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CSE445 Report

Group-7

Air Quality Index Prediction

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Paper Review 3	Olid	100
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Air Quality Index Prediction

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***Abstract*— Dhaka, Bangladesh's capital, has always been among the top 3 cities with the worst air quality worldwide. Dhaka's air quality is getting worse every day since it's one of the world's most densely inhabited cities and because of its overcrowding, transportation, and industrialization. Many deadly diseases, including respiratory, cardiovascular, cancer, neurological disorders, etc., are caused by air pollution. This project intends to predict the Air Quality Category to reduce these effects using machine learning. This paper aims to know the AQI Category based on some given pollutant (PM2.5) concentrations monitored in Dhaka for the past two years (2022,2023). The study utilized the Scikit-learn library to implement four machine-learning algorithms. We also used Explainable AI (LIME) to visualize the prediction results. We have also used smote to balance the class distribution. The evaluation metrics for these algorithms for the classification task were precision, recall, accuracy, and f1-score. The result shows that XGBoost and K-Nearest Neighbor achieved the highest cross-validation scores of 84.9% and 82.6%, respectively.**

Keywords*— *Air Quality Index (AQI), Dhaka, Machine Learning, Scikit-learn, PM2.5Concentration, Smote, Evaluation Metrics.

I. INTRODUCTION

The Air Quality Index is being used daily for reporting air quality. It detects if the air is clean or polluted and what type of health issue might arise. The Air Quality Index focuses on the health effects a person may encounter within a few hours or days after inhaling contaminated air.[1] Air pollution has become a significant problem globally. Air pollution occurs in the indoor or outdoor environment by any chemical, physical, or biological mechanism that reverses the natural elements of the climate.[2] Air pollution is known as a "silent killer" because it is not connected directly to the death. Air pollution is the globe's fourth leading contributing cause of early death, accounting for 0.29 of all deaths and diseases from lung cancer. 0.17 of all deaths and diseases are from critical lower respiratory infections. According to the IQAir report of 2021, Bangladesh ranked first for the annual average PM2.5 concentrations weighted by population (76.9 μg/m3). Traditional techniques for predicting the Air Quality Index (AQI) employ mathematical models that assess many aspects of meteorological states, emissions from different sources, chemical reactions in the air, and geographical attributes.[3] Traditional methods become complicated for specific necessities and public resources. Also, rely on statistical methods and practical connections obtained from monitoring data. [4]It integrates the machine learning model in the air quality index prediction to decrease complexity and make it an easy process for routine monitoring, air pollution predictions, and ambient air quality maintenance. Air quality monitoring is necessary for maintaining air quality, protecting health issues, and ensuring compliance with regulations.

Kothandaraman et al. [5] applied machine learning methods to predict the levels of pollutants and overall air quality in a specific area. The authors operated Meteorological and PM2.5 Datasets containing 49056 samples. However, there were some improper data with null values. These null values were restored using the mean value. The authors tested different machine learning models, such as LR, RF, KNN, RL, Xgb, and Adab models, where Adab models achieved the highest accuracy of 42.90%.

Natarajan and his team [6] attempted to predict the AQI(Air Quality Index) in various Indian cities using an unconventional machine learning model that combines Grey Wolf Optimization and a Decision Tree. They have considered the "Air Quality Data in India (2015-2020)" dataset from Kaggle. The verification measures used by the authors included RMSE, R-square, MAE, MSE, and accuracy. Compared to other classic machine learning techniques, a hybrid approach achieves an accuracy of up to 97.68%.

Gupta et al.[7] have predicted the Air Quality Index using Machine Learning in Indian Cities. This model uses SMOTE, SVR, RFR, and CR algorithms, and the original dataset includes 29532 rows and 16 columns. Among the cities, Hyderabad city has the highest Accuracy of 90.97% for Kolkata using an RFR of 97.6%.

Ravindiran and his team [8] employed machine learning for routine monitoring, air pollution predictions, and ambient air quality maintenance. The authors used the Indian Central Control Room (CCR) for the Air dataset for their research. The authors employed several machine-learning models from which the Catboost model achieved a high prediction accuracy of 0.9998 and a low RMSE (root mean square error) of 0.76.

For our project predicting air quality index (AQI), we used machine learning models like K-Nearest Neighbors (KNN), Random Forest, XGBoost, and AdaBoost. We used a bunch of data from the AirNow website to create models that predict how clean or polluted the air will be. We combined different machine learning techniques to determine the best model to predict air quality. Our project tackles the urgent need for cutting-edge predictive models in environmental science, emphasizing enhancing public health outcomes and empowering decision-makers to make informed choices about reducing air pollution. We work hard to conduct experiments and evaluate our findings to help improve the way we monitor and manage air quality.

We have structured our discoveries to provide a clear overview of our research findings. Section II outlines the proposed system, illustrating it using tables, figures, or flowcharts to enhance comprehension. In Section III, we delve into the captivating findings of our study, delving into the intriguing insights obtained from analyzing performance metrics. Finally, in Section IV, we summarize our research and propose ideas for further improvements. Our objective is to offer a comprehensive insight into our process of predicting air quality using advanced computer models.

