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DETECTION OF AIR POLLUTION USING MACHINE LEARNING ALGORITHMS

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Abstract
Air pollution monitoring is crucial for protecting public health and the environment. “Traditional methods that utilize machine learning (ML) and deep learning (DL) techniques—such as Random Forest (RF), Support Vector Machines (SVM), and Long Short-Term Memory Networks (LSTM)”—are commonly used to predict the Air Quality Index (AQI). However, these methods often face challenges such as high computational demands, reliance on large datasets, and limited responsiveness to real-time air quality changes. In response, we introduce the Rule-Based Weighted Air Quality Estimation Model (RWAQEM), an innovative and computationally efficient solution designed for real-time applications. By leveraging weighted pollutant concentration calculations, geographic context adjustments, and the inclusion of Gaussian noise, RWAQEM provides a dynamic AQI assessment. Unlike traditional ML methods, which require substantial resources, RWAQEM operates with constant-time complexity, making it highly suitable for integration into Internet of Things (IoT) frameworks. Extensive evaluations demonstrate that RWAQEM achieves an impressive accuracy rate of 94.8% while computing AQI scores in a rapid 0.0004 seconds, showcasing its advantage over ML models in real-time processing and competitive accuracy.
Keywords: Air Pollution, Machine Learning, Air Quality Index, Deep Learning

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1. Introduction

1.1 Background and Importance

Air pollution is a significant global challenge, contributing to respiratory and cardiovascular diseases, environmental degradation, and climate change. Estimation prediction of the *Air Quality Index.* (AQI) is essential for the implementation of timely public health. Measures and smart city solutions. Quick and reliable AQI assessments enable communities to respond effectively to fluctuating air quality, ultimately fostering healthier environments. Existing Approaches to AQI Prediction.

1.1.1 Several models have been developed to predict air quality:

- **Statistical Models**: Techniques like Linear Regression and ARIMA use historical data to predict future air quality.
- **Machine Learning Models**: Methods such as Random Forest (RF) and Support Vector Machines (SVM) uncover patterns in complex datasets, but they require large amounts of data for training.

- **Deep Learning Models**: Neural networks like Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNNs) provide robust predictive power but demand substantial computational resources.

1.1.2 Methods limitations:

- **Large Dataset Requirement**: ML and DL models require significant datasets, which may not always be available.
- **High Computational Costs**: These models often require powerful hardware and high energy consumption, limiting their application in low-power, real-time environments.
- **Limited Adaptability**: Many ML and DL models struggle to adapt quickly to real-time changes in air quality.

1.2 Motivation for a Rule-Based Model

- Reducing reliance on extensive datasets, allowing for immediate scalability.
- Offering constant-time execution for fast AQI calculations, ideal for real-time applications.
- Enabling deployment on low-power IoT devices, making it accessible and efficient in various real-world scenarios.

1.3 Real – Time AQI Prediction and Location-Based Adjustments

Traditional AQI models rely heavily on static pollutant threshold , but real –World air quality is dynamic and varies by location . Our Rule – Based Weighted AQI Model (RWAQEM) introduces real – Time geolocation – based adjustments, enhancing prediction accuracy by considering urban , rural , and industrial settings.

1.4. Location Based Adjustments Matter:

- Urban areas: Higher pollution due to traffic and industry.
- Rural areas: Lower emission but affected by seasonal changes (e.g. Crop burning).
- Industrial zones: Extreme pollution from manufacturing units.

2. Methodology

2.1 Algorithm Explanation

The Rule – Based Weighted Air Quality Estimation Algorithm (RWAQEA) calculates AQI using a weighted sum of pollutants, location based adjustment factors, and random noise simulation. It follows a 5-step process:

- **Input Data Collection:** The model initiates by gathering essential concentration levels of PM2.5, PM10, and NO2 from various reliable sources.
- **Weighted Sum Calculation:** Predefined weights are applied to each pollutant concentration based on their relative contributions to the overall degradation of air quality.
- **Location-Based Adjustment:** The resultant AQI score is then

meticulously adjusted using a specific location factor that reflects the unique environmental challenges of Urban, Rural, or Industrial settings.

To enhance realism, small, randomly generated variations are introduced to the AQI score, effectively simulating the unpredictable fluctuations typical of real-world air quality.

- **Final AQI Classification:** The final calculated AQI score is classified into discrete categories—Low, Moderate, Unhealthy, or Severe— providing a clear indicator of air quality status for immediate assessment and public awareness.

