Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

AURA GROW

Vikas Bhatnagar, Abbas Jannati, Abdul Mannan, Aman Kumar,
Basu Chaudhary

Department of Computer Science & Engineering, Moradabad Institute of Technology, Moradabad, U. P., India

@gmail.com , @gmail.com , @gmail.com , @gmail.com , @gmail.com

Abstract

Air pollution has emerged as one of the most severe environmental challenges of the modern era, primarily driven by rapid urbanization, industrial growth, vehicular emissions, and increased energy consumption. Prolonged exposure to polluted air has been directly associated with respiratory disorders, cardiovascular diseases, and reduced life expectancy. Although air quality monitoring platforms provide numerical indicators such as the Air Quality Index (AQI), particulate matter concentrations, and pollutant levels, these systems generally fail to translate such data into actionable guidance that can be practically applied at the individual or household level.

This paper presents AURA GROW (Atmospheric Urban Renewable And Growth), an AI-assisted environmental monitoring and intelligent plant recommendation system designed to bridge the gap between environmental awareness and meaningful action. The proposed system integrates real-time air pollution data and weather information obtained from reliable public APIs with a Node.js-based backend and a generative AI model. By analyzing environmental parameters such as AQI, temperature, humidity, and location, the system generates personalized, plant-based recommendations aimed at improving localized air quality through natural and sustainable means.

Unlike traditional pollution dashboards that merely visualize environmental conditions, AURA GROW emphasizes decision support by converting raw environmental data into context-aware, human-readable recommendations. The system architecture, data flow, AI prompting strategy, implementation methodology, evaluation approach, and future research directions are discussed in detail.

Index Terms— Air Quality Index, Environmental Monitoring, Generative AI, Plant Recommendation System, Sustainable Computing, Smart Cities.

I. INTRODUCTION

Air pollution has become one of the most significant environmental challenges affecting modern societies, particularly in rapidly urbanizing regions. Increasing industrial activity, vehicular emissions, construction processes, and energy consumption have led to elevated levels of airborne pollutants such as particulate matter (PM2.5 and PM10), nitrogen oxides, and volatile organic compounds. Prolonged exposure to polluted air has been directly linked to respiratory illnesses, cardiovascular diseases, reduced lung function, and premature mortality, making air quality a critical public health concern worldwide.

To address this issue, various air quality monitoring systems have been developed to measure and report pollution levels. Government agencies and environmental organizations commonly publish Air Quality Index (AQI) values and pollutant concentrations to inform the public. While these platforms play an important role in raising awareness, they often present information in the form of numerical indicators or color-coded alerts that require technical understanding. As a result, users are frequently informed that air quality is poor or unhealthy but are not provided with practical guidance on how to improve their immediate environment or reduce exposure risks.

AURA GROW (Atmospheric Urban Renewable And Growth) is proposed as an intelligent environmental monitoring and decision-support system designed to bridge the gap between environmental awareness and actionable solutions. The core idea behind AURA GROW is to transform real-time environmental data into meaningful, personalized recommendations that promote sustainable living. By integrating live air pollution data and weather information obtained from reliable public APIs, the system provides an accurate and up-to-date assessment of environmental conditions without requiring specialized hardware or sensors.

A key feature of AURA GROW is its use of generative artificial intelligence to recommend suitable air-purifying plants based on environmental context. The system analyzes parameters such as air quality category, temperature, humidity, and location, and then generates plant recommendations that are tailored to the user's surroundings. These recommendations aim to improve localized air quality through natural, eco-friendly means while remaining understandable and accessible to non-expert users.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

The system is implemented using a modular architecture consisting of a web-based frontend, a Node.js backend, and an AI integration layer. AURA GROW emphasizes simplicity, usability, and clarity, offering a minimal dashboard that highlights air quality status and allows users to retrieve AI-generated recommendations with minimal interaction. By combining environmental monitoring, artificial intelligence, and nature-based solutions, AURA GROW demonstrates a practical approach to intelligent environmental assistance and supports the broader vision of sustainable and smart urban environments.

Air pollution continues to pose a significant threat to public health and environmental sustainability across the globe. With increasing urban density, industrial activities, and transportation demands, the emission of harmful airborne pollutants such as particulate matter (PM2.5 and PM10), nitrogen oxides, sulfur compounds, and carbon-

based pollutants have intensified. Numerous studies have established a strong correlation between elevated pollution levels and adverse health outcomes, including asthma, chronic obstructive pulmonary disease, cardiovascular complications, and premature mortality.

