An Intelligent Geofenced Air Quality Monitoring System: Real-Time AQI Detection and Autonomous Location-Based Health Intervention Using Machine Learning

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Abstract: The rising level of air pollution in the urban environment triggers the need for intelligent air pollution monitoring systems and proactively protective health systems for the welfare of society as a whole. The paper presents the concept of the 'Intelligent Geo fenced Air Quality Monitoring System' that combines the strength of air pollution sensing using Internet-of-Things technology and health protective interventions with the power of machine learning analytics, as well as geographical-based health protective systems by using the Node MCU/Arduino platform with low-cost air pollution sensors such as MQ-135 & PM2.5 sensors. Advanced machine learning techniques are applied to bring about more analytical precision and predictive capability. The Random Forest models classify the state of air quality into safety categories, while the Long Short-Term Memory (LSTM) networks understand temporal dependencies in predicting AQI trends. GPS-enabled Geofencing, along with Haversine distance computation, identifies users within high-risk zones in real time. Once unhealthy conditions are detected, automated alerts are published through Firebase Cloud Messaging to mobile applications created on Android/Flutter systems. The proposed system contributes to a scalable, energy-efficient, cost-effective platform for smart air quality surveillance to enable preventive public health measures that support sustainable smart city ecosystems.

Keywords: *Air Quality Index (AQI), Internet of Things (IoT), Geofencing, Machine Learning, Random Forest, LSTM, Smart Cities, Health Alert System.*

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I. INTRODUCTION

Air pollution is one of the most important challenges for environment and health, especially in growing cities where car exhausts, factory emissions, and construction sources are major causes of air pollution [1]. The presence of CO, PM2.5, and VOCs in the air leads to serious health issues like asthma, cardiovascular disease, and chronic sickness [2][18]. Although conventional air quality stations are available for air analysis, their large installation cost, inadequate coverage, and slow dissemination of results make them inefficient for research in providing real-time and user-specific health notices [10]. Recent developments in the Internet of Things (IoT) technology have allowed the implementation of low-cost and distributed sensing systems for continuous environment monitoring [3]. In the proposed system, the use of gas sensors such as MQ-135 for general air quality monitoring and PM2.5 sensors for fine particle detection is implemented with microcontroller systems such as Node MCU/Arduino. These systems act as edge devices, sampling pollutant concentration values and relaying it to cloud-based servers using wireless communication technology such as Wi-Fi [4]. Raw measurements from sensors, however, are not enough to yield actionable insights due to environmental noise, sensor drift, and temporal variability. Machine learning-based analytics models are integrated at the cloud layer for this purpose. Random Forest algorithms are used for robust classification of safe/unsafe air quality conditions owing to their non-linear relationships and noise-handling capability in datasets [5]. Long Short-Term Memory (LSTM) networks are deployed to model temporal dependencies in sensor data history. This allows for short-term AQI forecasting with the added capability of issuing warnings about an uptrend in pollution [6][15]. Air pollution is a spatially relevant phenomenon; it demands precise location-aware intelligence. This system integrates GPS-based localization to obtain latitude and longitude coordinates of both sensing nodes and end users. A geofencing mechanism, implemented using the Haversine distance formula, dynamically infers user proximity to polluted zones within a predefined radius [8][17]. Such a spatial computation will enable real-time identification of individuals at potential health risk and make sure alerts are relevant and context-sensitive. For easier user interaction and intervention, the processed air quality information is provided via a cloud communication interface. To provide low latency push notifications to the Android and Flutter mobile application developed using the communication interface, the Firebase Cloud Messaging service is used [9]. The push notifications include suggestions like the use of masks or staying away from high-risk areas even when the application is running in the background. For better user situational awareness of pollution hotspots on the maps, services like map visualization are provided.[14][24].

➢ *Contribution of the Paper*

The major contributions of this work are summarized below:

- Low-cost IoT-based air quality monitoring system design in real time using both MQ-series and PM2.5 sensors.
- Integration of Random Forest Classification and LSTM-based Time Series Prediction for Intelligent AQI Analysis.
- Geofencing using GPS with Haversine distance calculation to show location-based health risk identification.
- Development of an autonomously apt cloud-to-mobile alerting methodology using Firebase Cloud Messaging for proactive intervention in health conditions.
- Demonstrate the architecture that is scalable and energy-efficient suitable for smart city and preventive healthcare application.

II. LITERATURE REVIEW

➢ *Traditional and IoT-Based Air Quality Monitoring Systems*

Conventional air quality monitoring infrastructures primarily rely on centralized, high-precision monitoring stations operated by regulatory authorities [1]. Although these systems provide accurate pollutant measurements, their high deployment and maintenance costs, along with limited spatial coverage and delayed data availability, restrict their effectiveness in addressing localized pollution events [2]. To handle this issue, several recent works proposed IoT-based air quality monitoring systems using low-cost sensors and embedded platforms [3].

