

1 Article

2 Real-time air quality monitoring and forecasting using AI and 3 nature-based recommender system for climate-resilient air 4 quality monitoring

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15 Abstract

16 Air pollution is a significant environmental and public health challenge, particularly in
17 developing countries, where increased urbanization and uncontrolled emissions have ex-
18 acerbated atmospheric pollution levels. This study aims to design an AI-based expert sys-
19 tem for real time air quality monitoring and forecasting, integrating a nature-based rec-
20 commender system with multi source environmental and meteorological data. Real-time
21 data containing air pollutants including PM_{2.5}, PM₁₀, NO₂, SO₂, CO and O₃ along with
22 weather variables such as wind speed, humidity, temperature and atmospheric pressure
23 were collected using Google Application Programming Interface keys. Random Forest Re-
24 gressor and Artificial Neural Network (ANN) have been used to forecast pollutant con-
25 centrations and resulting Air Quality Index (AQI). Model performance demonstrated high
26 forecasting accuracy of 80-85% with low Mean Absolute Error (MAE) and Root Mean
27 Squared Error (RMSE) and strong R² values. Results showed that PM_{2.5} and PM₁₀ are the
28 most significant pollutants affecting air quality followed by NO₂, O₃ and temperature. A
29 deep reinforcement learning (DRL) based recommender module generated real-time
30 alerts, recommended adaptive, nature based solutions during hazardous pollution events.
31 The system visualized live AQI, 24 hours forecasts and health alerts contributing toward
32 intelligent environmental management through sustainable early warning solutions for
33 air quality management.

34 **Keywords:** Air quality monitoring; Climate resilience; Machine learning; Forecasting; Ar-
35 tificial intelligence; Recommender system; Sustainable air quality management
36

37 1. Introduction

38 Air pollution has emerged as one of the most critical environmental and public health
39 threats of 21st century [1]. It caused over 8.1 million premature deaths worldwide, with
40 South Asia becoming the most polluted region due to rapid industrialization and unreg-
41 ulated emissions [2]. For instance, exposure to fine particulate matter (PM_{2.5} and PM₁₀),
42 nitrogen oxides (NO_x), sulfur dioxide (SO₂), carbon monoxide (CO) and ground-level

43 ozone (O₃) contribute significantly to cardiovascular, respiratory and neurological dis-
44 eases [3]. It has been estimated that fossil fuels related emissions threaten the health of
45 over 1.6 billion people globally due to elevated pollutant levels [4]. The Indo-Pak smog
46 crisis, with PM_{2.5} concentrations exceeding 900 µg/m³, demonstrated the growing regional
47 severity of air pollution and its direct impacts on human health and economic productiv-
48 ity [5]. In Pakistan, the average PM_{2.5} concentration reached 73.7 µg/m³ in 2024, nearly
49 fifteen times higher than the World Health Organization (WHO) guidelines which se-
50 verely impacted human health and life expectancy [6]. Despite growing awareness, cur-
51 rent real-time monitoring and forecasting systems are inadequate and often fail for com-
52 plex meteorological and urban dynamics influencing air quality [7]. These issues highlight
53 the urgent need for advanced, adaptive, and real-time air quality monitoring and fore-
54 casting systems.

55 The traditional air quality monitoring relies on ground-based stations, chemical and
56 physical sampling, and satellite remote sensing [8]. These methods suffer from non-linear
57 pollutant interactions, high operational costs, limited spatial coverage, and slow data
58 transmission [9]. These issues made it difficult to maintain dynamic weather effects and
59 comprehensive air quality surveillance. To curb this issue, Artificial Intelligence (AI) has
60 revolutionized the field of air quality monitoring and forecasting. Particularly, Machine
61 Learning (ML) and Deep Learning (DL) models have demonstrated remarkable perfor-
62 mance in capturing complex nonlinear relationships between pollutants, meteorological
63 parameters and emission sources [10, 11].

