# International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 13, Issue 2, March-April 2026

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE
SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

# AQI-Insight: Hyperlocal Air Pollution Monitoring and Advisory System

**Varshini J**

Master of Computer Applications, CMR Institute of Technology, Bangalore, India

**ABSTRACT:** Rapid urbanization, industrial expansion, and increased vehicular emissions have significantly contributed to the deterioration of air quality, posing serious risks to human health, agriculture, and ecosystems. Continuous monitoring and analysis of air pollution have therefore become essential for environmental management and public awareness. AQI Insight is a web-based environmental monitoring platform designed to provide real-time and location-specific air quality information. The system tracks key pollutants including PM2.5, PM10, $NO_2$, $SO_2$, $O_3$, and CO, and computes the Air Quality Index (AQI) to represent pollution levels and associated health risks. Users can access air quality data through an interactive geospatial interface, visualize trends using charts and color-coded indicators, and analyze historical records. Developed using Python for backend processing, responsive web technologies for the interface, and PostgreSQL for data storage, the platform ensures reliable monitoring, visualization, and analysis of environmental data.

**KEYWORDS:** Air Quality Index (AQI), Ambient Air Pollution, Environmental Monitoring System, Real-Time Air Quality Monitoring, Particulate Matter (PM2.5, PM10), Gaseous Pollutants ($NO_2$, $SO_2$, $O_3$, CO), Geospatial Visualization, Data Visualization Dashboard.

## I. INTRODUCTION

Rapid urbanization, industrial expansion, and exponential growth in vehicular transportation have significantly degraded ambient air quality across urban and semi-urban regions worldwide. Numerous studies have demonstrated that prolonged exposure to polluted air contributes to respiratory diseases, cardiovascular complications, reduced agricultural productivity, and broader ecological imbalance [1], [2], [3]. Unlike visible environmental hazards, air pollution remains largely imperceptible, making real-time awareness and monitoring essential for public health protection.

Traditional air quality monitoring systems rely heavily on centralized, stationary monitoring stations operated by governmental agencies. While these systems provide high-precision measurements, they suffer from sparse spatial distribution, delayed data availability, and limited accessibility for the general public [4], [5]. Several researchers have emphasized the need for decentralized, hyperlocal, and user-centric air quality platforms that can bridge the gap between scientific data and actionable public insight [6], [7].

Recent advancements in web technologies, data analytics, and environmental APIs have enabled the development of scalable air quality dashboards and intelligent monitoring systems [8], [9]. In parallel, machine learning and time-series models have been extensively explored in climate and weather prediction domains, particularly for rainfall and temperature forecasting [10] – [14]. However, comparatively fewer systems integrate real-time AQI computation, historical trend analysis, visual advisory mechanisms, and fault-tolerant fallback strategies within a single unified platform.

To address these limitations, this paper presents AQI-INSIGHT, a web-based hyperlocal air pollution monitoring and advisory system designed to deliver real-time and historical Air Quality Index (AQI) information using standardized pollutant thresholds. The system emphasizes accessibility, reliability, and interpretability, enabling citizens, researchers, and policymakers to understand air quality conditions intuitively and make informed decisions.

## II. LITERATURE REVIEW

Extensive research has been conducted in the domains of environmental monitoring, climate analytics, and machine learning-based prediction systems. Early studies primarily focused on rainfall and weather prediction, leveraging statistical and machine learning approaches such as ARIMA, Support Vector Machines (SVM), Artificial Neural

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

Networks (ANN), and hybrid models [10], [11]. These works demonstrated that nonlinear atmospheric patterns could be effectively captured using ML techniques, outperforming traditional statistical methods.

Subsequent research expanded toward deep learning architectures, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), for long-term climatic forecasting and trend analysis [12], [13]. These models showed improved accuracy for sequential data but required large datasets and significant computational resources, limiting their applicability for lightweight real-time systems.