An IoT-based monitoring architecture off the shelf reported in literature consists of gas and particulate sensors interfaced with microcontrollers such as Arduino or Node MCU, which in turn transmit the sensed data to cloud servers for storage and visualization [4]. Indeed, these systems bring about a much finer granularity and enable real-time acquisition of data. However, in most implementations, intelligent analytics and autonomous mechanisms of response have remained noticeably wanting beyond plain monitoring and visualization [5].

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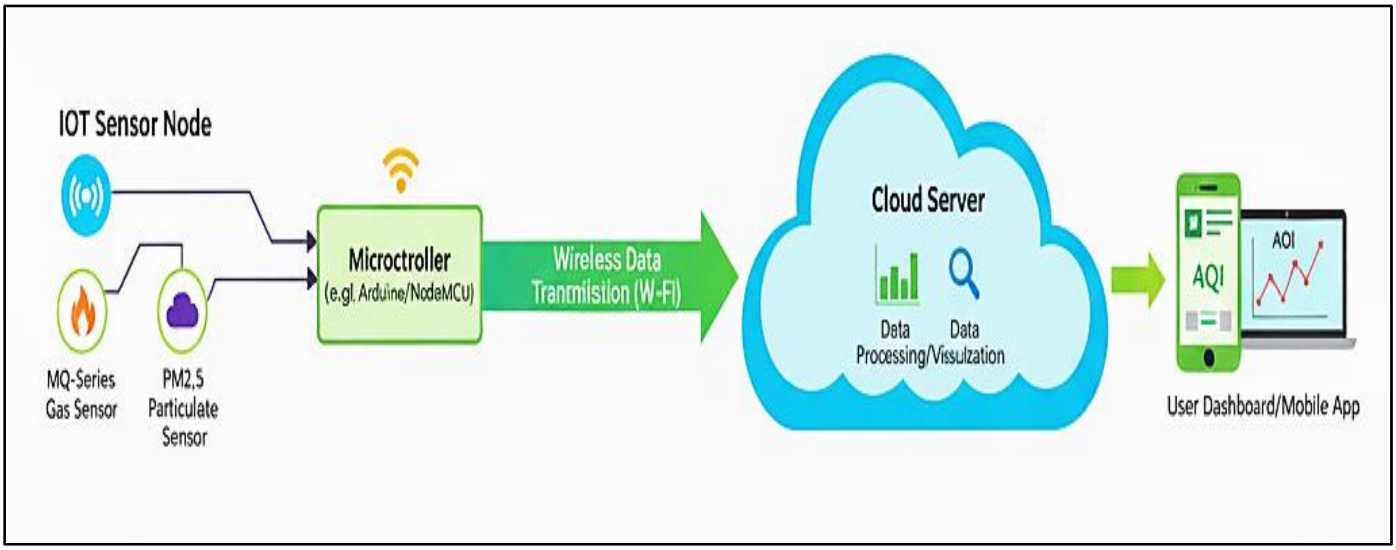

Fig 1 Architectural Workflow of a Conventional IoT-Based Air Quality Monitoring System Involving Sensor Nodes, Cloud Processing, and End-User Visualization Dashboards.

➢ *Machine Learning Techniques for Air Quality Classification*

In order to improve the interpretation of the data, various research works have proposed the inclusion of machine learning techniques into air quality studies [3][11]. Supervised machine learning algorithms, like Support Vector Machines, Decision Trees, and Random Forest Classifiers, have been rigorously tested for their effectiveness in classifying AQI [13]. Of these, Random Forest Classifiers have proved to be more robust due to the ensemble learning technique, which enables effective processing of noisy, nonlinear sensor data [5].

The general analysis process commonly used in the studies is depicted in Figure 2, where data from sensors is processed using preprocessing and feature extraction techniques prior to training machine learning classifiers [11] [13]. Although these methods enhance the efficiency of classifications, their effectiveness is, however, measured on offline data and not in live IoT settings [12].