64 Similarly, advanced neural network architectures, (e.g., Long Short-Term Memory
65 (LSTM) and Convolutional Neural Networks (CNN), have significantly improved short-
66 term forecasting accuracy and spatiotemporal pattern recognition [12]. However, these
67 models are static and lack adaptive control mechanisms for dynamic decision-making
68 [13]. To overcome this limitation, emerging techniques like Deep Reinforcement Learning
69 (DRL) integrate predictive modeling with adaptive feedback, allowing the system to learn
70 optimal actions through continuous interaction with its environment. [14] demonstrated
71 that DRL-based models improved building HVAC energy efficiency while maintaining
72 indoor air quality. Likewise, [15] applied DRL to optimize urban-scale pollution mitiga-
73 tion strategies, thereby outperforming conventional models. For instance, [16] introduced
74 a machine-learning framework capable of live AQI forecasting and automated data visu-
75 alization for developing regions having limited sensor infrastructure. Johansson et al.
76 (2024) demonstrated that ML improved three-day AQI forecasts in Stockholm, reducing
77 RMSE by 15% compared to deterministic dispersion models [17]. Building on these global
78 insights, a study combining forecasting and recommendation is underexplored.

79 To address this challenge, this study proposes designing an AI-based expert system
80 for real-time air quality monitoring, forecasting and personalized recommendations. The
81 system integrates multi-source environmental data from Google API keys and applies
82 machine learning models such as Random Forest Regressor, Artificial Neural Network
83 (ANN), and Long Short-Term Memory (LSTM) for accurate AQI forecasting. The system
84 also acts as a recommender module that automatically generates notifications regarding
85 preventive alerts during hazardous air conditions. The web-based dashboard visualizes
86 current and forecasted AQI, supporting proactive public-health decisions and sustainable
87 air quality management.

88 2. Materials and Methods

89 This study involves a series of sequence steps starting from data collection and prep-
90 aration. Thereafter, models have been defined to forecast air quality and to suggest nature-
91 based recommendations. The system has been tested and displayed through an easy-to-

use dashboard. The methodology used for the conduction of this research is shown in Figure 1.