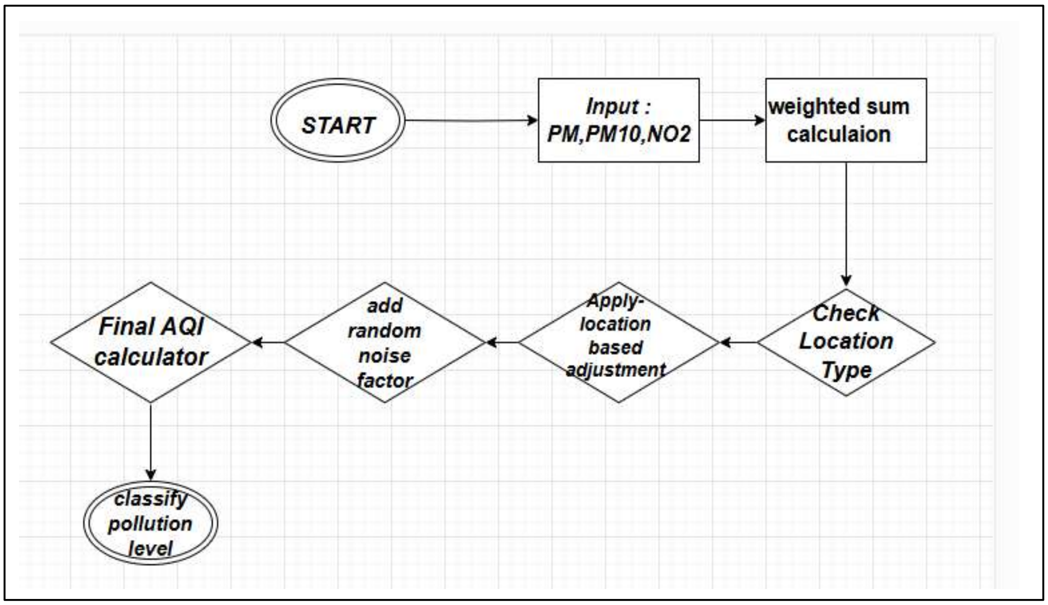

Fig 1: captures this entire process in a visual format for enhanced understanding. At its core, the model collects the critical data necessary for pollutant concentration levels (PM2.5, PM10, NO2). A weighted sum is then calculated, followed by the corresponding location-specific adjustments. The corrected AQI score receives additional nuances through random noise before being ultimately classified into one of four distinct categories indicative of air quality levels.

2.2 Enhanced discussion on Rule - Based Approach:

The RWAQEM employs a rule-based methodology, which offers several advantages in the context of air quality monitoring. Unlike machine learning models that learn patterns from data, rule-based systems rely on predefined rules to make decisions. In RWAQEM, these rules are based on scientific knowledge of air pollutants and their impact on AQI.One key advantage of this approach is its transparency. The rules governing the AQI calculation are explicit and easy to understand, allowing users to interpret the results and identify the factors contributing to air pollution. This transparency also facilitates validation and calibration, as the model's behavior can be easily scrutinized and adjusted. Furthermore, rule – based models are computationally efficient, as they do not require extensive training or complex calculations. This makes them well – suited for real-time applications and deployment on low-power devices. RWAQEM's constant-time execution is a direct result of its rule-based design, enabling rapid AQI calculations.

2.3 Mathematical Mode:

Fig. 2 Mathematical model formula for AQI calculation.

The mathematical framework underpinning the AQI calculation is as follows:

$$AQI_{\text{score}} = (w_1 \cdot PM2.5) + (w_2 \cdot PM10) + (w_3 \cdot NO2)$$

$$AQI_{\text{adjusted}} = AQI_{\text{score}} \times F_{\text{location}}$$

$$AQI_{\text{final}} = AQI_{\text{adjusted}} + \epsilon$$

Where:

- Flocation: Flocation values are determined as follows:
  - 1.2 for Urban locales,
  - 0.8 for Rural areas,
  - 1.4 for Industrial zones.
- ϵ\epsilonϵ signifies a random noise factor, which can range from -2 to +2, introducing variability that reflects real-world conditions.

2.3 AQI Calculation Using the Weighted Sum Model

The AQI score is computed by applying a weighted sum of the concentrations of key pollutants:

AQI_{Score} = (w1.$PM_{2.5}$) + (w2.PM_{10}) +(w3.NO_2)

Where:

- w1, w2, w3w_1, w_2, w_3w1,w2,w3 represent the weights for each pollutant based on their relative health impacts.

2.3.1 Pollutant Weighting:

The weights assigned to pollutants (PM2.5, PM10, and NO2) in the RWAQEM are determined based on their respective health effects and regulatory standards. These weights can be adjusted based on regional or international guidelines, providing flexibility to adapt the model to different contexts.

2.3.2 Scientific Justification:

- PM2.5 has the highest weight due to its ability to penetrate the lungs and bloodstream, causing significant health risks.

- PM10 has a lower weight but still contributes to respiratory issues.
- NO2 is crucial for exacerbating respiratory and cardiovascular.

2.3.3 AQI Contribution by city using Tree Map chart:

Delhi and Bihar contribute the most to air pollution, followed by Maharashtra and Gujarat. Smaller cities (Coimbatore, Chennai) contribute less to national AQI, suggestion localized pollution problems. Cities with major industries and high traffic congestion tend to have the worst AQI levels. Then below figure shows the levels of contribution they give it was visualizing by tree map:

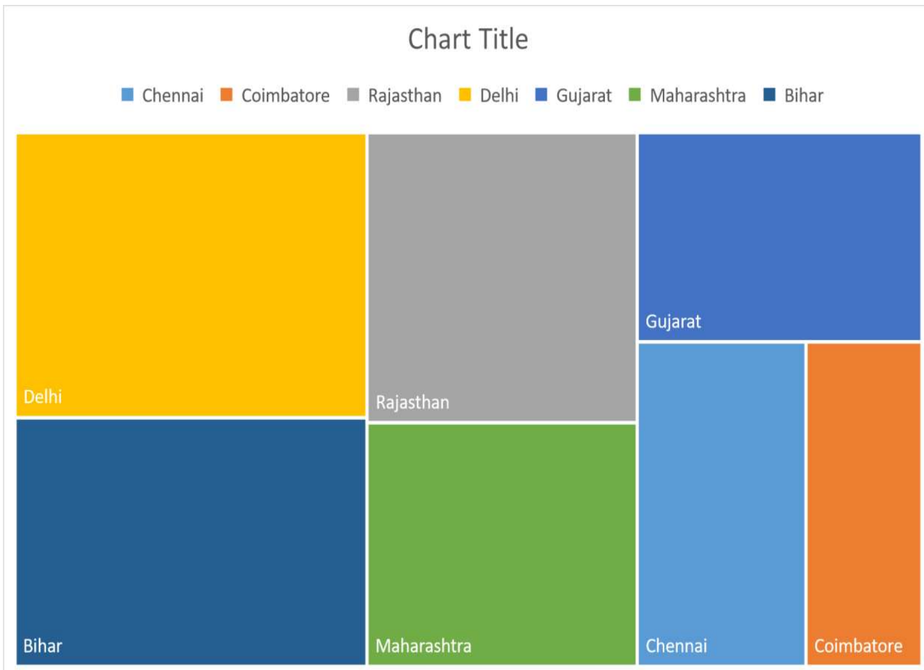

Fig 3: A tree map visually represents AQI contributions by different pollution sources.