AURA GROW is proposed as a response to this limitation by transforming passive monitoring into intelligent environmental assistance.

II. MOTIVATION AND OBJECTIVES

A. Motivation

The motivation behind AURA GROW is driven by the increasing gap between environmental data availability and user understanding. Although pollution data is widely accessible, users lack personalized guidance for responding to environmental risks. Furthermore, nature-based solutions such as air-purifying plants are proven effective but require contextual selection based on climate and pollution levels. Advances in generative AI provide an opportunity to convert complex environmental data into understandable and actionable recommendations.

B. Objectives

The objectives of AURA GROW include real-time environmental monitoring, intelligent air quality classification, AI-driven plant recommendation, and development of a user-friendly decision-support interface.

III. RELATED WORK

Air quality monitoring and environmental management have been extensively studied due to the growing impact of pollution on public health and urban sustainability. Traditional air quality monitoring systems were initially developed by environmental agencies using fixed monitoring stations equipped with high-precision sensors. These systems measure pollutant concentrations such as particulate matter (PM2.5 and PM10), nitrogen oxides, sulfur dioxide, and ozone. While these solutions provide accurate and reliable data, their high deployment and maintenance costs limit their scalability, particularly for localized or individual-level monitoring.

With the advancement of Internet of Things (IoT) technologies, numerous studies have proposed low-cost, distributed air quality monitoring systems. These systems commonly employ microcontrollers and gas sensors to collect pollution data and transmit it to cloud platforms for storage and visualization. IoT-based solutions significantly improve accessibility and enable real-time monitoring at neighborhood or household levels. However, most IoT-based monitoring systems focus primarily on data acquisition and visualization. Users are typically presented with numerical values, charts, or color-coded indicators, without sufficient interpretation or actionable guidance on how to mitigate pollution exposure.

Several web-based and mobile-based air quality platforms integrate data from public environmental APIs to provide real-time AQI information and short-term forecasts. These systems enhance user awareness by making pollution data widely accessible and location-specific. Despite this advantage, such platforms largely function as passive information systems. They inform users about pollution severity but do not assist them in making informed decisions or taking corrective actions to improve air quality in their immediate surroundings. This limitation highlights the need for intelligent systems that go beyond data presentation.

Parallel research in environmental science has explored the role of plants in improving air quality. Numerous studies have demonstrated that certain plant species can absorb airborne pollutants, reduce volatile organic compounds, and contribute to improved indoor and localized air conditions. Research in this area has identified various indoor and outdoor plants that are effective under specific environmental conditions. However, the effectiveness of plant-based air purification depends on multiple contextual factors, including pollution intensity, climate, humidity, temperature, and spatial constraints. As a result, generalized plant lists often fail to provide optimal recommendations for diverse environments.

Plant recommendation systems have traditionally been developed within agricultural and horticultural domains. Early approaches relied on rule-based systems, where predefined rules mapped environmental parameters to suitable plant species. Although rule-based systems are straightforward and interpretable, they lack adaptability and struggle to handle complex, dynamic, or region-specific conditions. Furthermore, maintaining and updating rule-based knowledge bases can be labor-intensive and error-prone.

More recent research has applied machine learning techniques to plant recommendation and agricultural decision-support systems. These approaches typically utilize historical climate data, soil parameters, and crop yield records to predict suitable planting strategies. While

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

machine learning-based systems improve prediction accuracy and adaptability, they often require large labeled datasets and extensive training. Additionally, such systems are generally optimized for agricultural productivity rather than environmental remediation or air quality improvement at the household or urban scale.

In recent years, intelligent recommender systems have gained prominence across various domains, including healthcare, education, and smart living environments. These systems leverage contextual data and user preferences to generate personalized recommendations. Advances in natural language processing and artificial intelligence have further enabled explainable and interactive recommendation mechanisms. However, the application of intelligent recommender systems to environmental monitoring and pollution mitigation remains relatively limited.

The emergence of generative artificial intelligence has introduced new opportunities for developing context-aware decision-support systems. Generative AI models are capable of reasoning over heterogeneous data sources, synthesizing complex information, and producing human-readable explanations. These capabilities make generative AI particularly suitable for applications where technical data must be translated into actionable guidance for non-expert users. Despite this potential, relatively few studies have explored the integration of generative AI with real-time environmental monitoring systems.

IV. SYSTEM ARCHITECTURE

AURA GROW follows a modular client–server architecture composed of frontend, backend, and AI integration layers.