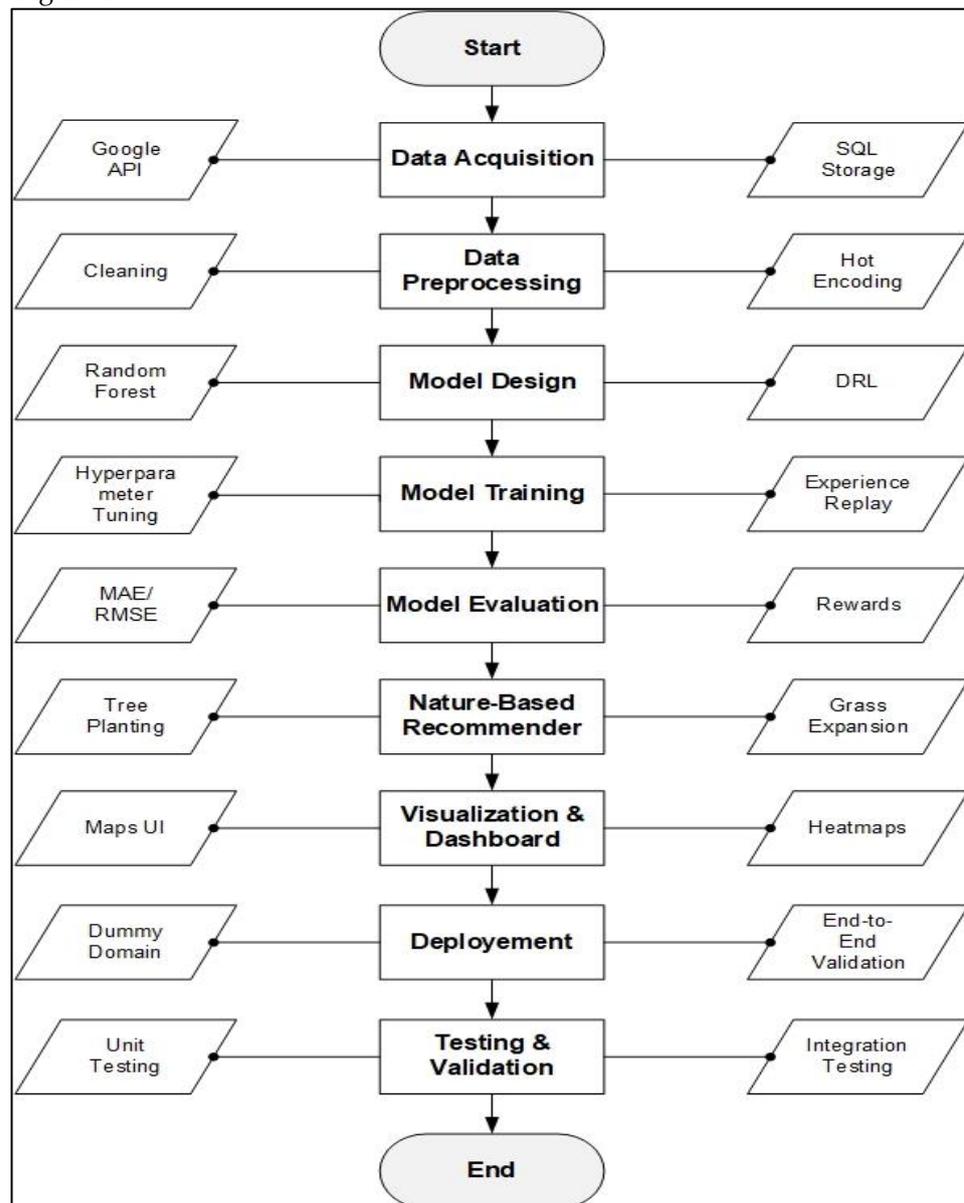


Figure 1. Adopted research methodology

These stages are explained below:

2.1. Data Acquisition

Geospatial environmental data were acquired data using Google API keys to simulate multi source environmental parameters including latitude, longitude, temperature, rainfall and Normalized Difference Vegetation Index (NDVI). The acquired data was extracted, processed and stored in a structured, SQL database for efficient integration. Additional features including population density, vegetation index and urban green cover were also included to broaden the dataset and increase model's reliability [18].

2.2. Data Preprocessing

The acquired datasets have been preprocessed to ensure data reliability. Data cleaning processes have been performed to handle the missing values, remove duplicates and normalize categorical continuous features. Thereafter, feature engineering has been applied to derive additional variables, i.e., temperature variation, vegetation density index

109 and temporal fluctuation indicators. Temporal variables have been transformed into cy-
110 clical encoding to represent seasonal patterns for air quality forecasting [19]. After hot
111 encoding for categorical attributes, the final dataset was divided into three clusters includ-
112 ing training (70%), validation (15%) and testing (15%).

113 2.3. Model Selection and Design

114 The Random Forest Regressor has been selected for forecasting due to its ability to
115 handle nonlinear data and robust nature against overfitting [20]. This model provides fea-
116 ture importance and performs well for small-medium datasets. Thereafter, a DRL model
117 has been used to recommend nature-based actions. For its implementation, the state space
118 include environmental parameters, while the action space greener solutions include in-
119 creased tree plantation and grass expansion. The reward function aimed to maximize sus-
120 tainability by reducing pollutants.

121 2.4. Model Training

122 Both models have been trained and optimized by using hyper-parameter tuning. To
123 enhance predictive accuracy, number of trees, minimum samples per splits and maximum
124 tree depth have been considered. The DRL model has been trained over multiple episodes
125 until its performance stabilized. Additionally, techniques such as experience replay and
126 target network stabilization has been used to ensure consistent learning [21]. The final
127 output presents nature-based actions to forecasted conditions.