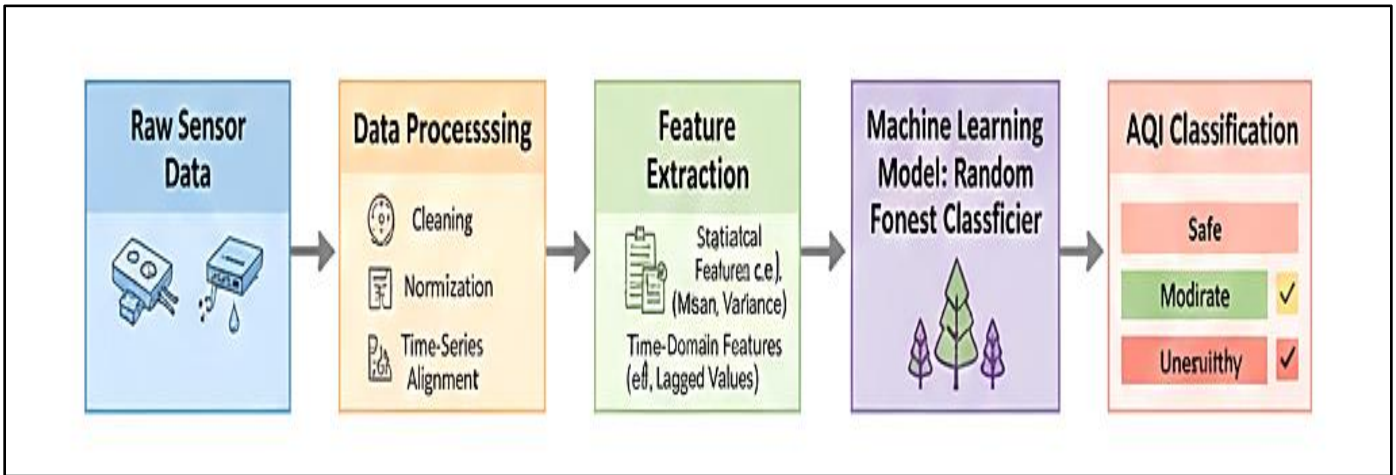

Fig 2 Schematic Representation of the Machine Learning Analytical Workflow for AQI Classification, Encompassing Data Preprocessing, Feature Engineering, and Ensemble-Based Random Forest Modeling.

➢ *Time-Series Forecasting of AQI Using Deep Learning*

Current literature stresses the effectiveness of predictive intelligence in the monitoring of air quality [13][15]. Time series forecasting tools, especially the concept of the Long Short-Term Memory (LSTM) network, have gained popularity in the prediction of the value of AQI for the days ahead using past records of the same pollutants [6][15]. LSTM can analyze the trends in the data accurately over time, performing better than any statistical tool [6][13]. As depicted in Fig.3, the LSTM-based approach for predicting AQI uses sensor data to forecast the trend of the same pollutants for the days ahead [15].

Although very effective, most of these methods work independently from location-aware mechanisms and do not activate immediate health notifications [17][19].

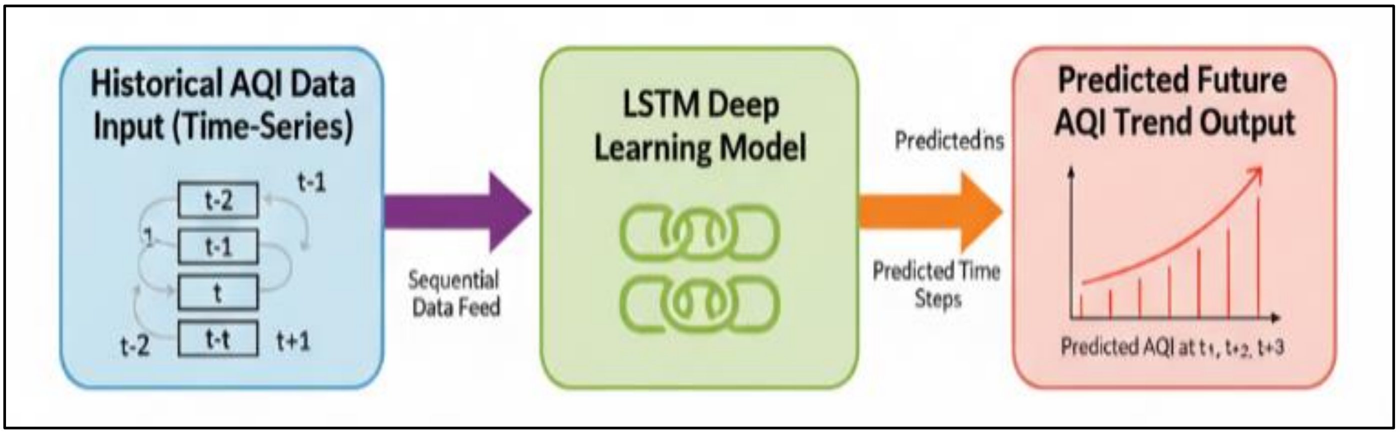

Fig 3 Architectural Framework of the LSTM-Based Deep Learning Model for Time-Series AQI Forecasting, Illustrating the Processing of Sequential Historical Data for Temporal Trend Prediction.

➢ *Location-Aware Methods of Tracking and Geofencing*

Variability in air pollution in space led to the involvement of GPS-based localization in air pollution systems as a way of monitoring and controlling the pollution levels in space [7][8]. Geo-tagging of sensor data, providing air pollution details on digital maps, is seen in many studies and systems [11][17]. These systems act as passive info aids.

Techniques of geofencing, as depicted in Figure 4, involve the creation of virtual boundaries around polluted areas using GPS coordinates and distance calculation techniques such as the Haversine formula [14]. Even though geofencing has shown potential in logistics-related application areas and emergency systems, it is not greatly adopted in air quality systems [24]. Existing implementations neither calculate the proximity of users nor provide risk information [19].