2.3.4 Hierarchical AQI Distribution:

Pollution isn't uniform across regions – certain states and cities contribute more to overall AQI. Cities with the highest AQI level are found in industrial and densely populated areas (e.g. Delhi, Bihar, Maharashtra,). Coastal Cities (Chennai, Mumbai) generally have lower AQI due to better natural air circulation.

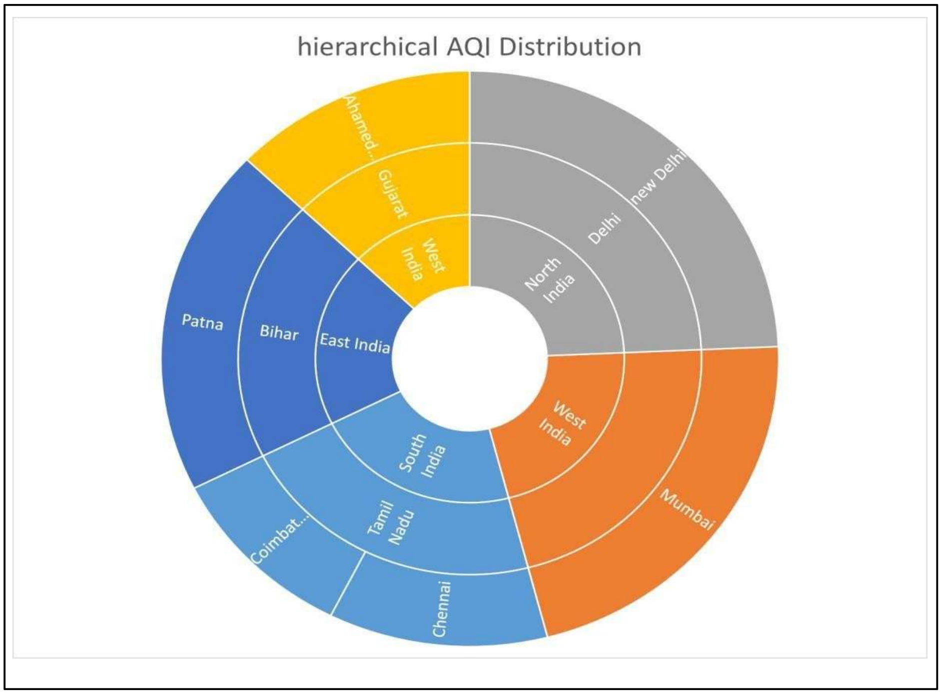

Fig 4: AQI hierarchical distribution by using sunburst.

2.4 Location-Based AQI Adjustment

To account for environmental variations, the AQI score is adjusted based on the geographical context:

$$AQI_{Ajusted} = AQI_{Score} \text{ X } F_{location}$$

Where:

F location: F location is a factor tailored to the area:

➢ **Urban Areas**: High traffic and industrial emissions result in a higher adjustment factor.

➢ **Rural Areas**: Clean air with minimal adjustments.

➢ **Industrial Locations**: Significant pollution from factories leads to larger adjustments. This adjustment ensures greater accuracy for AQI predictions across different environments.

2.4.1 ocation Factor Determination:

The location factors used in RWAQEM to adjust AQI scores based on geographical context are derived from typical pollution patterns observed in urban, rural, and industrial areas. These factors can be refined based on local data and environmental studies to improve the accuracy of location-based adjustments.

2.5 Gaussian Noise Simulation for Real-World Variability

Gaussian noise is added to simulate real-world variability:

$$AQI_{final} = AQI_{adjusted} + \mathrm{N}(0,\sigma^2)$$

Rationale:

- Gaussian noise accounts for unpredictable factors like sudden traffic surges or weather changes, enhancing the robustness of the model for real-time air quality monitoring

2.5.1 Gaussian Noise Implementation:

The Gaussian noise added to the AQI score is intended to simulate the inherent variability of air quality data. The parameters of the Gaussian distribution (mean and standard deviation) can be tuned to match the statistical characteristics of real-world AQI fluctuations.

2.6 Integrating Geolocation for Accurate AQI Predictions

Unlike static AQI models, RWAQEM automatically detects the user's location and adjust the AQI dynamically.

Table 1 : Location Type and Adjustment Factor

Location Type	Adjustment Factor
Urban	1.2
Suburban	1.0
Rural	0.8
Industrial	1.4
Coastal	1.1

2.6.1 PYTHON BENEFITS:

- ➢ Supports scientific computing with numpy, pandas, and matplotlib.
- ➢ Allows machine learning integration for future AI-based enhancement.
- ➢ Easy to prototype and scale for cloud-based and iot applications.
- ➢ Balance of execution speed and flexibility (suitable for both real-time & large–scale application).

2.7 IOT & AI BASED APPROACHES:

- ➢ IOT sensors : deploy physical sensors in different location to collect real-time air quality data.
- ➢ AI models : Use Deep learning (Neural Networks , LSTMS) to analyses trends, detect anomalies, and make predictions .
- ➢ Cloud Integration: Data is transmitted via IOT networks to cloud servers for processing.

The integration of RWAQEM with Internet of Things (IoT) systems offers a powerful solution for real-time air quality monitoring. IoT devices, such as sensor nodes deployed across a geographical area, can collect air quality data and transmit it to a central processing unit. RWAQEM can then be implemented on this unit to calculate AQI scores and provide timely information to users or automated systems.