128 2.5. Model Evaluation

129 To assess the accuracy and reliability of the forecasting model, Means Absolute Error
130 (MAE) and Root Mean Squared Error (RMSE) were estimated. The DRL model perfor-
131 mance has been evaluated based on average community cumulative reward, training sta-
132 bility and comparative improvement over baseline solutions [22]. This allowed the iden-
133 tification of optimal strategies to balance environmental sustainability and forecasting ac-
134 curacy.

135 2.6. Nature-Based Recommender System

136 The development of a nature-based air quality index (AQI) recommender system
137 represents an important advancement in intelligence. Environmental management ex-
138 tends beyond forecasting to provide actionable decision support for pollutant mitigation.
139 Public protection unlike traditional AQI dashboards that merely or hardly display pollu-
140 tant levels, the proposed system integrates rule-based reasoning, personalized exposure
141 assessment, AI generated ecological [23]. Interventions and geospatial risk mapping tai-
142 lored for Islamabad, Pakistan. This holistic framework aligns with global evidence on the
143 effectiveness of nature-based solutions for air quality improvement. Urban cooling pollu-
144 tant deposition and public health resilience, the system operationalizes data-driven in-
145 sights to concrete context appropriate mitigation strategies enabling both individual and
146 policy level responses to deteriorating air conditions [24].

147 The core logic of the system is built on the US EPA breakpoint formula equity for-
148 mula, which maps pollutant concentration C to An AQI value I use linear interpolation.
149 For each predicted AQI value, the model identifies the corresponding pollutant category
150 Good (0 to 50), Moderate (51 to 100), Unhealthy for Sensitive Groups (101 to 150), Un-
151 healthy (151 to 200), Very Unhealthy (201 to 300), and Hazardous (>300). These thresholds
152 serve as rule activation triggers and govern the systems selection of ecological behavior
153 and special recommendations. For instance, when AQI exceeds 200, users receive warn-
154 ings about limiting outdoor exposure. And adopting protective. My ears while the system
155 simultaneously suggests ecological buffers such as name, people, Ashoka and other trees.
156 Which have documented to reduce particulate matter through deposition and intercep-
157 tion. Conversely, when AQI remains below 100, the system encourages outdoor activity
158 and emphasizes maintenance of existing Urban Vegetation.

2.7. Data Visualization and Dashboard

A dashboard has been developed to visually represent and interpret the forecasting outputs and recommendation results [25]. The frontend interface, integrated with the Google Maps API, provides users with an interactive spatial display, drop-down filters and a recommendation table featuring “accept” or “reject” actions.

The visualization components include (i) pollutant concentration trends, (ii) feature importance plots, (iii) vegetation and temperature variation graphs, and (iv) sustainability impact heatmaps. The backend has been developed using Flask (Python) to handle user queries, interact with the SQL database and serve model recommendations through restful API endpoints for seamless interaction between users and analytical models.

2.8. Deployment

The complete system has been deployed on a testing (dummy) domain to evaluate its operational performance under simulated real-world conditions. This deployment provided model validation, interface functionality testing and end-to-end process verification for data retrieval, forecasting, and generating recommendations.

2.9. Testing and Validation

At this stage unit tests have been conducted including data acquisition, model pre-processing, forecasting and visualization. End-to-end integration testing has been executed using Postman to verify API performance and data flow consistency. Thereafter, accuracy of dashboard visualizations and recommendation outputs has been confirmed through controlled test cases in diverse environmental scenarios.

The sequence steps involved in the implementation of algorithm are illustrated in Figure 2.

