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Optimal Machine Learning Techniques to Predict Air Quality Index

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Contents of this Presentation

Base Paper

Paper Title: Impact of air pollutants on climate change and prediction of air quality index using machine learning models

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Abstract

- Air pollution demands better monitoring, rising pollution necessitates accurate air quality prediction, crucial for managing environmental quality.
- Costly limitations of traditional methods: Manual monitoring stations, though existing, are expensive and limited.
- Machine learning emerges as a powerful tool: Ensemble methods will be used to predict AQI using open-source CPCB data.
- Scalability and reusability are key: The research seeks a robust ML framework applicable to diverse cities with the CPCB data.

Literature Survey

S.No	Paper Title	Methodology	Merits	Limitations
1	Air Quality Index prediction using Machine Learning for Ahmedabad City	These are the methods used for the work: ● SARIMA ● SVM ● LSTM	Number of data-preprocessing methods are presented to remove the outliers, normalize the datasets, which are taken from different sources (CPCB boards) Can also be expanded to forecast other pollution indices at different levels.	Lots of missing values are present in the dataset of Ahmedabad city.
2	Air Quality Index prediction using Machine Learning Algorithms ~International Journal of computer Applications Technology and Research	These are the methods used for the work: ● ARIMA ● Auto Regression ● Linear Regression	Good prediction and Time Series Analysis was also used for recognition of future data points and air pollution prediction	Not able to show expected output as the data is not in sequence The error is high which they are working to overcome in near future.
3	Indian Air Quality Prediction And Analysis using Machine Learning	The model used for the work is: ● Naïve forest ● Linear regression ● Gradient Boosting Algorithms	Parameter reducing formulations for better performance than standard regression models	Low Accuracy

S.No	Paper Title	Methodology	Merits	Limitations
4	Air Pollution Prediction Using ML techniques. An approach to replace existing monitoring stations With virtual motoring stations	The model used for the work is: ● Ridge regression ● SVR ● Random Forest ● Xtreme Gradient Boosting	Hyperparameter tuning developed technique can be transferred to any location where pollutant prediction is required benefit from incorporating other neural networks such as CNN-LSTM (Convolution Neuron Network - Long Short Term Memory) in capturing temporal dependencies and patterns in data	The limitation of this study is that the forecasting of pollutant concentration is not possible as the data from other monitoring stations is required for prediction1
5	Detection and Prediction of air Pollution using Machine Learning models	The model used for the work is: ● Logistic regression ● Auto regression	Mean accuracy and standard deviation accuracy to be 0.998859 and 0.000612 respectively.	No gaseous pollutants were considered Taken very less data
6	Air Quality prediction by using ML models: a case study on the Indian coastal city Visakhapatnam	The model used for the work is: ● Random Forest ● Light GBM ● Cat Boost ● Adaptive boosting	Cat Boost model yielded high prediction accuracy (0.9998) and low RMSE (0.76). Cat Boost incorporates parameters that help mitigate overfitting in datasets	Performance needs to be validated under diverse air quality conditions The covid lockdown has affected the AQI levels

Problem Statement

- To enhance accuracy in AQI forecasting to facilitate informed decision-making for environmental regulation.
- To provide timely warnings and precautions to the public regarding air quality levels.
- To Enable proactive measures for mitigating the impact of air pollution on public health.