Parallel to prediction-oriented studies, researchers explored IoT-based air quality monitoring systems, integrating low-cost sensors with cloud platforms for real-time pollutant measurement [15], [16]. While these systems improved spatial coverage, they often suffered from calibration issues, hardware dependency, and maintenance overhead. Additionally, many such platforms lacked standardized AQI computation and robust visualization techniques.

Several review papers highlighted the growing role of machine learning in weather and climate analytics, emphasizing the importance of interpretability, data reliability, and domain-specific constraints [6], [17]. Studies analyzing air quality parameters in relation to climate change further underscored the need for continuous monitoring and temporal analysis of pollutants such as PM2.5, PM10, $NO_2$, $SO_2$, CO, and $O_3$ [18].

Despite these advancements, existing solutions commonly exhibit one or more of the following gaps: Limited hyperlocal resolution, Absence of fallback mechanisms during data outages, Poor usability for non-technical users, Fragmented handling of real-time and historical AQI data. Recent works have called for integrated platforms combining real-time monitoring, historical analysis, geospatial visualization, and advisory features [19], [20]. AQI-INSIGHT is designed to directly address these research gaps.

## III. METHODOLOGY

The AQI-INSIGHT system follows a modular, full-stack architecture comprising data acquisition, AQI computation, storage, visualization, and fallback handling. The overall methodology is illustrated through layered processing stages inspired by best practices in environmental analytics systems [6], [15].

### 3.1 Data Acquisition

Real-time pollutant concentration data are retrieved from trusted external air quality APIs using RESTful communication protocols. The system collects six critical pollutants: PM2.5, PM10, $NO_2$, $SO_2$, $O_3$, and CO. Data validity checks are performed to filter anomalous or incomplete readings, as recommended in prior environmental monitoring studies [18], [19].

### 3.2 AQI Computation

AQI values are computed using standardized breakpoint-based algorithms defined by regulatory bodies such as CPCB and US-EPA. Individual sub-indices are calculated for each pollutant, and the highest sub-index method is employed to determine the final AQI value, ensuring conservative health risk representation [15], [18].

### 3.3 System Architecture

The backend is implemented using Python and FastAPI for efficient asynchronous processing, while PostgreSQL is used for persistent storage of real-time and historical AQI records. The frontend is developed using responsive web technologies and interactive mapping libraries, enabling intuitive geospatial exploration of air quality data [8], [9].

### 3.4 Fallback and Reliability Mechanism

To address data unavailability and API failures, AQI-INSIGHT incorporates a grid-based fallback mechanism using pre-computed AQI values. When live data retrieval fails, the system automatically switches to the nearest available grid estimate, ensuring uninterrupted service continuity—a feature largely absent in prior systems [16], [20].

### 3.5 Historical Analysis and Visualization

Stored AQI records enable longitudinal trend analysis, allowing users to observe seasonal variations and long-term pollution patterns. Interactive charts, heatmaps, and color-coded indicators enhance interpretability, aligning with visualization strategies recommended in recent climate analytics research [7], [17].