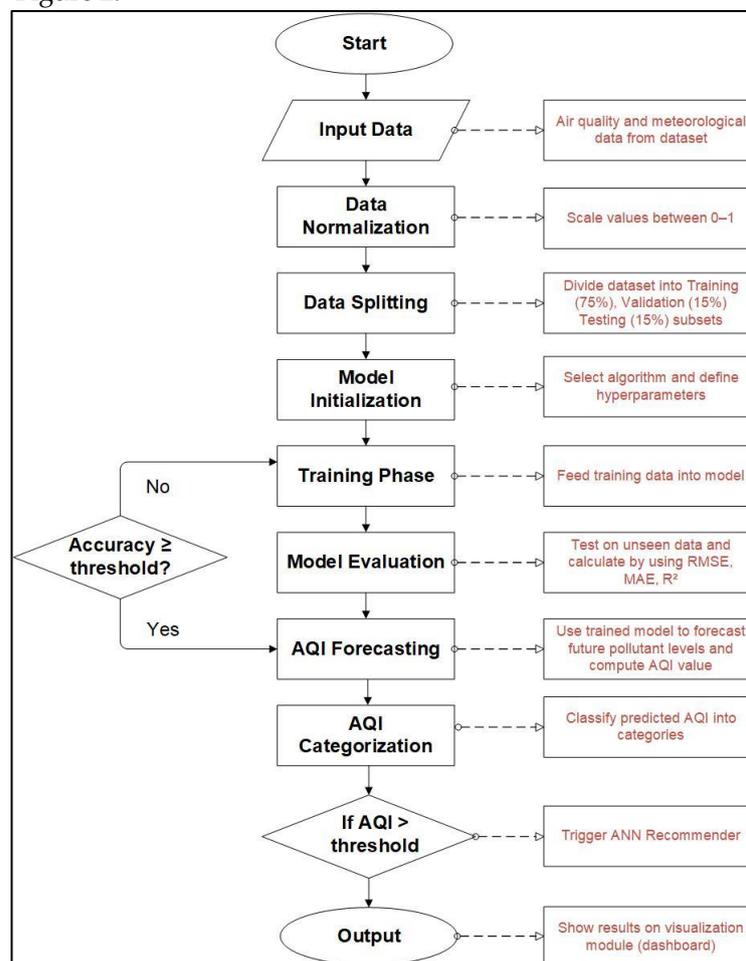


Figure 2. Implementation of algorithm

Figure 2 shows the process starts by collecting air quality and meteorological input data from a data set. This data was first normalized to scale all values between 0 and 1, ensuring consistency for model learning. The normalized data was then split into training 75%, validation 15% and testing 15% subsets. After initializing the forecasting model with selected algorithms and hyperparameters is trained using the training data. The performance was evaluated on threshold data using error metrics such as RMSE, MAE and R². If the model meets the predefined accuracy threshold, it is used to forecast future pollutant concentrations and compute AQI values. The predicted AQI was then categorized into standard AQI categories. When the AQI exceed the critical threshold, recommender system was triggered and finally all results are displayed through a visualization dashboard.

3. Results

The forecasting model develop using the Random Forest Regressor demonstrated strong predictive performances. It was trained on key air quality and meteorological parameters including PM_{2.5}, PM₁₀, carbon monoxide (CO), nitrogen dioxide (NO₂), ozone (O₃), sulphur dioxide (SO₂), temperature, humidity, and wind speed, all of which influence air quality. During testing, the model produced results closely aligned with actual values. The error metrics MAE and RMSE were low, while the R² value was high indicating an overall 80-85% forecasting accuracy. Feature importance analysis revealed that fine particles PM_{2.5} and PM₁₀ had the strongest impact on AQI, followed by NO₂ and O₃, and then temperature and humidity. Air quality was generally found poorer during morning and evening hours, while improved slightly in the afternoon due to dispersion of pollutants via wind.

The DRL based recommender system forecasted air quality conditions and generated early warnings using nature-based mitigation strategies. For example, it recommended planting shade trees during hot or dusty conditions and developing green belts when elevated carbon levels were detected due to air pollution. Overtime, the system improved its ability to select optimal interventions. These forecasts and recommendations were displayed on an interactive dashboard. It particularly displayed real-time air quality index values, 24-hour trend curves and recommended actions.