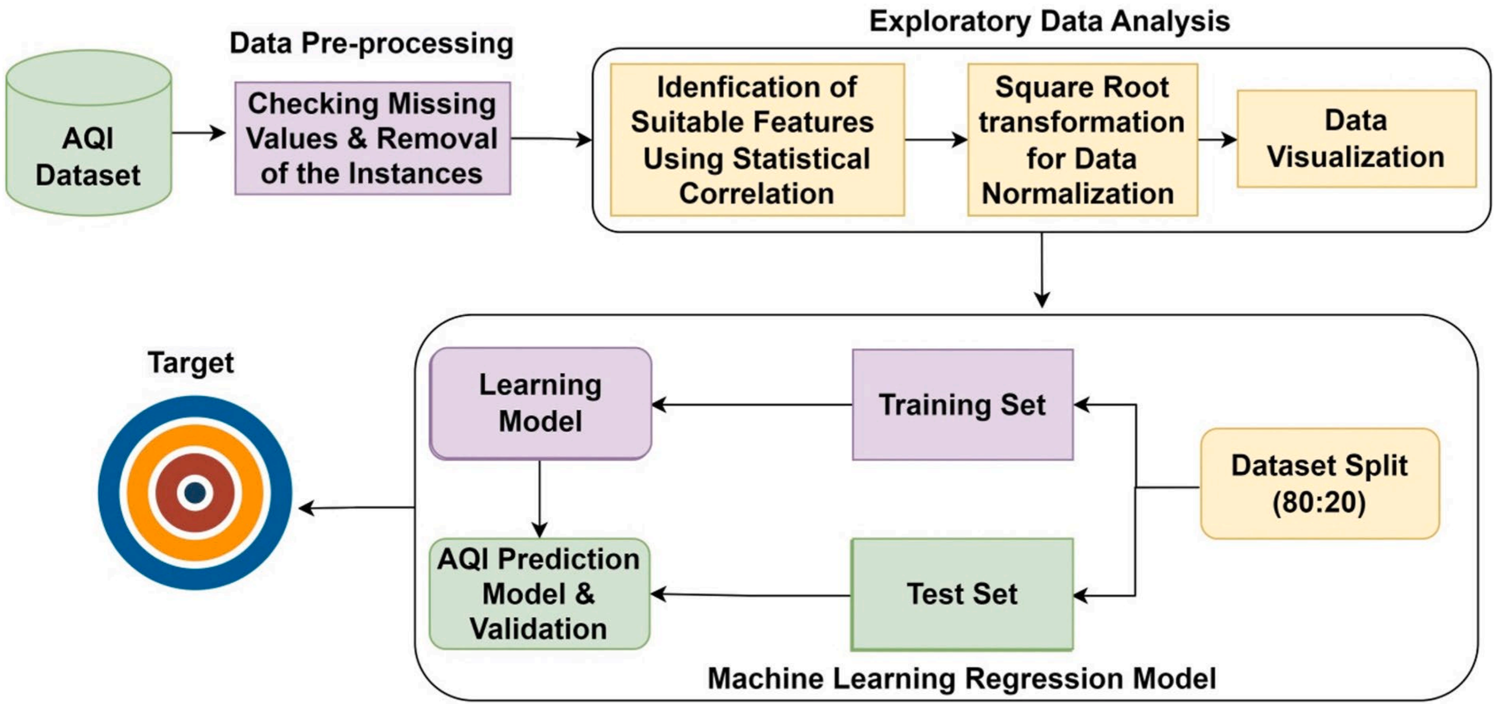
Objectives

- Implement advanced machine learning techniques on CPCB data to enhance accuracy and reliability in AQI prediction.
- Evaluate the performance of developed models against existing methods to validate effectiveness.
- Demonstrate the potential of the proposed approach to optimize environmental management strategies and safeguard public health against air pollution hazards.

Methodology

- We chose Tirupati monitoring station to work with and apply the base paper.
- Initially, data is processed to remove noises and handle missing values. Then the data is explored for patterns and a comprehensive analysis is made using apt tools like correlation matrix.
- Data is transformed and standardized before fitting it to the model for training and testing.
- To ensure the robustness of the models, we used 5-fold cross-validation, computed MAE, MSE, RMSE, and R2 scores for each fold, and reported the mean and standard deviation of each metric across all folds. When a model has a higher R2 score and lower MAE and MSE scores, it is generally regarded as performing better
- Models and methods - Random Forest, XGBoost, Bagging Regressor, LGBM Regressor
- Python libraries and modules - numpy, pandas, seaborn, sklearn.model_selection, GridSearchCV

System Architecture/Flow diagram of the work



Dataset

1. Source: Central Pollution Control Board (CPCB), India
2. Content: Continuous ambient air quality measurements
3. Parameters: PM2.5, PM10, NO, NO2, NOx, NH3, CO, SO2, Benzene, Toluene, Ozone, RH, Xylene, BP,AT, RF, Temp, SR
4. Time period: From 01-01-2017 to 31-12-2022
5. Location: Tirumala, Tirupati, Andhra Pradesh, India
6. Data format: A comma-separated value (CSV) file
7. Potential uses: The dataset can be used to train machine learning models to predict air quality index (AQI), analyze air quality trends, and assess the impact of air pollution on public health.