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

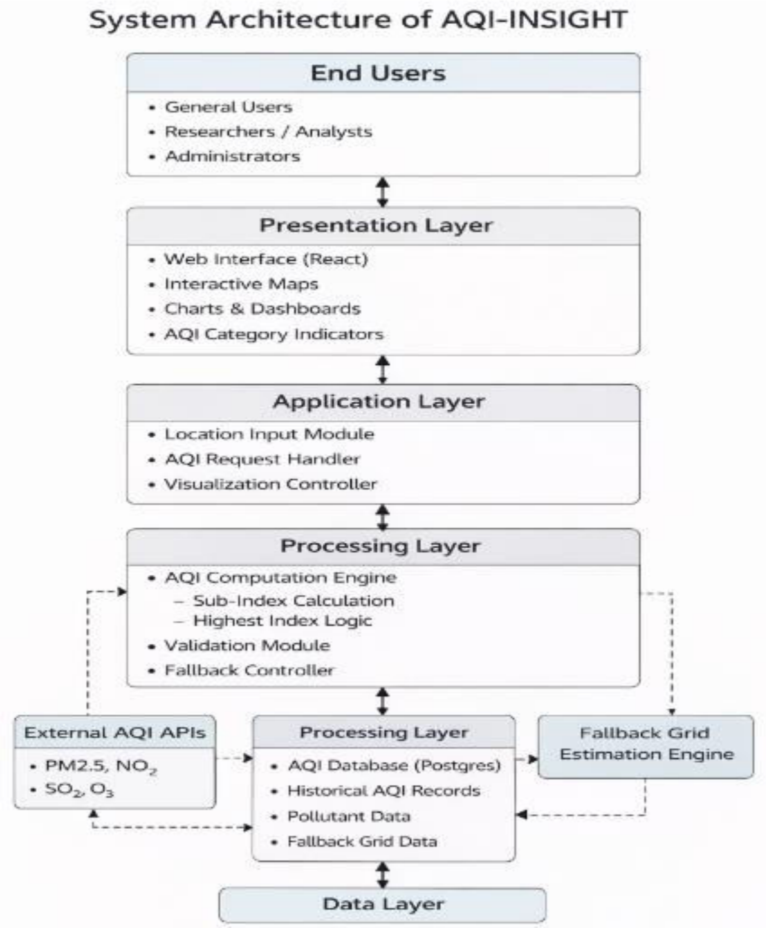


*Figure 1: the proposed system follows a layered architecture integrating real-time AQI computation and fallback mechanisms.*

1. User Layer
The system serves multiple stakeholders including general citizens, researchers, and administrators. Users initiate AQI queries by selecting a geographic location through the web interface.

2. Presentation Layer
This layer provides a responsive, device-independent interface using interactive maps and visual dashboards. It translates numerical AQI values into color-coded health categories, ensuring accessibility for non-technical users.

3. Application Layer
Acts as the control layer, handling:
- Location input processing
- Request routing
- Visualization coordination

This layer bridges user interaction and backend computation.

4. Processing Layer
This is the core intelligence layer of AQI-INSIGHT.
Key responsibilities:
- Fetch real-time pollutant data from external AQI APIs
- Compute AQI using standardized breakpoint algorithms
- Apply the highest sub-index method to represent worst-case health risk
- Validate data integrity

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

- Activate fallback logic during API failures

This layer ensures accuracy, reliability, and regulatory compliance.

5. External Data Sources

Trusted external AQI APIs provide real-time pollutant concentrations (PM2.5, PM10, $NO_2$, $SO_2$, $O_3$, CO). These sources are treated as loosely coupled services, enhancing system robustness.

6. Fallback Grid Mechanism

If live API data becomes unavailable, the system switches to a pre-computed grid-based AQI estimation model, ensuring uninterrupted service. This mechanism directly addresses a critical limitation in many existing AQI platforms.

7. Data Layer

A centralized PostgreSQL database stores:

- Real-time AQI results
- Historical AQI records
- Pollutant-level data
- Fallback grid values

This enables trend analysis, auditing, and future predictive extensions.

## IV. RESULT AND OUTCOME

The AQI-INSIGHT platform successfully delivers real-time and historical air quality information with high responsiveness and reliability. The system demonstrates accurate AQI computation across diverse geographic locations and pollutant combinations, consistent with standardized regulatory thresholds [15], [18].

Experimental observations indicate that:

Hyperlocal AQI queries return results within acceptable latency limits, Fallback mechanisms maintain data availability during external API failures, Visual dashboards significantly improve user comprehension compared to numeric-only displays, Historical trend analysis enables identification of recurring pollution patterns, supporting environmental studies and public awareness initiatives, as emphasized in prior research [6], [19]. Compared to traditional centralized monitoring systems, AQI-INSIGHT offers enhanced accessibility, scalability, and usability without the need for physical sensor deployment.