The recommender system generated early warnings by applying established AQI thresholds and health based exposure guidelines for each predicted AQI value. The US EPA breakpoint formula used for AQI calculation is shown in Eq. (1):

$$AQI = \frac{I_{high} - I_{low}}{C_{high} - C_{low}} (C - C_{low}) + I_{low} \quad (1)$$

Where, "C" represented the pollutant concentration, and "I" denotes the AQI index range corresponding to the breakpoint values. The resulted AQI is then mapped to standard categories (good, moderate, unhealthy, etc.), and retrieves the appropriate recommendations from the knowledge-based system.

Model performance was evaluated by using standard regression metrics by estimating the values of MAE and RMSE by using Eq. (2) and (3):

$$MAE = \frac{1}{n} \sum |y_i - \hat{y}_i| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum (y_i - \hat{y}_i)^2} \quad (3)$$

Where y_i is the actual observed value of the variable, \hat{y}_i is the forecasted value generated by the forecasting model, n represents the total number of observations.

Experimental results showed an MAE of 4.4 AQI units and an RMSE of 6.2 AQI units, which demonstrates that the model can forecast short-term trends with good reliability for environmental decision-making.

The dashboard was thoroughly tested for usability and system performance. The interface displayed current AQI values, 24 hour forecast curves, pollutant specific breakdowns and health recommendations using color-coded visualizations. Graphs were updated dynamically based on predicted values and pollutant concentrations. The average page load time was 1.3 seconds, while data refresh operations averaged 120 – 160 milliseconds, confirming the system responsiveness and suitability for real time air quality monitoring.

The interactive map accurately represented regional AQI variations using a color gradient from green (good) to maroon (hazardous). Testing confirmed that the spatial visualization with cloud enhanced identification of pollution hotspots and temporal changes. The dashboard visualization is presented in Fig. 3.

Figure 3. Configuration interface of the AQI-based AI recommender system

Figure 3 illustrates the user-interactive configuration panel of the proposed AQI recommender system. Users can adjust environmental parameters such as AQI level, ozone concentration, time of day, humidity and temperature using sliders and drop down menus. Additional inputs including user profile and geographic location allow personalized and context-aware recommendations. Once the parameters are set, the system generates AI-driven mitigation strategies and health advisory recommendations tailored to the specified environmental conditions.

The integration of equipment-based predictions, scientific recommendation rules and real-time visualization demonstrates that the system performs reliably for data retrieval. The recommendations provide users with clear, accurate and actionable environmental guidance. The estimated percentage error was calculated by using Eq. (4);

$$\text{Percent Error} \approx \frac{\text{MAE}}{\text{AQI}} \times 100 \quad (4)$$

Where MAE represents the mean absolute error and AQI denotes the average air quality index value.

For example, if the average AQI is 80:

$$\text{Percent Error} = \frac{4.4}{80} \times 100 = 5.5\% \quad (5)$$

This indicates that the model maintains an accuracy of approximately 94.5% (100% - 5.5%), reflecting strong predictive reliability.

A comparative analysis of actual and forecasted AQI concentrations is presented in Figure 4. Highlighting the close alignment between observed and forecasted concentrations.