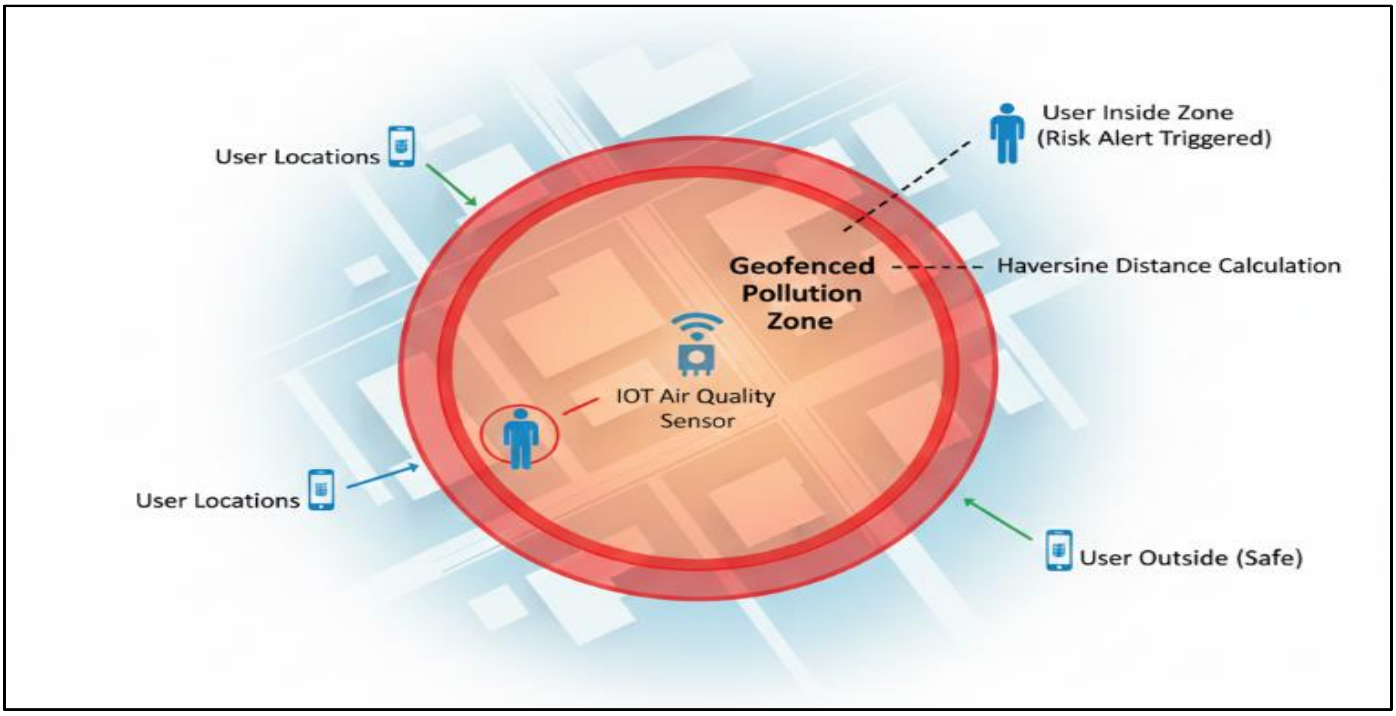

Fig 4 Schematic Illustration of GPS-Based Geofencing for Pollution Zone Identification, Depicting the Virtual Boundary Perimeter and User-Proximity Detection Logic.

➢ *Cloud Platforms and Mobile Alert Systems*

Cloud computing platforms are equally important Acting as a backbone of integration of sensing, analytics, and communication layers [4][14]. Cloud computing services like Firebase, AWS IoT, and Thing Speak help to scale up data storage, processing, and compatibility between systems [9,23]. Mobile apps form a friendly interface between the user and access to air quality data.

For example, as depicted in Figure 5, most of the current mobile alert systems are based on the static AQI values or use APIs [4][11]. Though push notification systems like FCM support low latency alert notifications, they are not often integrated with the current sensor values, prediction logic from machine learning, and geo fence logic in a single system [9][14][24].