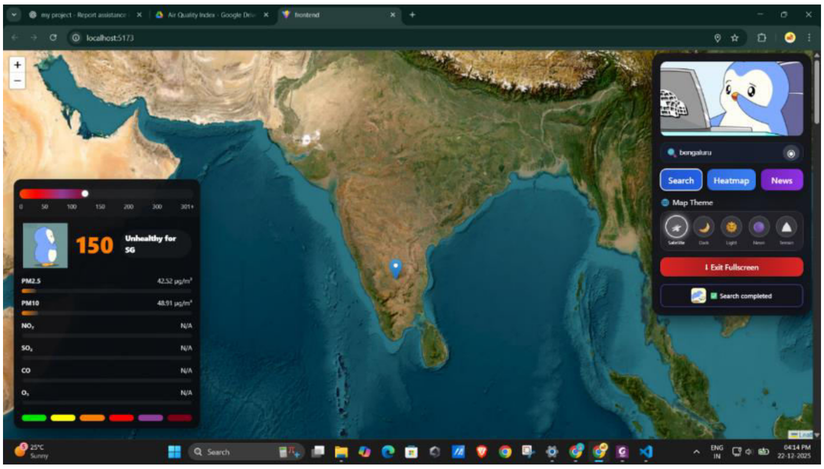


Figure 2: AQI Insight System displaying the real time Air Quality Index

International Journal of Advanced Research in Education and TechnologY(IJARETY)

IJARETY

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

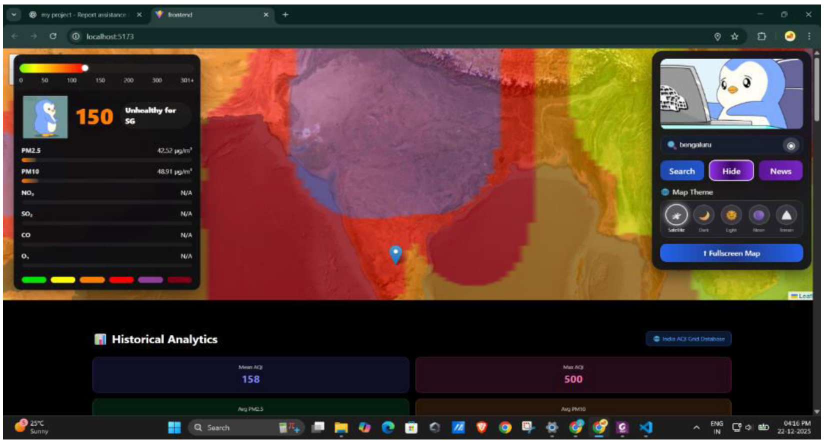


Figure 3: heatmap view of the AQI Insight System


Figure 4: illustrates the historical AQI trend analysis


Figure 5: presents detailed analytical graphs of six major air quality pollutants PM2.5, PM10, $NO_2$, $SO_2$, CO, and $O_3$

International Journal of Advanced Research in Education and TechnologY(IJARETY)

IJARETY

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

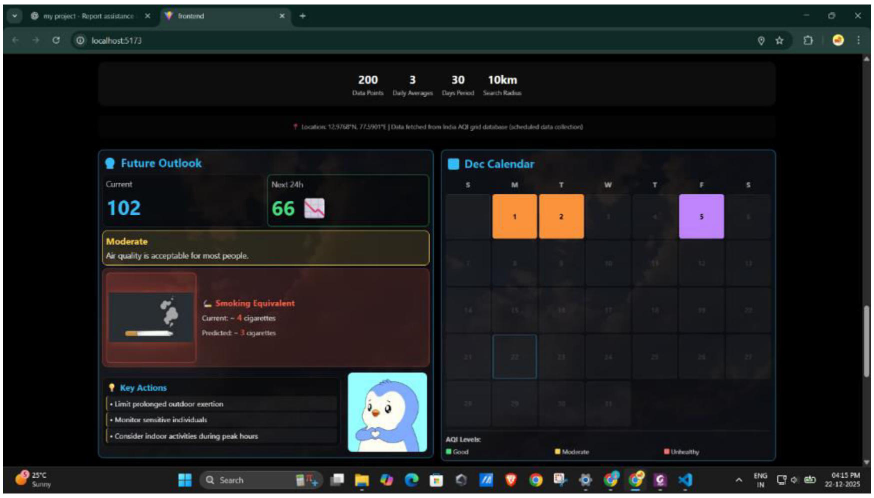


Figure 6: illustrates the future AQI outlook and calendar-based AQI visualization