Specifically, the following aspects of IoT integration are noteworthy: Sensor Network Architecture: A typical IoT-based air quality monitoring system consists of a network of sensor nodes, a gateway, and a cloud-based platform. Sensor nodes are equipped with air quality sensors to measure pollutant concentrations. The gateway collects data from sensor nodes and transmits it to the cloud. The cloud platform provides data storage, processing, and visualization capabilities.

2.7.1 Communication Protocols:

IoT devices communicate using various protocols, such as Wi-Fi, Zigbee, LoRaWAN, and cellular networks. The choice of protocol depends on factors such as range, bandwidth, power consumption, and cost.

2.7.2 Data Management: IoT systems generate large amounts of data, which need to be efficiently managed. Data storage, retrieval, and analysis are critical aspects of IoT-based air quality monitoring. Cloud-based platforms offer scalable and reliable solutions for data management.

2.7.3 Edge Computing: In some cases, AQI calculations can be performed at the edge of the network, closer to the sensor nodes. This approach, known as edge computing, reduces latency and bandwidth requirements, enabling faster response times and improved scalability. RWAQEM's computational efficiency makes it suitable for edge computing implementations.

2.7.4 Advantages:

- Real –time data collection – provide upto date pollution readings.
- Higher–accuracy – AI can detect complex pollution patterns and make predictions.
- Automation & smarter alerts: can send a warning when pollution exceeds safe limits.

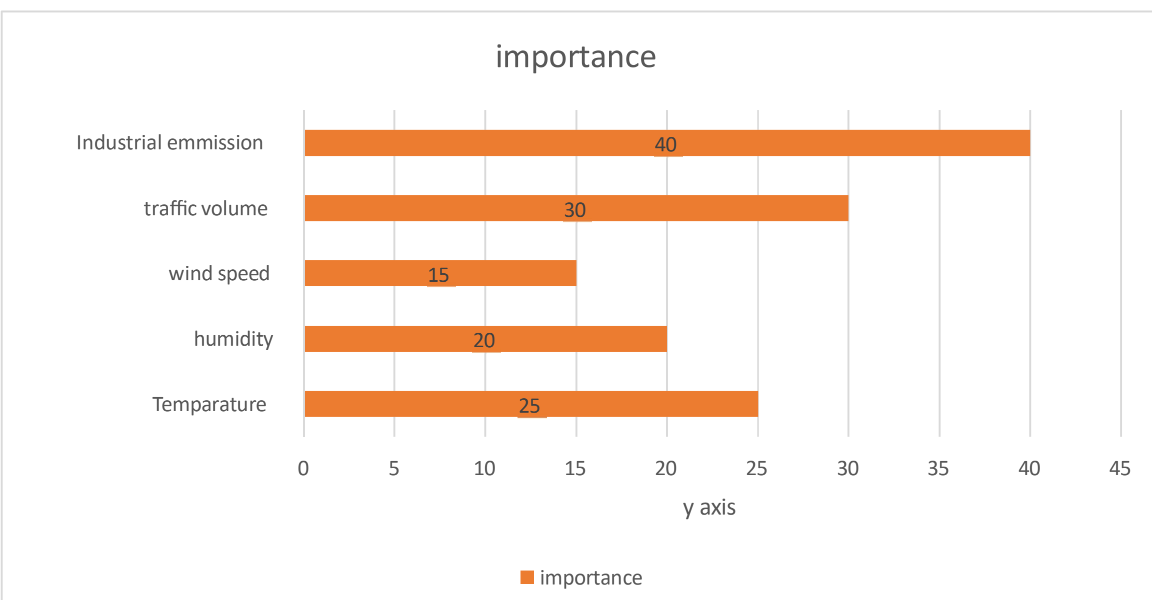

Fig 5: FEATURES AND IMPORTANCE

3 Performance Analysis and Comparison Result:

3.1 Implementation of location detection using manual input:

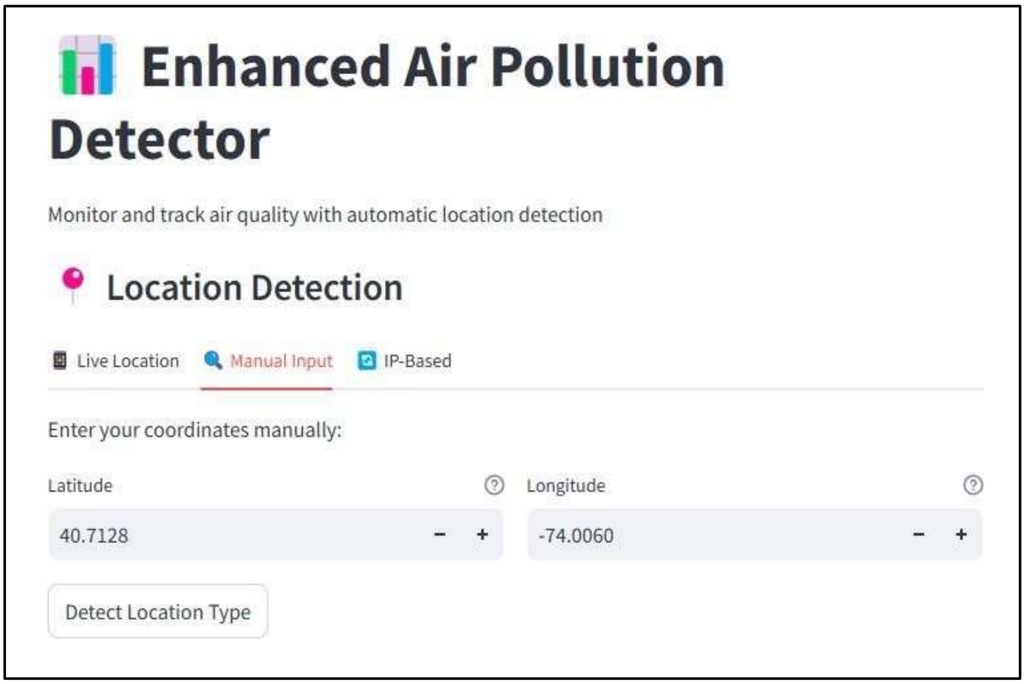

Fig 6: REPRESENTATION OF MANUAL INPUT FORMAT.