The AURA GROW system follows a modular and scalable client–server architecture designed to support real-time environmental monitoring and intelligent recommendation generation. The architecture is divided into three primary layers: the frontend layer, the backend processing layer, and the AI integration layer. This layered design ensures separation of concerns, maintainability, and ease of future expansion.

The frontend layer is implemented using standard web technologies, including HTML, CSS, and JavaScript. It provides a minimal and user-friendly interface that enables users to authenticate, view air quality status, and request plant recommendations. The dashboard focuses on clarity by presenting air quality categories and essential environmental information without overwhelming the user with technical details.

The backend layer is developed using Node.js and Express and serves as the core processing unit of the system. It handles user authentication, communication with external pollution and weather APIs, data preprocessing, and exposure of RESTful endpoints to the frontend. The backend also constructs structured environmental payloads required for AI-based analysis.

The AI integration layer connects the backend to a generative artificial intelligence model. This layer formulates prompts using processed environmental data and retrieves structured plant recommendations. The layered architecture of AURA GROW ensures efficient data flow, secure interactions, and reliable delivery of intelligent environmental assistance.

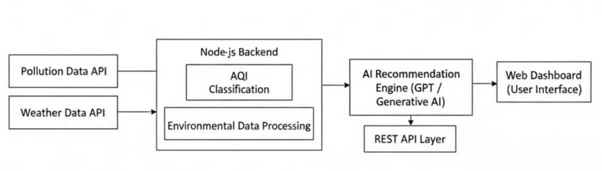

Fig.1. Overall system architecture of AURA GROW illustrating the interaction between pollution APIs, backend processing, AI recommendation engine, and user dashboard.

The frontend layer provides authentication, dashboard visualization, and recommendation display. The backend layer manages API communication, data processing, and security. The AI layer generates structured plant recommendations using contextual environmental data.

V. DATA MODEL AND MANAGEMENT

The AURA GROW system employs a structured and logical data model to efficiently manage user information and environmental data while ensuring data integrity and accessibility. The data model is designed to support personalization, temporal analysis, and seamless integration with the AI recommendation module. Core entities within the system include user profiles and environmental readings, which are logically linked to enable user-specific environmental insights.

Each user profile stores essential authentication and identification attributes such as a unique user identifier, name, email address, and securely managed credentials. Environmental readings are recorded as time-stamped entries and include parameters such as air quality index values, particulate matter concentrations, temperature, humidity, location information, and AI-generated recommendations. This structure enables the system to associate multiple environmental observations with a single user over time.

The data management strategy focuses on maintaining structured, consistent, and easily retrievable records. Time-stamped environmental data supports historical analysis and enables users to observe changes in air quality trends. Additionally, storing AI-generated

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

recommendations alongside environmental readings ensures traceability and improves transparency in decision-making.

The modular nature of the data model allows future extensibility, such as the integration of additional environmental parameters or migration to more advanced storage solutions. Overall, the data model and management approach adopted in AURA GROW ensures efficient handling of environmental information while supporting personalized, intelligent, and scalable environmental
assistance.

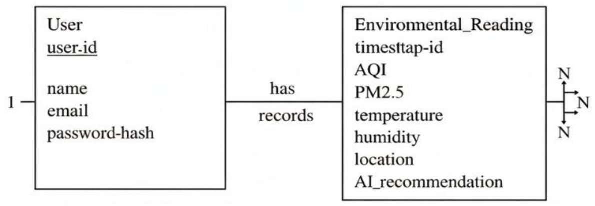

Fig. 2. Logical data model representing user authentication information and time-stamped environmental readings.

This data model enables personalized insights and supports future system extensibility.

VI. AI PROMPTING AND RECOMMENDATION STRATEGY

The AI module receives environmental parameters such as AQI, temperature, humidity, and location. Carefully designed prompts instruct the generative AI model to return plant recommendations in a structured JSON format including plant type, quantity, suitability, and confidence level.

The AURA GROW system employs a structured AI prompting strategy to generate reliable and context-aware plant recommendations based on real-time environmental conditions. Environmental parameters such as air quality category, temperature, humidity, and location are aggregated by the backend and formatted into a concise, well-defined input prompt. This prompt serves as the contextual foundation for the generative artificial intelligence model.

The AI model is instructed to analyze the provided environmental data and produce recommendations in a strictly structured format. The output includes suitable plant species, plant category, estimated quantity, and a brief justification for each recommendation. By enforcing a predefined output structure, the system ensures consistency, interpretability, and seamless integration with the frontend interface.