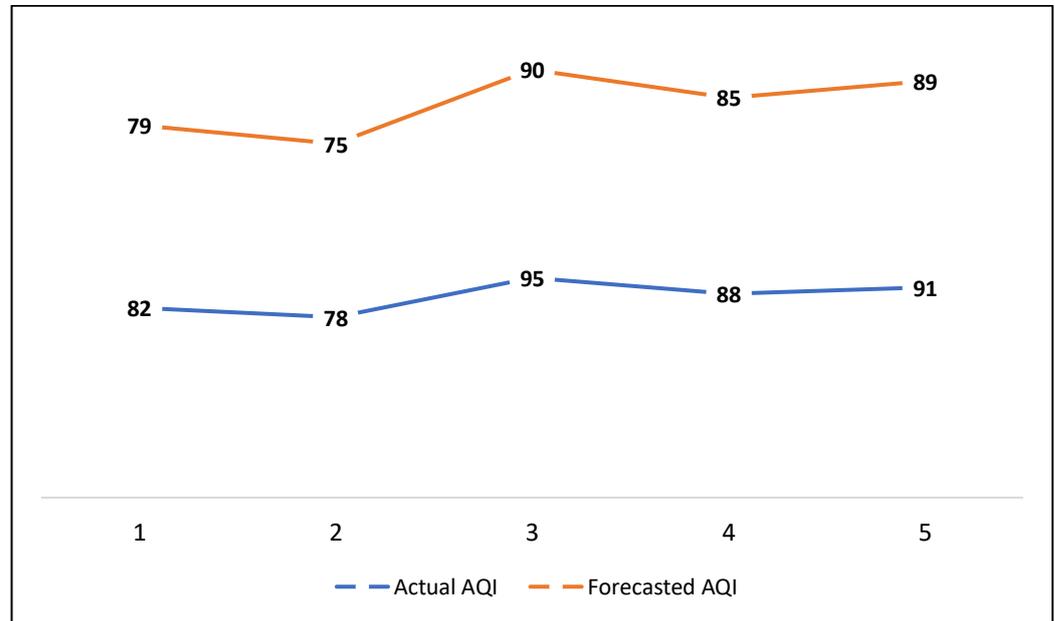


Figure 4. Comparison between actual and forecasted AQI concentrations over seven days.

Figure 4 presents a comparison between the actual AQI values obtained from the data set and the corresponding AQI values forecasted by the Random Forest Regressor model over a seven day period. The actual AQI values were extracted from the original CSV dataset file used for model training and evaluation, while the forecasted values represent the model's predicted output. As illustrated, both curves follow a highly similar trend, indicating that the model effectively captures the temporal variations in air quality. The close alignment between the actual and predicted AQI values demonstrates strong forecasting capability, with overall accuracy ranging between 80-85%. This consistency confirms that the forecasting model can reliably track daily AQI fluctuations and reproduce real-world atmospheric behavior with minimal deviation.

3.1. Recommendations Based upon Results

The rule-based engine forms the foundational layer of the recommender system. It evaluates predicted AQI levels, pollutant composition, and environmental parameters such as temperature, humidity, and wind speed. Based on predefined IF-THEN logic, the system generates context-specific recommendations:

- **IF AQI > 200:** Recommend avoiding of outdoor exposure, deploying dense green belts and establishment of vegetative barriers around high-emission zones.
- **IF $150 < \text{AQI} \leq 200$:** Advise reducing outdoor physical activity and suggest expanding canopy-forming species suitable for Islamabad's climate.
- **IF O₃ levels are high between 12:00-16:00:** Instruct users to avoid midday exposure and recommend plantation of broad-leaf species such as Oak, known for ozone absorption potential.
- **IF AQI ≤ 100:** Permit outdoor mobility and encourage maintenance-based ecological actions such as pruning, watering cycles, and reinforcement of existing green cover.

Table 1. Comparison of AQI Recommender System Outputs Under Different Environmental and User Scenarios