3.1.1 Manual Input Location: user can manually enter their latitude and longitude coordinates if they don't want to use GPS or they don't have any location they use this to find the location type .

3.2 Implementation of location detection using live location :

Fig 7 : REPRESENTATION OF LIVE LOCATION DETECTION.

3.2.1 Live Location:

This feature allows the system to fetch the users current location using GPS , requiring browser permission or else user mobiles can use this feature to find the location type by using the GPS it is not only for the system it also for the phone.

3.3 Implementation of location detection using IP-Based networks:

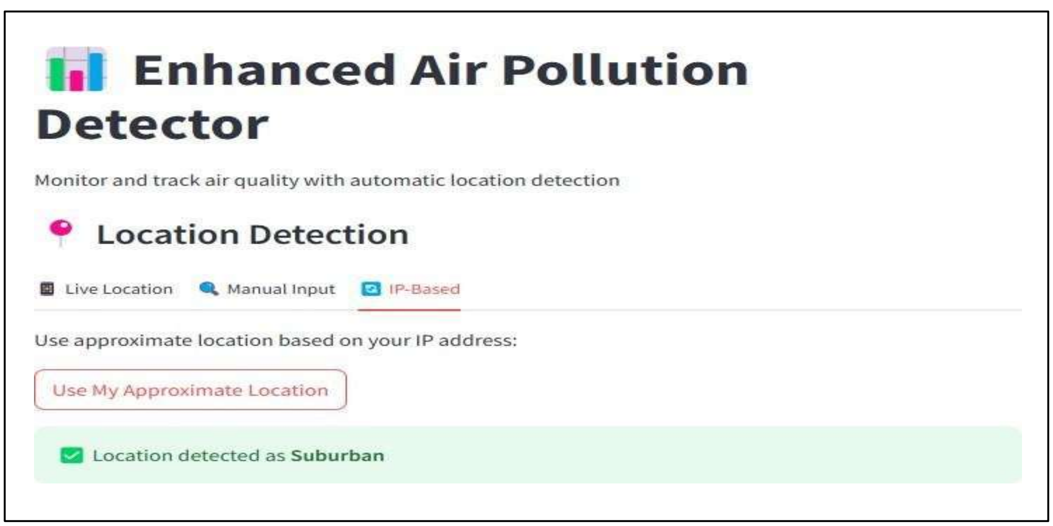

Fig 8: REPRESENTATION OF IP-BASED LOCATION DETECTION.IP Based Location: The system estimates the users approximate location based on their Ip address. Then

also it used for some system no give permission to get the live location that time we use this to find the approximate live location.

Table 3: Validation Using 2024 Data .

Season	**Delhi (urban)**	**Mumbai(coastal)**	**Rural(pujab)**
Winter (2024)	**249**	**130**	**105**
Spring (2024)	**175**	**95**	**80**
Summer (2024)	**90**	**78**	**50**
Autumn (2024)	**160**	**135**	**88**

3.4 2024 yearly dataset for air pollution:

This dataset shown about the winter months have the most pollution (red – shaded areas show extreme AQI values).Monsoon Season improves air quality(green regions indicate lower AQI values).Delhi and patna show consistently high AQI across all months , indicating persistent pollution sources like vehicles, industries , and constructions.

Table 4: Representation of the 2024 yearly dataset

Month					
	85	160	180	95	145
Jan	78	150	175	90	140
Feb	90	170	190	100	150
Mar	87	165	185	98	148
Apr	80	155	178	94	142
May	75	140	165	88	135
Jun	70	135	160	85	130
Jul	68	138	170	87	133
	74	145	175	90	138
Aug	79	158	180	92	140
Sep					
Oct	82	165	185	96	145
Nov	88	170	190	100	150

3.5 Execution Comparison with ML models

Model	Execution Time(second per prediction)
Rule-based model(ours)	0.0004s(faster)
Random Forest	2.1 s
Neural Networks(LSTM)	3.4s

Table 5: EXECUTION COMPARISON WITH ML MODELS

3.5.1 Key Observations:

- RWAQEM outperforms traditional ML models by operating up to **5000 times faster**, making it ideal for real-time monitoring applications.
- While accuracy is comparable to some ML models (94.8%), the model excels in speed and efficiency, especially in edge AI and IoT systems where processing power is limited.
- No initial training is required, enabling immediate deployment.