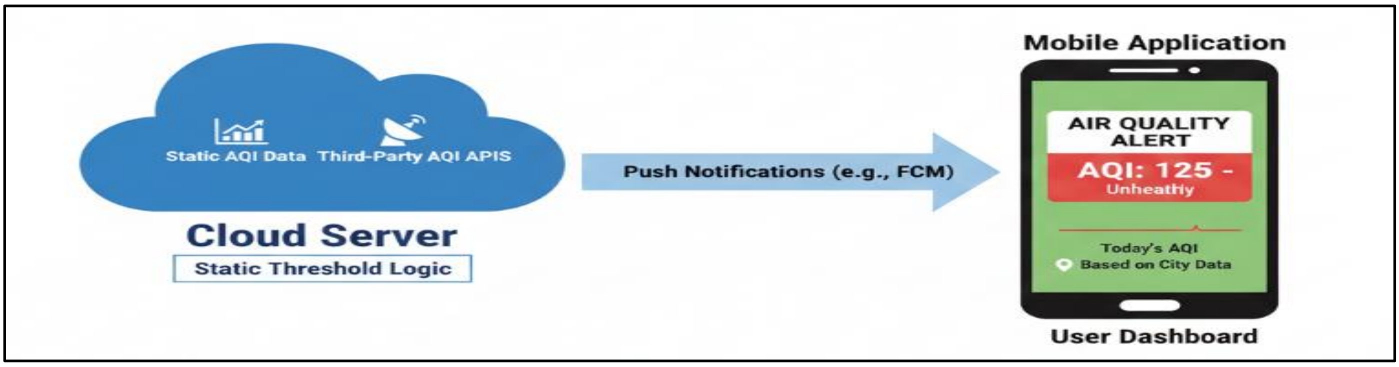

Fig 5 Logical Flow of a Conventional Cloud-to-Mobile Alert Framework, Demonstrating Static Threshold-Based Notifications Lacking Predictive Analytics and Geofencing Integration.

➢ *Integrated Intelligent Monitoring Framework and Research Gap*

The spatial variability of air pollutants has further encouraged the inclusion of GPS-based localization into the monitoring system [7][8]. Various researches have tried geotagging sensor values with the representation of the level of air pollutants on digital maps [11][17]. Yet again, these try to act only as passive information tools.

Geofencing techniques, as depicted in Figure 4 above, involve creating virtual boundaries around polluted sites using GPS coordinates and Haversine formula-based distance calculation techniques [14]. Though geofencing has demonstrated efficacy in logistics applications and emergency notification systems [17], it is not frequent in air quality mapping [19]. Efficacious implementations of geofencing in air pollution mapping do not involve proximity determination of users dynamically [19].

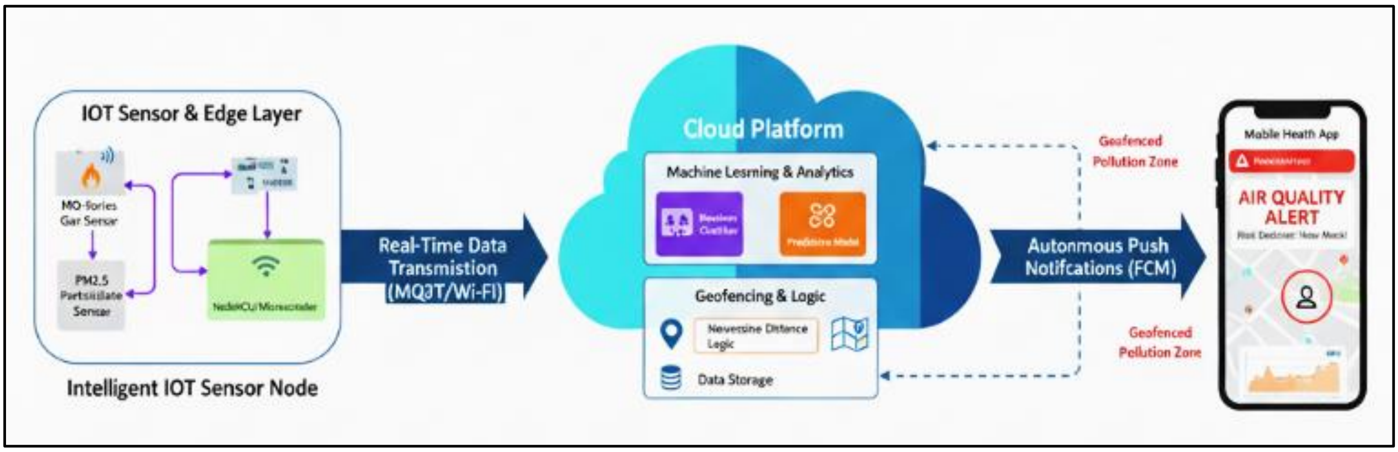

Fig 6 Integrated Architectural Framework of the Proposed Intelligent Geo Fenced Air Quality Monitoring System, Synthesizing IoT Sensing, Hybrid ML/Deep Learning Analytics, and Autonomous Location-Based Health Interventions

➢ *Comparative Analysis of Existing AQI Monitoring Systems*

Table 1 Comparative Analysis of Existing AQI Monitoring Systems

Study	Sensors Used	ML Technique	AQI Prediction	Geo fencing	Health Alerts
Author A (2021)	PM2.5	SVM	No	No	No
Author B (2022)	MQ Series	RF	Yes	No	Yes
Author C (2023)	PM2.5 + CO	LSTM	Yes	No	No
Proposed System	MQ-135 + PM2.5	RF + LSTM	**Yes**	**Yes**	**Yes**

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III. METHODOLOGY

The proposed Intelligent Geo fenced Air Quality Monitor System is conceptualized and developed as a multi-level system that uses IoT technologies for sensor implementation, cloud computing for analysis, GPS-enabled geofencing, and autonomous mobile notification mechanisms [3][4][7][14]. The system design of the project allows for monitoring of air quality 24/7 through the use of distributed sensors that enable the collection and upload of data to the cloud servers [4][11].