II. PROPOSED SYSTEM

In this section, we will describe the theory of all the software components/algorithms and hardware tools you will need for your capstone project. You can include circuit diagrams/equations or flowcharts of your capstone project.

A. Dataset

The dataset utilized in our study was sourced from the airnow.gov [5] website, comprising 17,130 samples collected over two years, each year contributing 8,413 samples. The dataset encompasses various features relevant to air quality monitoring, including Site, Parameter, Year, Month, Day, Hour, NowCast Conc., AQI, Raw Conc., Conc. Unit, Duration, QC Name, and Date. Among these features, the primary focus was predicting the AQI Category, which serves as the target variable for our analysis. Each sample in the dataset provides valuable information about air quality measurements, enabling us to explore relationships between different parameters and their impact on AQI categorization. Through rigorous dataset analysis, we aim to develop robust predictive models for assessing and forecasting air quality conditions.

index	Year	Month	Day	Hour	NowCast Conc.	AQI	Raw Conc.
count	17131	17131	17131	17131	17131	17131	17131
mean	2022.50	6.52	15.62	11.50	98.63	167.17	98.94
std	0.50	3.47	8.76	6.92	83.95	78.34	90.24
min	2022	1	1	0	-999	-999	-999
25%	2022	3	8	5	44.8	124	43
50%	2023	7	16	11	74.5	161	73
75%	2023	10	23	18	136.5	193	137
max	2024	12	31	23	648.5	598	985

Tabl-II: Max, min, mean value of features

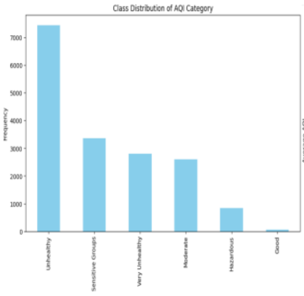

Fig-1: Class Distribution by AQI category

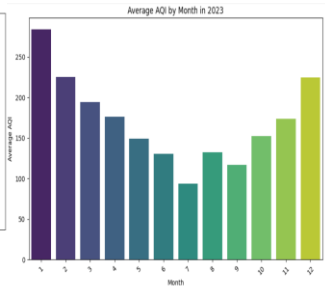

Fig-2: Average AQI by month of 2022

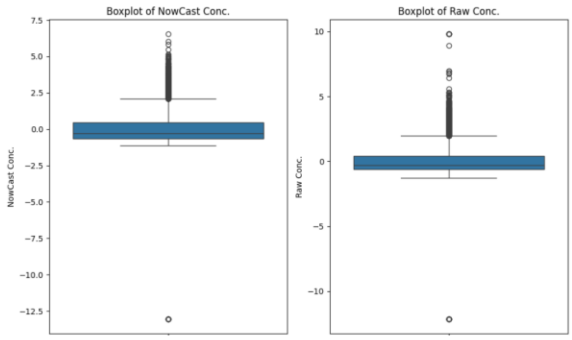

Fig-3: Box-Plot of Nowcast Concentration

B. Dataset Preprocessing

To improve the computational efficiency we dropped the Date(Local Time) and Date features from the dataset as we can effectively derive this information from Year, Month, Day, and Hour features. We used the Label Encoding method for our target variable 'AQI Category'. We assigned 6 unique values to the classes Good: 0, Hazardous: 1, Moderate: 2, Unhealthy: 3, Unhealthy for Sensitive Groups: 4, Very Unhealthy: 5, nan: 6. We filled the most frequent AQI Category to impute the missing values of our target variable.

We used the standard scaler method for a balanced scale.

$$X_{new} = \frac{X - X_{mean}}{standard\ deviation} \quad (1)$$

Fig-4: Standard Scaler Formula

For outlier detection, we used the Boxplot method using the quartile Range. After removing outliers, we used the min-max scaler to scale our data between 0 to 1.

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

Fig-5: Min-Max Scaler Formula

We used Pearson's Correlation Coefficient method to find the linear relation of our features only on the training dataset of X. Then, we dropped both 'AQI' and 'Raw Conc.' features respectively from the training and testing set as their threshold value is above 85%. X

$$r = \frac{n\,(\Sigma xy - (\Sigma x)(\Sigma y))}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma y)^2]}} \quad (3)$$

Fig-6: Pearson's Correlation Coefficient Formula

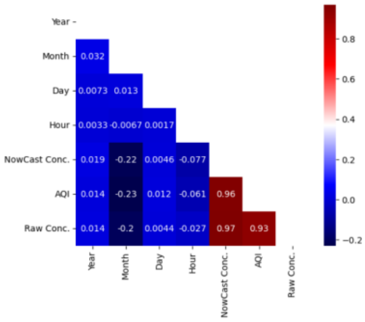

Fig-7: Pearson's Correlation Coefficient

C. *Machine Learning Models;*

We used four machine learning models K-Nearest Neighbors (KNN), Random Forest, XGBoost, and AdaBoost to predict the air index quality.