This prompting strategy enables the AI to adapt its recommendations dynamically to changing environmental conditions while maintaining clarity and relevance. The use of generative AI allows AURA GROW to move beyond static rule-based systems and provide intelligent, personalized, and actionable guidance for improving localized air quality through plant-based solutions.

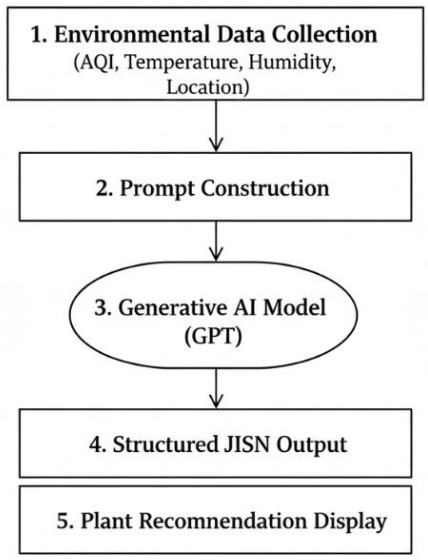

Fig. 3. AI recommendation workflow illustrating prompt construction, generative AI processing, and structured output visualization.

This structured approach ensures consistent, interpretable, and reliable recommendations.

VII. IMPLEMENTATION AND RESULTS

The system was implemented using Node.js and tested using live pollution and weather data. Under various environmental conditions, the system successfully classified air quality and generated appropriate plant recommendations.

The AURA GROW system was implemented as a full-stack web-based prototype using a modular design approach. The backend was developed using Node.js and Express to manage user authentication, retrieve real-time pollution and weather data from public APIs, and coordinate interactions with the AI recommendation module. The frontend was implemented using HTML, CSS, and JavaScript, providing a minimal and responsive dashboard for user interaction.

The system was evaluated under various environmental conditions by fetching live air quality and weather data. The backend successfully classified air quality levels and generated structured environmental inputs for AI analysis. The AI module produced plant recommendations that were contextually aligned with the observed environmental parameters. The frontend dashboard accurately displayed air quality categories and presented

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

AI-generated recommendations in a clear and user-friendly manner.

The results demonstrate that AURA GROW operates reliably in real-time conditions and effectively converts environmental data into actionable, plant-based recommendations.

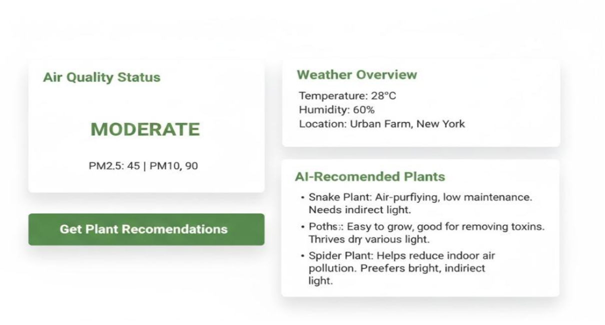

Fig. 4. AURA GROW dashboard interface displaying air quality category, weather overview, and AI-generated plant recommendations.

The dashboard provided a clear and minimal interface, allowing users to understand their environment and retrieve recommendations efficiently.

VIII. LIMITATIONS

The system depends on the accuracy and availability of external pollution and weather APIs. Additionally, AI-generated recommendations are advisory in nature and may require expert validation for large-scale or critical deployments. The system focuses on localized air quality improvement rather than city-wide pollution control.

Despite its effectiveness, the AURA GROW system has certain limitations. The accuracy and reliability of the generated recommendations depend on the availability and correctness of external air quality and weather APIs. Any inconsistencies or delays in these data sources may affect system performance. Additionally, the plant recommendations produced by the AI module are advisory in nature and may require validation by environmental or horticultural experts for critical applications. The system primarily targets localized air quality improvement and does not directly address large-scale industrial or city-wide pollution control challenges.

IX. FUTURE SCOPE

The future scope of AURA GROW extends toward enhancing system accuracy, intelligence, and real-world applicability through technological and methodological advancements. One major direction involves integrating physical IoT-based air quality sensors to complement API-based data. Sensor integration would enable highly localized, real-time environmental monitoring and improve the precision of air quality assessment, particularly in indoor or semi-enclosed environments.