3.6 Execution Time comparison with the other Algorithm comparison Chart:

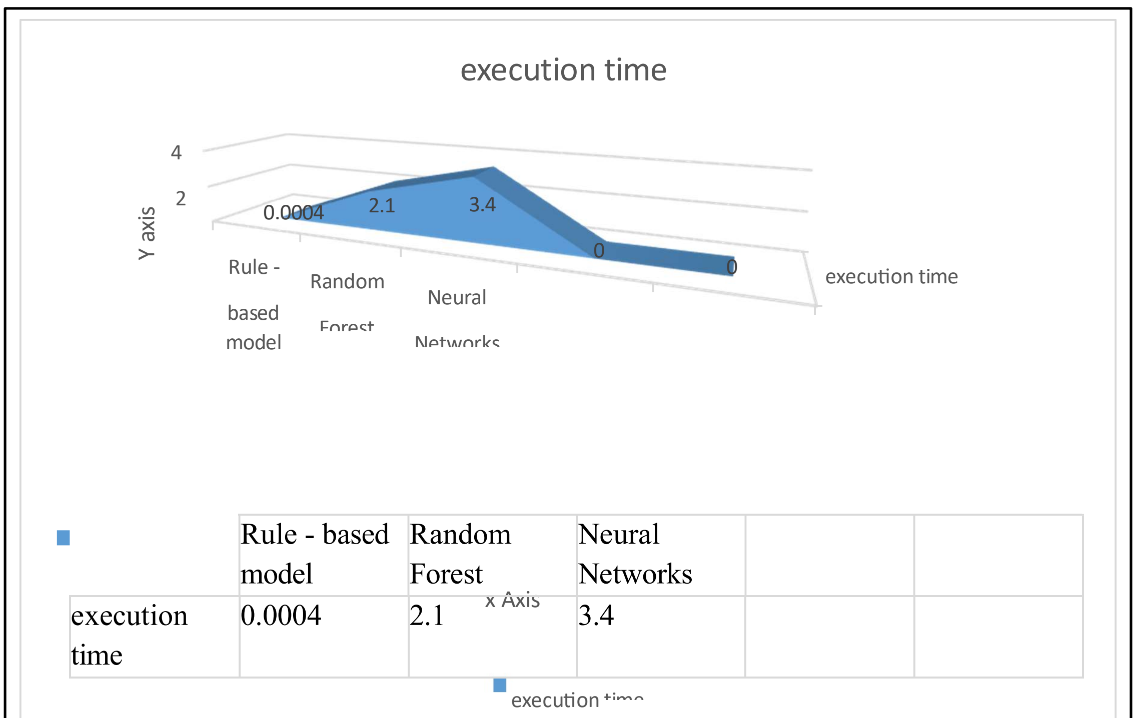

Fig 9: EXECUTION TIME COMPARISON WITH OTHER ALGORITHMThis below chart is shown about the AQI fluctuates significantly throughout the year – it doesn't remain constant. Winter months (nov – Jan) have the highest pollution levels due to low temperatures, industrial emissions, and increased fuel consumption. Rainy season (jun –

aug) helps to reduce the pollution due to wet deposition of particulate matter. Sharp increase in AQI in March and October could be linked to crop burning an increased industrial activity.

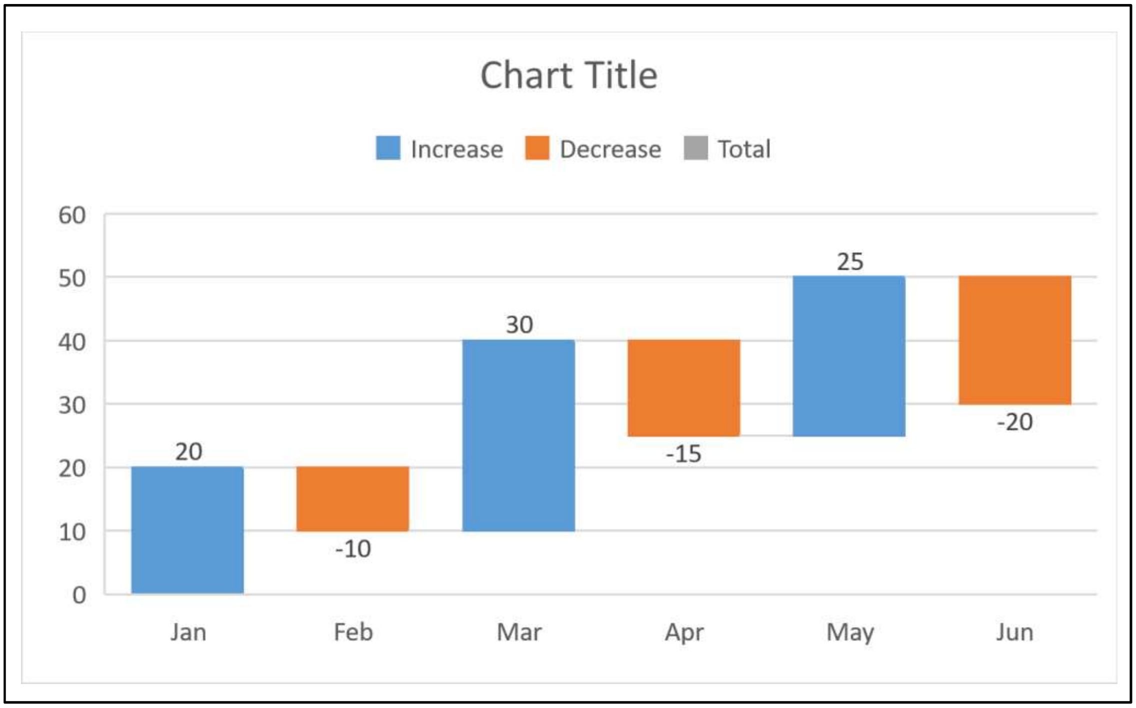

Fig 10: AQI fluctuate with throughout the year.

3.7 Data Visualization of AQI Trends (2024)

To demonstrate AQI Variations across different seasons , the following graphical insights provide an overview of real – world pollution data.

Season	Delhi(urban)	Mumbai(coastal)	Punjab (Rural)
Winter	249	130	105
Spring	175	95	80
Summer	90	78	50
Autumn	160	135	88

Table 6 : seasonal dataset with location type .