Dataset : Central Control Room for Air Quality Management - All India

Modules

- Module 1: Data Preprocessing, Exploratory Data Analysis, Data transformation
- Module 2: Data spilt and fitting the models
- Module 3: Comparative Analysis, Performance valuation, Result and Discussion

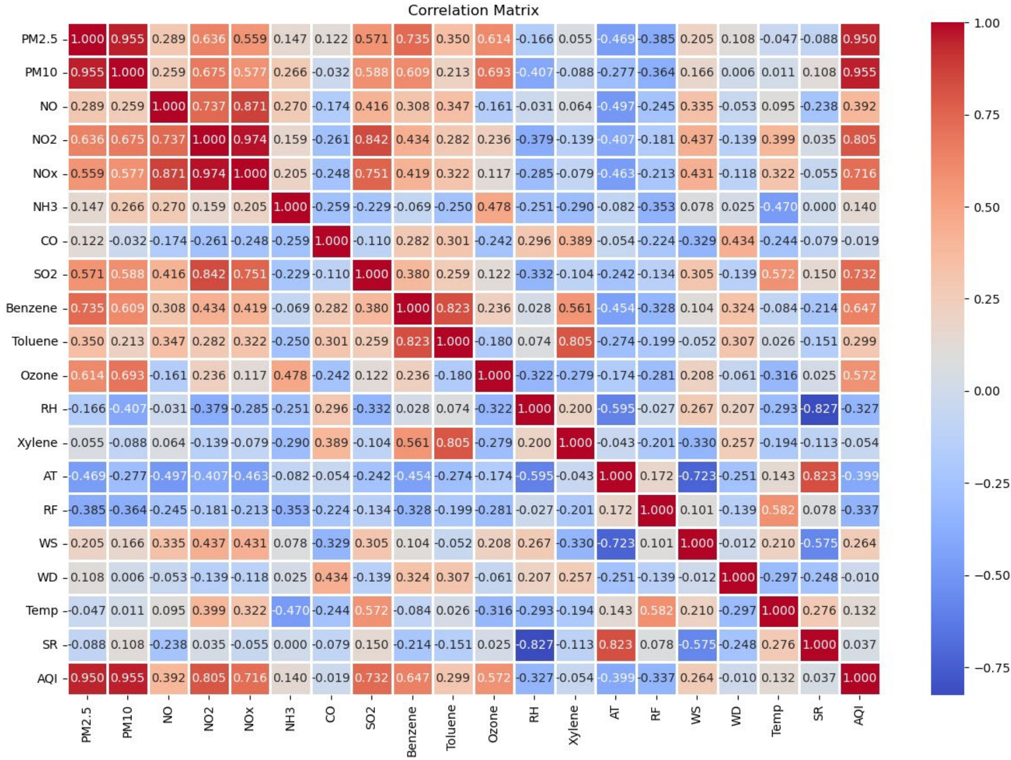
Module 1 – Data Preprocessing

- The datasets were obtained from the Central Pollution Control Board's - Central Control Room for Air (CPCB-CRR). They include measurements of air pollutants and meteorological parameters.
- Raw dataset contained a total of 2191 observations spanning from 01-01-2017 to 31-12-2022, which included 20 variables (13 Air pollutant attributes, 06 Meterological factors, and 1 AQI)
- Removed rows of instances with null values for the target variable (AQI) and BP (Barometric Pressure) parameter was removed since it had only 47 instances of recorded data and not helpful.
- **Handling Missing Values**: Used forward fill (previous day values) for null and 'None' values

Module 1 – EDA

The pollutants with the highest heat map values had a significant impact on AQI predictions

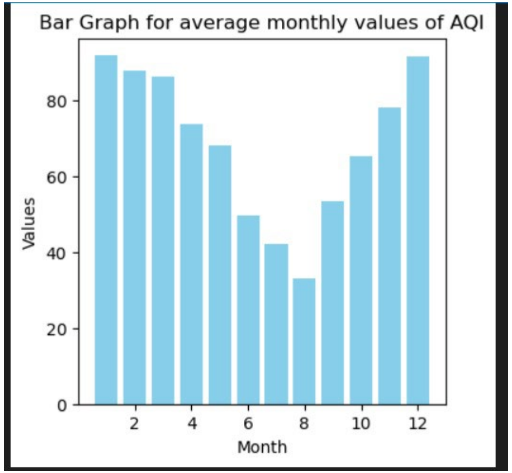
- When compared to the negative or inversion correlation, the positive correlation plays a major role in AQI prediction.
- With a correlation coefficient of 0.95, the highest among all parameters, the relationship between PM10 and AQI is significant, indicating that PM10 and PM2.5 plays a crucial role in determining the AQI.