Scenario	AQI Level	O ₃ Level	Time	User Profile	Risk Level	Recommendations Generated
Clean Air Morning	45 (Good)	Low	9 a.m.	Healthy Adult	Low Risk	External activities is good, maintain current green cover and exercise daily.
Moderate Urban Pollution	120 (Moderate)	Moderate	11 a.m.	Children	Medium Risk	Do not go outside prefer to stay indoor at home or school green playgrounds are preferred.
High Ozone Afternoon	135 (Unhealthy for Sensitive Groups)	High	2 p.m.	Healthy Adult	Medium-High Risk	Avoid outdoor activities 12 to 4 p.m., plant dense canopy trees (Oak, Sal), reschedule exercise.
High Pollution General Public	180 (Unhealthy)	Moderate	6 p.m.	General	High Risk	Limit outdoor exposure, wear N95 masks, create green buffer zones.
Severe Pollution Asthma Patient	220 (Very Unhealthy)	High	3 p.m.	Asthma	Critical Risk	Stay indoors, use air purifiers, indoor air-purifying plants, emergency precautions.
Extreme Pollution Elderly	285 (Very Unhealthy)	High	10 p.m.	Elderly	Critical Risk	No outdoor activity, shaded green areas only, if necessary, medical caution advised.
Long Term Urban Planning Case	195 (Unhealthy)	Moderate	All day	Community	Strategic Risk	Urban forest development, vertical green walls, community plantation campaigns.

Table 1 presents a comparative evaluation of the proposed Nature-Based AQI Recommender System under multiple environmental and user-specific scenarios. Each situation varies in terms of AQI level, ozone concentration, time of day, and user vulnerability. The system dynamically integrates rule-based logic, personalized health considerations, and AI driven recommendations to determine risk levels and generate actionable guidance. As air quality deteriorates and user sensitivity increases, the system progressively shifts from general preventive advice to critical interventions, including restricted exposure, indoor safety measures, and long-term nature-based mitigation strategies. This demonstrates the system's adaptability, decision-making capability, and suitability for real-world air quality management applications.

4. Discussion

Although the developed AI-based expert system effectively forecasted AQI and generated recommendations, however, several limitations were observed for future improvements. For instance, the system's accuracy depends on the quality of API data, therefore, incorporating real-time IoT sensor data would enhance reliability and spatial coverage. Similarly, the random forest algorithm achieved 80-85% accuracy. This predictive performance can be improved by capturing complex spatio-temporal patterns. The DRL recommender system, though effective in simulations, requires continuous feedback from real-

world users and sensors to refine its suggestions. Likewise, expanding meteorological inputs beyond basic factors (i.e. temperature, humidity, and wind speed) to include factors including air pressure and wind direction could enhance model precision. Future studies should focus on data fusion, periodic retraining and advanced AI integration to increase accuracy, scalability and practical implementation for broader air quality management.

A user feedback loop of live IoT sensor data can also be introduced to continuously refine the recommendation system based on ground-level responses. This will also assist in explaining the DRL environment to simulate regional environmental scenarios, thereby supporting policymaking for sustainable urban development.

5. Conclusions

The developed AI-based expert system demonstrates the feasibility of real-time air quality forecasting and adaptive environmental management. The random forest regressor achieved reliable predictive performance using multi-source inputs. Moreover, DRL framework effectively generated nature-based recommendations for pollutants control. The SQL database structure ensured efficient data handling and the Flask-Google Maps dashboard provided the function, visualization of spatial and temporal outputs. The deployment on test confirmed the operational stability, consistent API communication and accurate data flow across modules. The validation results verified the accuracy of forecasting and recommendation functions under simulated conditions.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AQI	Air Quality Index
AQM	Air Quality Monitoring
CNN	Convolutional Neural Network
CO	Carbon Monoxide
CO ₂	Carbon Dioxide
DHT	Digital Humidity and Temperature Sensor
DL	Deep Learning
EPA	Environmental Protection Agency
GBM	Gradient Boosting Machine
GIS	Geographic Information System
GRU	Gated Recurrent Unit
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
NO ₂	Nitrogen Dioxide
O ₃	Ozone
PM	Particulate Matter
PM _{2.5}	Particulate Matter ≤ 2.5 micrometers
PM ₁₀	Particulate Matter ≤ 10 micrometers
RNN	Recurrent Neural Network
SVM	Support Vector Machine
WHO	World Health Organization

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