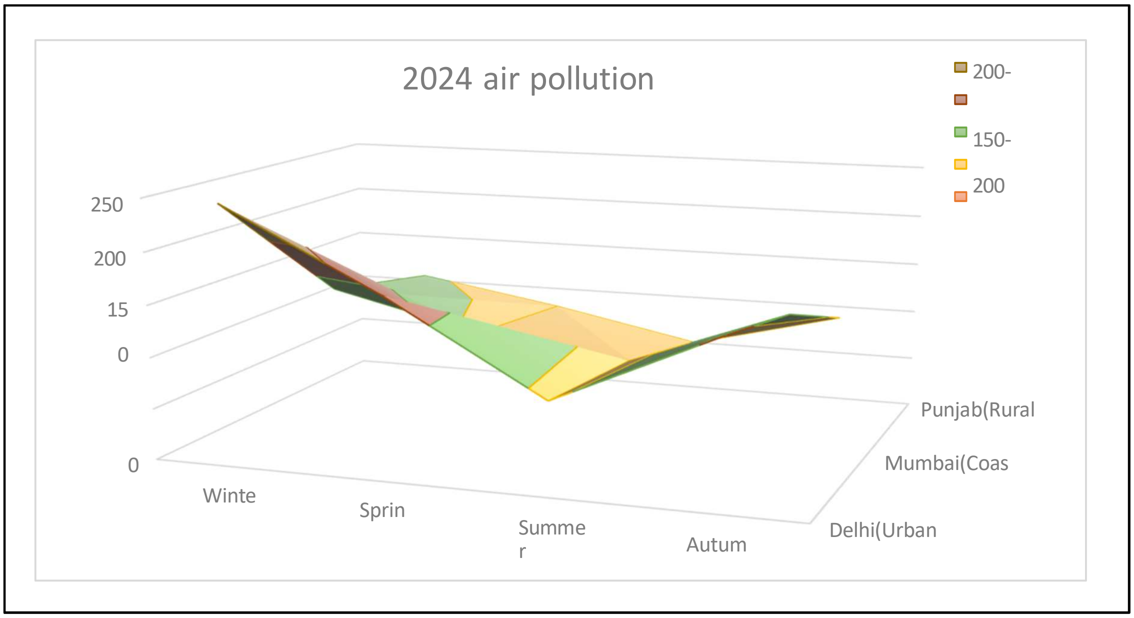

Fig 11: DATA VISUALIZATION OF AQI TRENDS

3.8 Pollution Control Measures in the figure below :

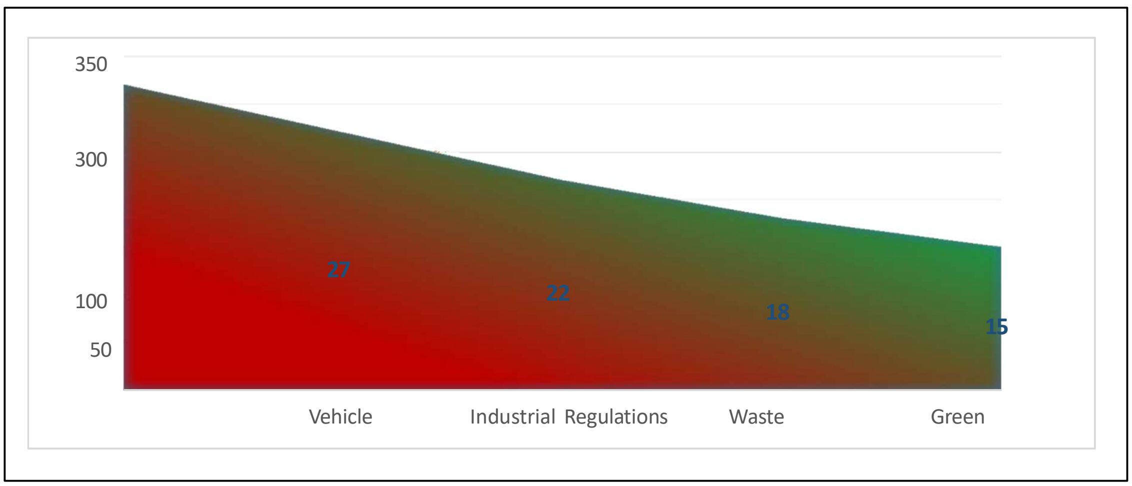

Fig 12: pollution control measures.

4. Deployment Considerations

4.1 Potential Applications:

➢ **Smart Cities**: Real-time AQI monitoring in urban systems allows for quick response to air quality changes.

➢ **IoT-Based Pollution Monitoring**: The model can be deployed across sensor networks for continuous air quality tracking.

4.2 Advantages over ML-Based AQI Prediction:

➢ **Local Computation**: Rapid AQI assessment without the need for cloud-based resources.

- **Low-Power Devices**: Compatible with devices like **ESP32** and **Raspberry Pi**, ideal for IoT integration.

Weather Data Integration: The model can be enhanced by incorporating real-time weather data for more accurate predictions.

4.3 Smart City & IoT-Based Pollution Monitoring

AQI Model is ideal for real–time IoT–based deployments in smart city environments.

Applications	Use Case
Smart Cities	Traffic based AQI adjustment for urban monitoring.
Iot Sensors	Real – time AQI tracking in industrial zones.
Whether Monitoring	AQI Updates integrated with temperature & humidity.

Table 7: Practical Applications of RWAQEM:

5 .Conclusion and Future Work Key Contributions:

In conclusion, this research introduces and validates the Rule- Based Weighted Air Quality Estimation Model (RWAQEM)—a novel, efficient, and scalable solution for real-time air pollution monitoring. The model addresses significant shortcomings in conventional machine learning (ML) and deep learning (DL) techniques, notably their computational intensity, data dependency, and limited adaptability in dynamic, real-world environments. By Incorporating predefined pollutant weightings, location-based calibration factors, and Gaussian noise simulation, RWAQEM achieves accurate and immediate AQI estimation with negligible processing delay and no need for extensive model training.