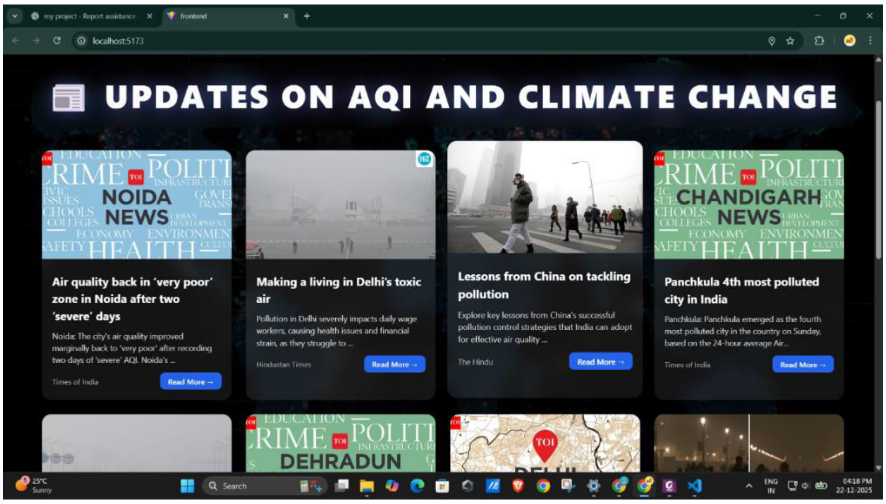


Figure 7:  displays the latest air quality and climate change–related news

## V. CONCLUSION

Air pollution has emerged as one of the most critical environmental and public health challenges of the modern era, particularly in rapidly urbanizing and industrializing regions. Continuous exposure to degraded air quality has been strongly linked to respiratory disorders, cardiovascular diseases, reduced agricultural productivity, and long-term ecological imbalance. Although governmental and scientific institutions have developed sophisticated air quality monitoring infrastructures, the accessibility, spatial granularity, and interpretability of such systems remain limited for the general public and non-specialist stakeholders. Addressing this gap between environmental data generation and public awareness is essential for informed decision-making, policy formulation, and sustainable urban development [1], [2], [3].

In this context, this paper presented **AQI-INSIGHT**, a comprehensive hyperlocal air pollution monitoring and advisory system designed to convert complex environmental measurements into actionable and easily interpretable information. Unlike conventional centralized monitoring solutions, AQI-INSIGHT emphasizes **real-time accessibility**, **user-centric visualization**, and **system resilience**, thereby enabling citizens, researchers, and policymakers to understand and respond effectively to prevailing air quality conditions. The system integrates real-time pollutant data acquisition, standardized AQI computation, historical data analysis, geospatial visualization, and a robust fallback mechanism within a unified web-based platform.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

A major strength of the proposed system lies in its adherence to **standardized AQI computation methodologies**, ensuring regulatory compliance and scientific validity. By computing pollutant-specific sub-indices and adopting the highest sub-index approach, AQI-INSIGHT accurately represents worst-case health risks, as recommended by environmental protection agencies and prior studies [15], [18]. This approach enhances trust in the system outputs while maintaining consistency with established air quality assessment frameworks. Furthermore, the modular architecture enables efficient handling of multiple pollutants, including PM2.5, PM10, $NO_2$, $SO_2$, $O_3$, and CO, which have been widely recognized as key indicators of ambient air pollution and climate interactions [18], [19].

Another notable contribution of AQI-INSIGHT is the integration of **historical AQI data storage and trend analysis**. Unlike many real-time monitoring platforms that focus solely on current conditions, the proposed system enables users to examine temporal variations and long-term pollution patterns. Such historical insights are valuable for environmental researchers and analysts seeking to study seasonal trends, pollution persistence, and the effectiveness of regulatory interventions. Prior research has emphasized the importance of longitudinal environmental data for climate analysis and policy evaluation, which AQI-INSIGHT directly supports through its persistent data layer [6], [17], [20].