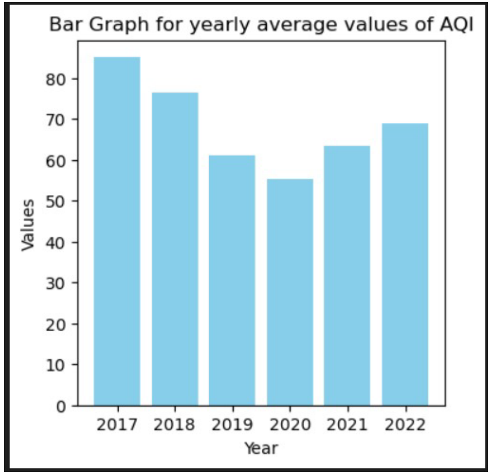


Heat Map – Input parameters with AQI

Module 1 – EDA

- The results show that AQI levels were extremely high in Dec and Jan. Seasonal variation may be the reason for the highest level of AQI in these months. These months fall under the winter season when temperatures are lower and more mist formation is observed. Because of the presence of moist air in the atmosphere, this could result in the formation of a temperature inversion and the pollutants emitted from the source get retained in the atmosphere.





Seasonal and annual variation of AQI

Module 1 – Data Transformation

- The most commonly used data transformation techniques are Box-Cox transformation, log transformation and square root transformation.
- Log transformation is a powerful tool to reduce skewness in data. It works by compressing larger values and spreading out smaller ones.
- Log transformation was used to change the data to make it more normal.

Before transformation

	Skew	Kurtosis
PM2.5	1.08	0.96
PM10	0.8	1.43
NO	1.49	2.74
NO2	2.06	9.4
NOx	1.59	5.04
NH3	1.11	0.62
CO	5.88	58.01
SO2	1.81	2.9
Benzene	2.87	19.29
Toluene	3.36	18.35
Ozone	1.12	1.17
RH	-0.66	-0.01
Xylene	6.09	61.63
AT	-0.01	-0.74
RF	10.13	103.69
WS	1.03	1.34
WD	-0.06	-0.54
Temp	4.31	27.93
SR	1.04	2.66
AQI	1.53	3.96

After transformation

	Skew	Kurtosis
PM2.5	-0.27	0.07
PM10	-0.36	-0.38
NO	-0.44	1.05
NO2	-0.21	-0.13
NOx	-0.97	5.09
NH3	-0.99	6.17
CO	-4.66	26.7
SO2	0.26	0.35
Benzene	-4.01	22.12
Toluene	-3.78	26.74
Ozone	-0.32	0.75
RH	-1.08	1.08
Xylene	-2.24	6.13
AT	-0.21	-0.75
RF	1.13	-0.48
WS	-0.31	-0.29
WD	-0.98	1.68
Temp	3.21	16.23
SR	-1.4	2.0
AQI	0.29	-0.59

Module 2 – Model Development: Data Split (80:20) and Standardization

- We assign the target variable AQI to the variable y and all other features except AQI to the variable X as explanatory variables.
- Input parameters : X → X_train, X_test   Out parameters : Y → Y_train, Y_test
- We utilize the sklearn.model_selection module to split the data into two distinct sets: training and testing, using the train_test_split() function. The dataset is split into 80% for training and 20% for testing.
- An inadequately selected split can lead to the model being overfit or underfit, which can result in inadequate predictions on unseen data. Therefore, it is crucial to select the split carefully and assess the model's performance on the test data to ensure that it can generalize well to new data.
- To normalize the features of the training and testing sets, we use the StandardScaler() function from the sklearn