Machine learning algorithms used in analytics improve the decision-making power of the system via predictive analysis and classification of air pollution levels. Combination of the Random Forest algorithm and the predictive model using LSTMs helps in precise estimation of the present and future air pollution levels [5][6][15].

Moreover, geofencing using GPS technology adds an important feature of identifying user proximity to polluted areas, thus sending personalized warnings within set safety limits [8][17]. Finally, incorporating Firebase Cloud Messaging ensures that warnings are sent instantly to the user through mobile communication platforms, thus providing real-time interventions in healthcare [9][23].

With the integration of IoT sensor capabilities, intelligent data analysis, geographical awareness, and notification services on the mobile platform, the proposed approach represents a scalable and proactive method for air quality and public health protection systems [14][21][25].

- *Overall System Design and Workflow*

The proposed design for the Intelligent Geo fenced Air Quality Monitoring System has been conceptualized as an elaborate framework comprising IoT sensing, cloud analysis, GPS geofencing, and mobile alerts [3][4][14]. The proposed system architecture allows for constant air quality monitoring through the use of environmental sensing nodes that can relay data from cloud servers for analysis [11][23]. Analytics with machine learning algorithms can further improve the efficiency of decision-making by providing the capability to forecast the tendencies of pollution as well as health hazards [6][15]. The deployment of GPS geofencing technology makes the function of notifications location aware by able to detect the user's presence within the area with high levels of pollution [8][17]. For the efficient dissemination of alerts, cloud messaging services like Firebase Cloud Messaging are used in this system to have real-time communication between the server and the mobile clients [9]. In this way, the system allows for scalable, intelligent, and responsive air quality monitoring, which is suitable for smart city implementation as well as health protection [21][24].

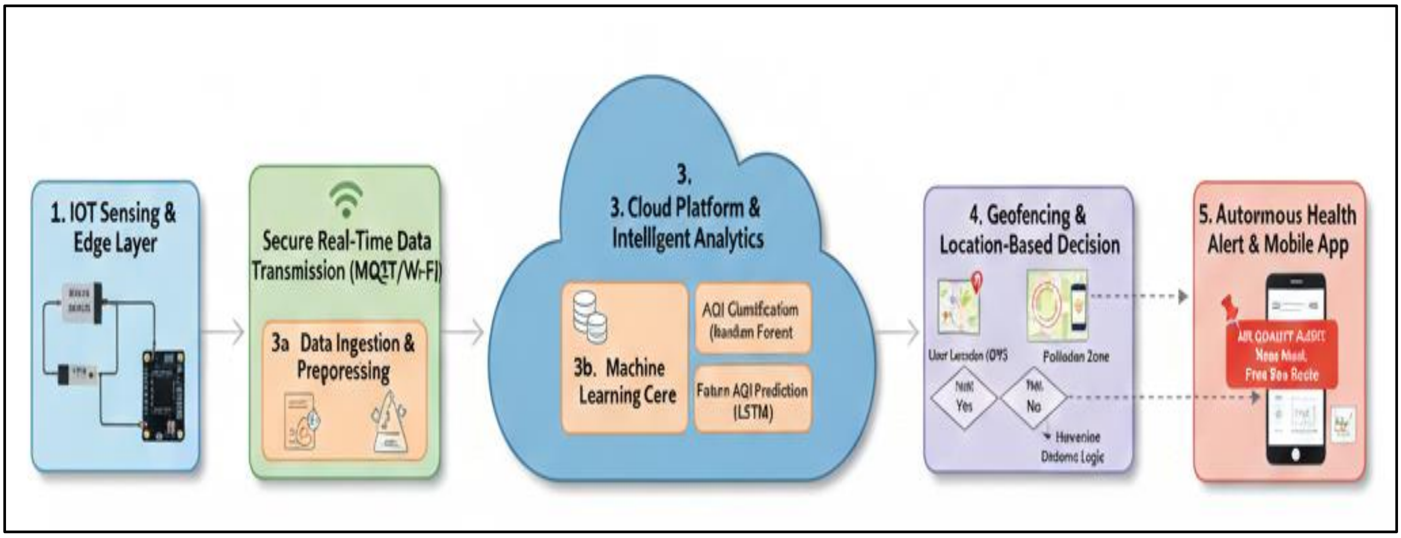

Fig 7 Comprehensive Methodological Workflow of the Proposed Intelligent System, Demonstrating the Sequential Integration of IoT Data Acquisition, Machine Learning Analytics, Geofencing Evaluation, and Autonomous Notification Dissemination.