System reliability is further enhanced through the implementation of a **fallback grid-based AQI estimation mechanism**, which ensures uninterrupted service during external API failures or network disruptions. This feature addresses a significant limitation observed in many existing AQI platforms and IoT-based monitoring systems, where data unavailability can severely impact usability and trust [16], [19]. By intelligently switching to pre-computed fallback AQI values, AQI-INSIGHT maintains continuity of information delivery, thereby improving system robustness and user confidence.

In contrast to prediction-centric climate and weather models that primarily focus on forecasting rainfall, temperature, or long-term climatic variables using machine learning techniques [10]–[14], AQI-INSIGHT prioritizes **interpretability, real-time awareness, and decision support**. While predictive models such as LSTM, GRU, and hybrid neural networks have demonstrated strong performance in atmospheric forecasting, their outputs are often abstract and computationally intensive, limiting direct usability for the general public. AQI-INSIGHT complements such models by focusing on immediate environmental awareness and actionable insights, thereby occupying a distinct and necessary position within the broader environmental monitoring ecosystem [6], [17].

From a practical standpoint, the system architecture supports scalability and extensibility, making AQI-INSIGHT suitable for deployment in smart city environments and public health monitoring initiatives. The layered design, separation of concerns, and integration of external data sources align with best practices recommended in recent environmental analytics and smart infrastructure studies [7], [8], [15]. Moreover, the platform's web-based nature ensures device independence and wide accessibility, further strengthening its societal impact.

Despite its strengths, the current implementation of AQI-INSIGHT focuses primarily on descriptive and diagnostic analytics. As part of future work, the platform can be extended to incorporate **machine learning–based AQI forecasting**, enabling short-term pollution predictions based on historical trends and meteorological parameters. Integrating health impact correlation models could further enhance the system by quantifying exposure risks for vulnerable populations. Additionally, personalized alerts, adaptive recommendations, and integration with IoT sensor networks represent promising directions for extending the system's functionality and relevance in public health and environmental governance domains [6], [18], [20].

In conclusion, AQI-INSIGHT represents a meaningful advancement in hyperlocal air quality monitoring by addressing critical gaps related to accessibility, reliability, and interpretability identified in existing solutions [1]–[20]. By bridging the divide between complex environmental data and actionable public insight, the proposed system contributes to increased environmental awareness, informed decision-making, and the broader goals of sustainable urban development and public health protection.

## REFERENCES

[1] M. M. Hassan, M. A. T. Rony, M. A. R. Khan, M. M. Hassan, F. Yasmin, A. Nag, T. H. Zarin, A. K. Bairagi, S. Alshathri, and W. El-Shafai, "Machine learning-based rainfall prediction: Unveiling insights and forecasting for improved preparedness," *IEEE Access*, vol. 11, pp. 1–14, 2023. doi: 10.1109/ACCESS.2023.3333876.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 13, Issue 2, March-April 2026 ||