Module 2 – RandomForest

- Random forest regression employs a collection of decision trees trained on random feature subsets and data instances. Implemented via scikit-learn, we use classes like RandomForestRegressor for model creation, GridSearchCV for hyperparameter optimization, and k-fold for cross-validation.
- The model is fitted to the training data using the fit() method of the GridSearchCV object.
- The RandomForestRegressor object is initialized with preset hyperparameters: max_depth of 15, max_features set to 'auto', min_samples_leaf at 1, min_samples_split of 2, and n_estimators of 100, alongside a designated random_state.

```
# creating model: # defined hyperparameters are 'max_depth': 15, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_
randFor = RandomForestRegressor(n_estimators=100,max_depth=15,max_features='auto',min_samples_leaf=1,min_samples_split=2)
# Fitting the model
randFor.fit(X_train,Y_train)
```

```
]: RandomForestRegressor(max_depth=15)
```

```
randFor.score(X_train,Y_train) * 100
```

```
]: 98.4699814378327
```

Module 2–RandomForest algorithm

- The random forest algorithm uses the bagging technique for building an ensemble of decision trees. Bagging is known to reduce the variance of the algorithm.
- For each tree in the forest, we select a bootstrap sample from S where S(i) denotes the ith bootstrap. We then learn a decision-tree using a modified decision-tree learning algorithm.
- At each node of the tree, we randomly select some subset of the features f ⊆ F, where F is the set of features. The node then splits on the best feature in f rather than F. In practice f is much, much smaller than F. By narrowing the set of features, we drastically speed up the learning of the tree.

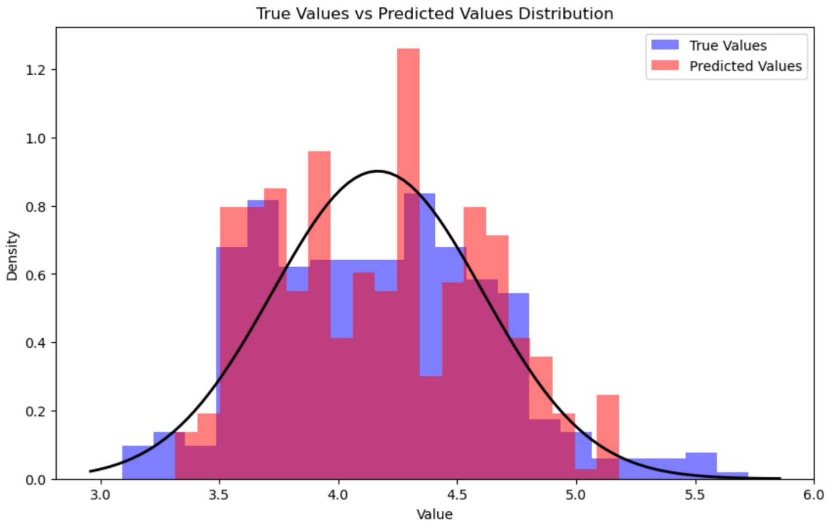
Algorithm 1 Random Forest

Precondition: A training set $S := (x_1, y_1), \dots, (x_n, y_n)$, features F, and number of trees in forest B.

function RANDOMFOREST(S, F)
    $H \leftarrow \emptyset$
    for $i \in 1, \dots, B$ **do**
        $S^{(i)} \leftarrow$ A bootstrap sample from S
        $h_i \leftarrow$ RANDOMIZEDTREELEARN($S^{(i)}, F$)
        $H \leftarrow H \cup \{h_i\}$
    end for
    return H
end function
function RANDOMIZEDTREELEARN(S, F)
    At each node:
        $f \leftarrow$ very small subset of F
        Split on best feature in f
    return The learned tree
end function

Module 2–RandomForest algorithm

- Visualizations like histograms and scatter plots are crucial for analysing the performance of the random forest regressor model



Histogram for Random Forest

Normal distribution for Random Forest

Module 3

- Comparative analysis on performance of the ensemble methods and implemented models.
- AQI predictions made using machine learning models
- Normal distribution of datasets, Residual plots, Residual Histograms of different predictive models
- Comparison of performance by different ML models in Training and Validation/Testing
- Result discussion and Conclusion

WORK PLAN

Review Period	Work Particulars	% of Work Completed
Zeroth Review	• Base paper Confirmation • Problem identification • Literature Review	-
First Review	• System architecture design • Module identification • Proposed Algorithm implementation	40%
Second Review	• Proposed algorithm implementation • Comparative Analysis • Providing security features	100%

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Thank you