- *Sensing and Data Acquisition Layer*

The sensing layer deals with real-time measurement of the parameters of the quality of the ambient air. MQ-135 sensors are employed for the measurement of general air pollutants such as ammonia, benzene, and smoke, whereas the PM2.5 sensor measures the concentration of fine particles of the air matter, which reveals the most important information related to the threat of respiration damage [1][2]. They are then linked with Node MCU (ESP8266) or an Arduino microcontroller. It works as an edge computing module that can deal with the real-time measurement of the data with low power consumption [3][4]. The microcontrollers are responsible for sampling sensor information and undertaking basic signal stabilization to suppress noise levels in measurement values just before transmitting to the cloud layer [11][20]. Such pre-processing at the edge increases system efficiency due to improvements in reliability and suppression of unwanted communication costs [16].

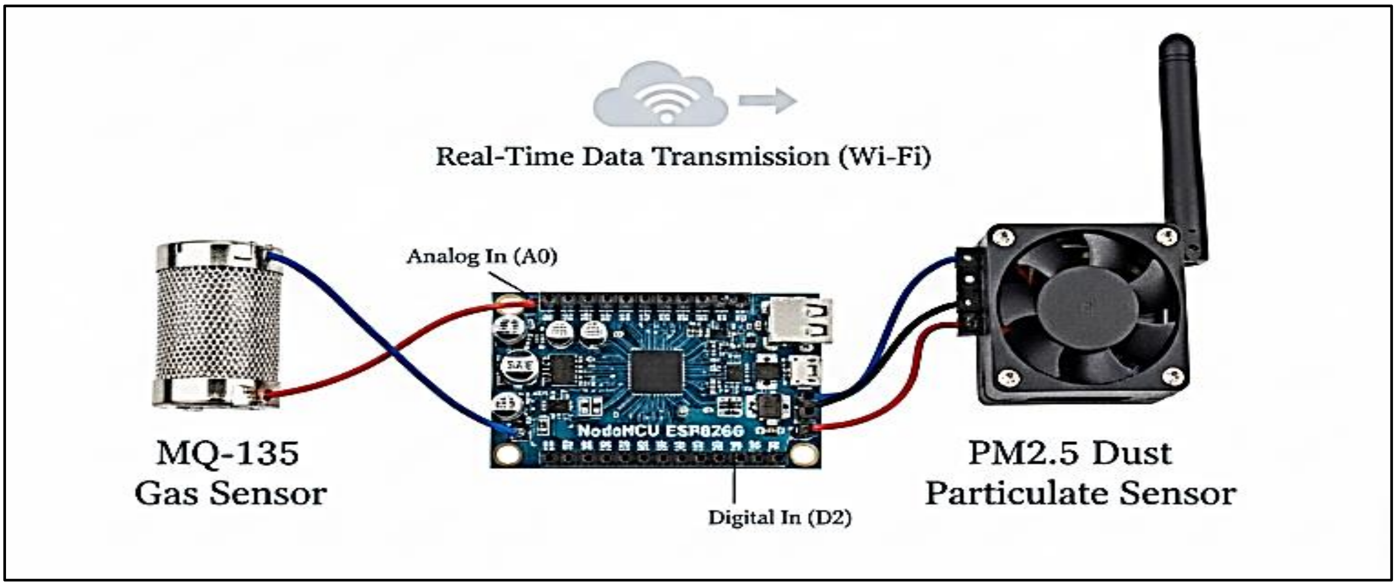

Fig 8 Hardware Architecture of the IoT-Based Air Quality Sensing Layer, Showcasing the Integration of MQ-135 and PM2.5 Sensors with the Node MCU (ESP8266) for Real-Time Data Acquisition.

The sampling is done at fixed time intervals for consistency across time. The gathered data involves values of pollutant concentrations, time, and sensor identifier.

➢ *Data Transmission and Cloud Infrastructure*

The sensor data are wirelessly communicated to a cloud platform via MQTT protocol. This was selected considering its low communication overhead and efficiency of power consumption [23][9][3]. MQTT protocol supports a reliable streaming of data in real time even with a low bandwidth. This makes it ideal even in large IoT networks. The cloud infrastructure acts as a centralized data repository/processing platform where the incoming data flows from the sensors can be stored, processed, and analysed [4][14]. The scalability of data handling, real-time analytics, including system interoperability, can be achieved with platforms such as Firebase, AWS-IoT platforms, Thing Speak platforms [9][14], thereby handling the sensor data flows efficiently.

➢ *Data Pre-Processing and Feature Engineering*

Raw data tends to be noisy because of environmental variations and sensor drifts. Hence, to analyze using machine learning techniques, certain pre-processing is carried out [10][11]. This involves removing noise and smoothing the data, missing values handling, normalizing the sensor data values, aligning multi sensor data with time [13][15], and then creating new features like moving averages, pollutant variation rates, time trends [18].

