055220	1.832064	28.098723	5.254108	54.796443
min	6.000000	0.000000	0.000000	0.000000	0.000000
25%	39.000000	1.000000	21.000000	0.000000	35.000000
50%	55.000000	1.000000	31.000000	1.000000	54.000000
75%	79.000000	1.000000	40.000000	4.000000	79.000000
max	500.000000	133.000000	235.000000	91.000000	500.000000

Table 3: Air Quality Index guideline

Index Values	Levels of Health Concern	Cautionary Statements
0-50	Good	None
51-100*	Moderate	Unusually sensitive people should consider reducing prolonged or heavy exertion outdoors.
101-150	Unhealthy for Sensitive Groups	Active children and adults, and people with lung disease, such as asthma, should reduce prolonged or heavy exertion outdoors.
151-200	Unhealthy	Active children and adults, and people with lung disease, such as asthma, should avoid prolonged or heavy exertion outdoors. Everyone else, especially children, should reduce prolonged or heavy exertion outdoors.
201-300	Very Unhealthy	Active children and adults, and people with lung disease, such as asthma, should avoid all outdoor exertion. Everyone else, especially children, should avoid prolonged or heavy exertion outdoors.
301-500	Hazardous	Everyone should avoid all physical activity outdoors.

(Source: US Environmental Protection Agency 2024)

Air Quality Health Impact

The exploratory data analysis (EDA) conducted on the AQI for 23,463 dataset was utilised in developing a Machine Learning (ML) model using AQI parameters (NO_2, CO, O_3, $PM_{2.5}$) to predict their climatic impact on health in the African region. Amongst the selected African countries, South Africa, Nigeria, Ethiopia, Mali, and Cameroon are more polluted than the remaining countries with a higher value of $P.M_{2.5}$ concentration (Table 4) while, Libya, Kenya, Ethiopia, Egypt and Angola are polluted by Ozone.

Also, South Africa, Nigeria, Kenya, Cameroon and Angola are highly polluted by Carbon monoxide. Similarly, South Africa, Nigeria, Kenya, Egypt and Angola are slightly polluted by NO_2. Hence, the developed models predicted AQI values for selected African countries were compared with the health impacts associated with pollution exposure in the AQI guideline

(Table 3). However, amongst the pollutant considered in this study P.M 2.5 has the highest value and associated health risks include heart attack and respiratory diseases. Ozone levels are also high with the risk of Chronic Obstructive Pulmonary Disease (COPD) and exacerbations. The values for CO and NO_2 are moderate. Thus, in general most of the African countries are polluted which can be attributed to anthropogenic activities caused by seasonal variation.

Table 4: AQI Values for Selected African Countries

S/N	Country Name	AQI value	CO (ppm)	O_3 (ppm)	NO_2 (ppm)	P.M 2.5 ($\mathscr{M}$g/m^3)
1	Angola	81.9	3.75	27.1	2.25	97.6
2	Cameroon	69.0	3.37	24.7	0.61	100.0
3	Egypt	95.8	1.40	67.0	2.53	94.2
s4	Ethiopia	78.7	1.24	27.4	0.06	100.0
5	Kenya	74.0	3.19	28.7	1.39	99.8
6	Libya	103.0	0.949	40.3	0.34	97.3
7	Mali	83.2	1.25	24.8	0.48	100.00
8	Nigeria	99.6	3.83	25.9	2.28	100.0
9	South Africa	113.0	4.76	14.7	5.90	100.0

CONCLUSION

The findings of this study demonstrate that machine learning techniques hold significant potential to predict the Air Quality Index (AQI) and assess health risks across urbanized, industrialized, and rural regions using climatic parameters, particularly in African regions where conventional monitoring infrastructure is scarce. Amongst the models evaluated, Random Forest proved to be the most effective, largely due to its capacity to capture intricate, nonlinear relationships between climatic factors and AQI.

Based on this study, the following recommendations are suggested to reduce the health impact of air pollution in the African region,

i. Investment in the expansion of ground-based Air Quality Index monitoring system and equipment to complement satellite data and machine learning predictions, for, reliable data which will further improve model accuracy and also guide interventions.
ii. Integration of Machine Learning into Public Health planning, through the incorporation of ML-driven AQI forecasts into early warning systems for pollution-related health risks, especially for vulnerable groups.
iii. Introduction of public awareness campaign to educate citizen about the health dangers associated with air pollution and the provision of daily AQI alerts for citizens to take preventive actions.
iv. Encouragement of regional collaboration amongst African region since air pollution transcends borders. African nations should collaborate on sharing of data, technology, and best practices in combating climate-health challenges.
v. Future research should explore deep learning methods, integrate socioeconomic factors, and assess long-term climate change scenarios to build more holistic predictive models.

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