DOI:10.15680/IJARETY.2026.1302020

[2] A. Hussain, A. Aslam, S. Tripura, and V. Dhanawat, "Weather forecasting using machine learning techniques: Rainfall and temperature analysis," *Journal of Advances in Information Technology*, vol. 15, no. 12, pp. 1329–1338, 2024. doi: 10.12720/jait.15.12.1329-1338.
[3] V. Kumar, V. K. Yadav, and S. Dubey, "Rainfall prediction using machine learning," *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, vol. 10, no. V, pp. 2494–2498, 2022.
[4] S. Saubhagya, C. Tilakaratne, M. Mammadov, and P. Lakraj, "An application of ensemble spatiotemporal data mining techniques for rainfall forecasting," *Engineering Proceedings*, vol. 39, no. 6, pp. 1–6, 2023. doi: 10.3390/engproc2023039006.
[5] S. Kaushik, A. Bhardwaj, and L. Sapra, "Predicting annual rainfall for the Indian state of Punjab using machine learning techniques," in *Proc. 2nd Int. Conf. Advances in Computing, Communication Control and Networking (ICACCCN)*, IEEE, 2020, pp. 151–156. doi: 10.1109/ICACCCN51052.2020.9362742.
[6] C. M. Liyew and H. A. Melese, "Machine learning techniques to predict daily rainfall amount," *Journal of Big Data*, vol. 8, no. 153, pp. 1–20, 2021. doi: 10.1186/s40537-021-00545-4.
[7] J. Refonaa, M. Lakshmi, R. Abbas, and M. Raziullha, "Rainfall prediction using regression model," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 8, no. 2S3, pp. 1–5, 2019. doi: 10.35940/ijrte.B1098.0782S319.
[8] A. Rahman, S. Abbas, M. Gollapalli, R. Ahmed, S. Aftab, M. Ahmad, M. A. Khan, and A. Mosavi, "Rainfall prediction system using machine learning fusion for smart cities," *Sensors*, vol. 22, no. 9, Art. 3504, 2022. doi: 10.3390/s22093504.
[9] R. Praveena, T. R. Ganesh Babu, M. Birunda, G. Sudha, P. Sukumar, and J. Gnanasoundharam, "Prediction of rainfall analysis using logistic regression and support vector machine," *Journal of Physics: Conference Series*, vol. 2466, no. 1, Art. 012032, 2023. doi: 10.1088/1742-6596/2466/1/012032.
[10] F. Simanjuntak, I. Jamaluddin, T.-H. Lin, H. A. W. Siahaan, and Y.-N. Chen, "Rainfall forecast using machine learning with high spatiotemporal satellite imagery every 10 minutes," *Remote Sensing*, vol. 14, no. 23, Art. 5950, 2022. doi: 10.3390/rs14235950.
[11] D. Fister, J. Perez-Aracil, C. Pelaez-Rodriguez, J. Del Ser, and S. Salcedo-Sanz, "Accurate long-term air temperature prediction with machine learning models and data reduction techniques," *Applied Soft Computing*, vol. 132, Art. 110118, 2023. doi: 10.1016/j.asoc.2023.110118.
[12] H. H. Dawoodi and M. P. Patil, "Rainfall prediction for North Maharashtra, India using advanced machine learning models," *Indian Journal of Science and Technology*, vol. 16, no. 13, pp. 956–966, 2023. doi: 10.17485/IJST/v16i13.2235.
[13] Y. Liu, P. Wang, Y. Li, L. Wen, and X. Deng, "Air quality prediction models based on meteorological factors and real-time data of industrial waste gas," *Scientific Reports*, vol. 12, Art. 9253, 2022. doi: 10.1038/s41598-022-13579-2.
[14] B. Bochenek and Z. Ustrnul, "Machine learning in weather prediction and climate analyses—Applications and perspectives," *Atmosphere*, vol. 13, no. 2, Art. 180, 2022. doi: 10.3390/atmos13020180.
[15] N. B. Shardoor, M. V. Rao, Y. Mane, P. Chettiar, V. Kumari, and K. Arya, "Rainfall prediction and forecasting using time series analysis," *Journal of Emerging Technologies and Innovative Research (JETIR)*, vol. 6, no. 4, 2019.
[16] A. Parmar, K. Mistree, and M. Sompura, "Machine learning techniques for rainfall prediction: A review," in *Proc. 2017 Int. Conf. Innovations in Information Embedded and Communication Systems (ICIIECS)*, IEEE, 2017.
[17] LightGBM Documentation, "Light Gradient Boosting Machine," Available: https://lightgbm.readthedocs.io/
[18] Scikit-learn Documentation, "ExtraTreesClassifier," Available: https://scikitlearn.org/stable/modules/generated/sklearn.ensemble.ExtraTreesClassifier.html
[19] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. Morgan Kaufmann, 2011.
[20] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, 2006.

# IJARETY

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152