1) RANDOM FOREST: The Random Forest ensemble approach uses random data selections to create several independent decision trees. Combining predictions from each tree produces the final prediction, which lowers variance and enhances model generalization.

2) K-Nearest Neighbours (KNN): Using the training data as a starting point, this non-parametric classification technique groups data points according to how similar they are to their k nearest neighbors.

3) XGBOOST: Extreme Gradient Boosting, or XGBoost, is an ensemble learning method that builds a robust model by combining several weak decision trees. XGBoost is renowned for managing complicated datasets well and can stop overfitting.

4) ADABOOST: Adaptive Boosting, or AdaBoost, is a method that repeatedly refines a weak learner by emphasizing instances that the prior learner misclassifies. AdaBoost produces a more robust final model by adaptively increasing the weights of difficult occurrences.

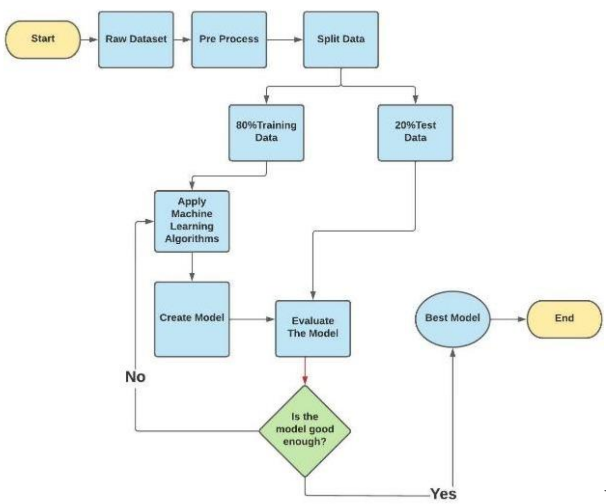

Fig-8: Working sequences of the proposed diabetes prediction system.

III. Results and Discussion

We fine-tune the settings of our machine-learning models to make them even better at predicting things. On top of that, we also look at what other researchers have done in this area, showing how our system takes things to the next level. Additionally, we use the LIME explainable AI library to understand how our models make predictions. This helps us see what factors are essential in determining air quality and makes our models more transparent and easily understood.

Model	Hyperparameter Value Range	Optimized value
Random Forest	n_estimators: [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000], max_features: [auto, sqrt, log2], max_depth: [10, 120, 230, 340, 450, 560, 670, 780, 890, 1000], min_samples_split: [2, 5, 10, 14], min_samples_leaf: [1, 2, 4, 6, 8], criterion: [entropy, gini]	n_estimators: 1800, min_samples_split: 2, min_samples_leaf: 1, max_features: log2, max_depth: 560, criterion: entropy
KNN	n_neighbors: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20], weights: [uniform, distance], metric: [euclidean, manhattan, chebyshev, minkowski], n_iter: 50, scoring: accuracy, cv: 3, verbose: 1, n_jobs: -1, random_state: 20	n_neighbors: 2, weights: distance, metric: manhattan
XGBoost	n_estimators: [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000], learning_rate: [0.01, 0.1, 0.2, 0.3], max_depth: [3, 5, 7, 9], min_child_weight: [1, 5, 10], gamma: [0, 0.1], subsample: [0.8, 0.9, 1.0]	subsample: 0.8, n_estimators: 800, min_child_weight: 1, max_depth: 9, learning_rate: 0.1, gamma: 0.1
AdaBoost	n_estimators: [50, 100, 200, 300], learning_rate: [0.01, 0.1, 0.2, 0.3], base_estimator__max_depth: [3, 5, 7, 9], base_estimator__min_samples_split: [2, 5, 10], base_estimator__min_samples_leaf: [1, 2, 4]	n_estimators: 300, learning_rate: 0.1, base_estimator__min_samples_split: 5, base_estimator__min_samples_leaf: 2, base_estimator__max_depth: 9

Table-II: hyperparameter values' ranges for all the ML models.

Fig-9: Machine learning model prediction interpretation by LIME explainable AI library.

References	ML model	Accuracy	Precision	Recall	F1- Score
[1]	Random Forest	71%	0.72	0.71	0.72
[2]	KNN	82.63%	0.69	0.65	0.66
[3]	XGBoost	83.19%	0.70	0.71	0.71
[4]	AdaBoost	80.13%	0.73	0.73	0.73
[5]	Adab	42.90%	-	-	-
[6]	DT	97.68%	-	-	-
[7]	RFR	90.97%	-	-	-

[8]	Catboost	99.98%	-	--	-

Table III- comparison of our model results with existing works

IV. CONCLUSIONS

The forecast for Dhaka's AQI and AQI categories between 2022 and 2023 was examined in this study. The winter season saw an increase in AQI levels beginning in October, followed by an abrupt drop in AQI starting in April. The most essential element for determining the AQI category was discovered to be Nowcast Concentration. Compared to other machine learning models, the results show that XGBoost produced the best cross-validation score of 84.9% following hyperparameter optimization. Adding more data for future models could increase their accuracy. Alternative feature engineering methods, such as one-hot encoding, can be applied to enhance the model's effectiveness.

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