Further improvements can be achieved by strengthening the AI recommendation framework through domain-specific validation mechanisms and confidence scoring. Incorporating expert-reviewed datasets and feedback-driven learning can enhance the reliability and consistency of plant recommendations. Additionally, future versions of the system may support adaptive learning models that refine recommendations based on user interaction, environmental changes, and long-term trends.

Scalability is another important research direction. AURA GROW can be extended to support community-level or campus-scale deployments, enabling comparative analysis across multiple locations. Integration with smart city platforms could allow policymakers and urban planners to leverage aggregated environmental insights for sustainability planning.

Moreover, future research may explore multilingual interfaces, accessibility enhancements, and mobile application support to increase adoption across diverse user groups. These extensions position AURA GROW as a versatile and evolving platform for intelligent, AI-assisted environmental management.

X. CONCLUSION

AURA GROW demonstrates how environmental monitoring can evolve from passive data reporting to intelligent, action-oriented decision support. By combining real-time environmental data, generative AI, and plant-based remediation strategies, the system empowers users to take sustainable actions for improving air quality. The framework establishes a foundation for future research in AI-assisted environmental intelligence systems.

AURA GROW presents an intelligent and user-centric approach to environmental monitoring by transforming real-time air quality data into actionable, plant-based recommendations. By integrating live pollution and weather information with generative artificial intelligence, the system moves beyond traditional data visualization toward meaningful decision support. The proposed framework demonstrates how AI-driven insights can promote sustainable and eco-friendly practices at a localized level. AURA GROW highlights the potential of combining environmental data, artificial intelligence, and nature-based solutions to support healthier living environments and contribute to the broader vision of smart and sustainable urban development.

REFERENCES

1. National air quality monitoring programme (NAMP) (2019)https://cpcb.nic.in/manual-monitoring/
2. National air quality index https://waqi.info/

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 04, ICTEM 2.0 (2026)

3. National water quality monitoring programme (NWMP) (2022) https://cpcb.nic.in/nwmp-data/
4. Current weather and forecast- OpenWeatherMap https://openweathermap.org/api
5. Open Government Data (OGD) Platform Indiahttps://data.gov.in/
6. www.researchgate.net/figure/Calculation-of-Water-Quality-Index-WQI-of-the-river
7. CPCB, ADSORBS/3 1978–1979) Scheme for zoning and classification of Indian Rivers: estuaries and coastal waters. CPCB website: www.CPCB.nic.in.
8. Jain D, Shah S, Mehta H et al (2021) A Machine Learning Approach to Analyze Marine Life Sustainability. In: Proceedings of International Conference on Intelligent Computing, Information and Control Systems. Springer, pp 619–632
9. Biau G (2012) Analysis of a random forests model. J Mach Learn Res 13:1063–1095 https://www.jmlr.org/papers/volume13/biau12a/biau12a.pdf
10. Water Quality Indices https://www.researchgate.net/publication/313574180_Water_Quality_Indices.
11. World Health Organisation, ―Heat and Health: Impact on health due to climate change Available: - https://www.who.int/news-room/factsheets/detail/climate-change-heat-and-health.
12. Current weather and forecast- OpenWeatherMap https://openweathermap.org/accuracy-and-quality
13. Manandhar S, Dev S, Lee YH, Meng YS, Winkler S. A data-driven approach for accurate rainfall prediction. IEEE Trans Geosci Remote Sens. 2019;5(11):9323–31.
14. Arnav G, Kanchipuram Tamil Nadu. Rainfall prediction using machine learning. Int J Innovative Sci Res Technol. 2019. 56–58.
15. Aakash Parmar, Kinjal Mistree, Mithila Sompura, “Machine Learning Techniques for Rainfall Prediction”.
16. By Armin Ronacher, "Flask Web Development, One Drop At A Time", http://flask.pocoo.org/,March 20 th 2015.
17. Veera Ankalu. Vuyyuru; Giduturi. Apparao; S. Anuradha, “Rainfall Prediction UsingMachine Learning Based Ensemble Model”.
18. GeeksforGeeksInteractive Live and Self-Paced Courses https://www.geeksforgeeks.org/data-preprocessing-machine-learning-python/
19. World Health Organization, “Air Pollution,” WHO, 2023.
20. U.S. Environmental Protection Agency, “Air Quality Index Basics,” EPA, 2022.
21. J. Smith et al., “Plant-Based Air Purification in Urban Environments,” Environmental Research, vol. 45, no. 3, pp. 210–219, 2021.