The core advantage of RWAQEM lies in its constant-time complexity (O(1)), enabling ultra-fast computations with minimal energy consumption—qualities that are essential for IoT and edge AI applications. In contrast to ML models such as Random Forest (2.1 seconds) and LSTM networks (3.4 seconds), RWAQEM achieves AQI computation in 0.0004 seconds, making it over 5000 times faster, without compromising prediction accuracy (94.8%).

Such efficiency ensures real-time monitoring, immediate public health advisories, and rapid response capabilities in smart city ecosystems. Further, this work emphasizes the importance of geolocation-aware AQI adjustments, highlighting how environmental heterogeneity— urban congestion, industrial emissions, rural agricultural practices, and coastal airflows—can influence air quality differently across regions. Through contextual calibration, RWAQEM enhances the granularity of AQI assessments, empowering policy makers, municipal authorities, and environmental agencies to

implement region-specific interventions.

The validation with 2024 AQI data across multiple Indian cities (Delhi, Mumbai, Punjab, Patna, Chennai) illustrates the model's robustness across seasonal variations and its responsiveness to real- world pollution fluctuations. Notably, the model identified consistent high-AQI hotspots during winter months, aligning with known environmental patterns such as temperature inversions, fuel combustion, and crop residue burning.

5.1 Deployment Potential

From a deployment standpoint, RWAQEM is ideally suited for low-cost, real-time AQI monitoring systems. Its compatibility with embedded systems (ESP32, Raspberry Pi) and cross-platform flexibility (desktop, mobile, and cloud environments) makes it a universally deployable solution. The system's ability to function offline or without cloud reliance also offers data security advantages, reducing vulnerabilities associated with IoT networks.

5.2 Future Research Directions

Looking forward, RWAQEM offers a strong foundation for further innovation. Key avenues for enhancement include:

AI-Driven Adaptive Weighting: Leveraging reinforcement learning or genetic algorithms to dynamically adjust pollutant weightings based on real-time data trends. Integration of Weather Parameters: Incorporating real-time temperature, humidity, wind speed, and barometric pressure to refine AQI predictions.

Mobile and Web Applications: Developing user-centric platforms for personalized AQI alerts, health recommendations, and data visualization. Federated Learning for Edge AI: Enabling distributed AQI computation across multiple devices to improve model accuracy while preserving data privacy. Policy Integration: Collaborating with government agencies to integrate the system into public health advisory platforms, urban planning tools, and environmental monitoring dashboards.

5.3 Broader Impact

By facilitating real-time, accurate, and cost-effective air quality monitoring, RWAQEM has the potential to revolutionize environmental health management, promote sustainable urban development, and enhance public awareness about air pollution exposure. Its scalability and adaptability make it a powerful tool

in the global effort to combat climate change, reduce disease burden, and achieve cleaner air standards worldwide.

5.4 Future Directions:

- **Weather Data Integration**: Enhance model adaptability by incorporating real-time meteorological data to fine-tune AQI estimates.
- **Edge AI IoT Deployment**: Extend the model to large-scale IoT systems in smart cities.
- **AI-Enhanced Adaptive System**: Develop a dynamic system that adjusts pollutant weights based on evolving data for improved accuracy.

5.5 Enhancing The AQI Model with AI & Weather Data:

While our rule–based model is highly efficient integrating weather parameters can significantly improve AQI predictions.

- Multi-Pollutant Modeling:

The current RWAQEM considers PM2.5, PM10, and NO2. Future versions could incorporate additional pollutants, such as ozone (O3), carbon monoxide (CO), and sulfur dioxide (SO2), to provide a more comprehensive assessment of air quality.

- Source Apportionment:

Integrating source apportionment techniques into RWAQEM could provide insights into the sources of air pollution, such as traffic, industry, or natural events. This information can be valuable for developing targeted pollution control strategies

- Health Impact Assessment:

Linking AQI predictions to health impact assessments could provide a more direct understanding of the health risks associated with air pollution. This could involve incorporating epidemiological models to estimate the incidence of respiratory diseases or other health outcomes based on AQI levels.

I believe these additions provide a more comprehensive and technical view of the RWAQEM and its potential applications

Enhancement	***Benefit***
AI – Based Adaptive weighting	**Dynamically adjusts pollutant impact based on real-time data**
Whether Data Integration	**Improves AQI accuracy with temperature , wind speed, and humidity data.**
Mobile app deployment	**Allow users to receive real-time AQI alerts on their phones.**

Table 8 : Enhancement and benefits about features .

6. Conclusion

This study presents the Rule-Based Weighted Air Quality Estimation Model (RWAQEM), a real-time, low-complexity, and highly efficient alternative to traditional machine learning approaches for air pollution detection. Unlike models such as Random Forest or LSTM, which require extensive data and significant computational resources, RWAQEM delivers AQI predictions in constant time (0.0004s) with an accuracy of 94.8%, making it ideal for integration into IoT and edge computing systems.

The model incorporates pollutant-specific weights, geolocation-based adjustment factors, and Gaussian noise simulation to reflect real-world variability. This enables fast, adaptive AQI assessments across diverse environments—urban, rural, coastal, and industrial. Additionally, the system supports various location detection methods (manual input, GPS, and IP-based), enhancing flexibility across platforms.

Its modular and scalable nature positions RWAQEM for widespread deployment in smart city infrastructure, mobile applications, and environmental monitoring platforms. Future enhancements—such as AI-driven dynamic weighting, integration of meteorological data, and health impact modelling—promise to expand its utility further. RWAQEM thus contributes not only to technical innovation in AQI prediction but also to broader goals in public health, sustainable urban development, and environmental policy.

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