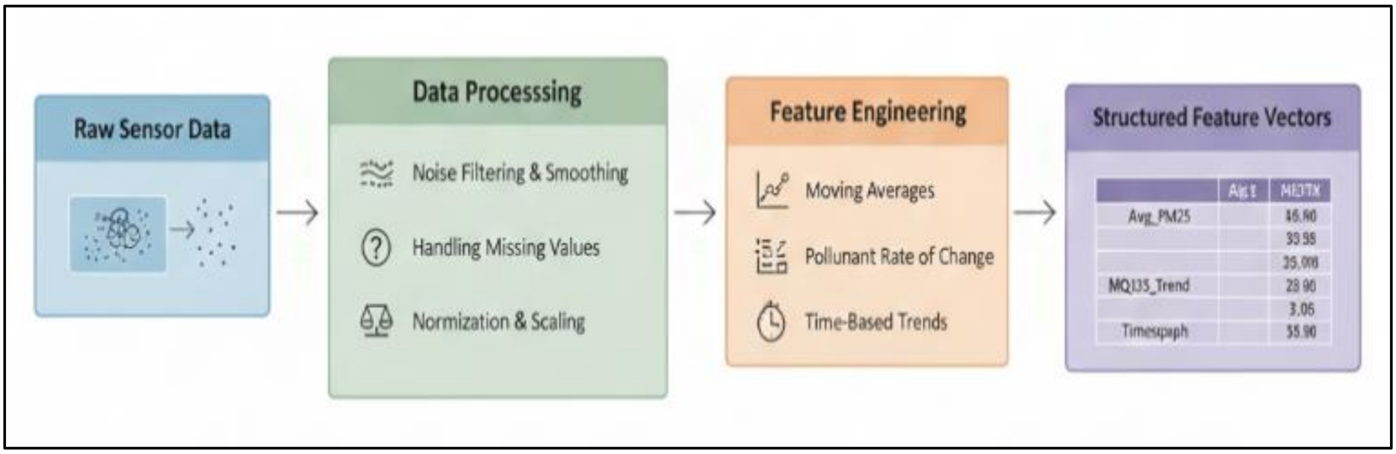

Fig 9 Schematic Representation of the Data Pre-processing and Feature Engineering Pipeline, Illustrating the Transformation of Raw Multi-Sensor Inputs into Structured Feature Vectors.

➢ *AQI Classification Using Random Forest*

For real-time air quality conditions assessment, a Random Forest classifier is employed. The classifier performs the mapping of extracted features to AQI categories like Safe, Moderate, and Unhealthy [5][13]. Random Forest models are preferred since they are ensemble learning, which prevents overfitting, and can handle nonlinear relationships in high-dimensional environmental datasets [5][13]. The workflow of the classification process is depicted in Figure 10.

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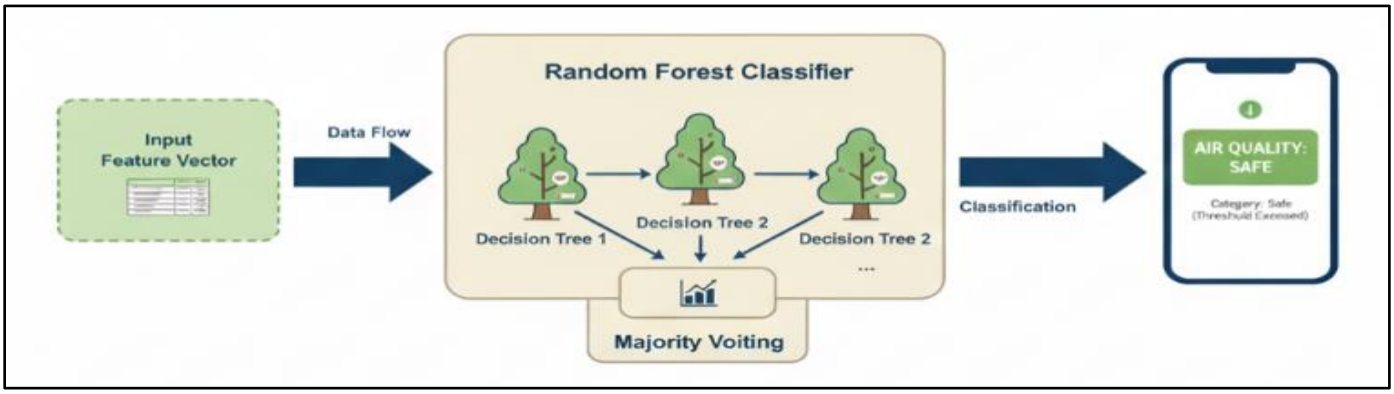

Fig 10 Architectural Flow of the Random Forest–Based AQI Classification Model, Showcasing the Ensemble Learning Process Through Multiple Decision Trees and Majority Voting for Category Mapping.

The output AQI category serves as a trigger for further predictive analysis and alert generation.

➢ *Time Series AQI Forecasting Using LSTM*

For proactive health intervention, the system uses the Long Short-Term Memory (LSTM) neural network approach for forecasting the AQI levels [6][15]. The LSTM approach has the capability to learn the past time-series data to understand.

The patterns of air quality, which are essential in predicting air quality levels [6]. Figure 11 above illustrates how LSTM-based AQI prediction models analyze sequential sensor readings to predict the trend of air pollution in the future to allow for early warning of dangerous situations [15].

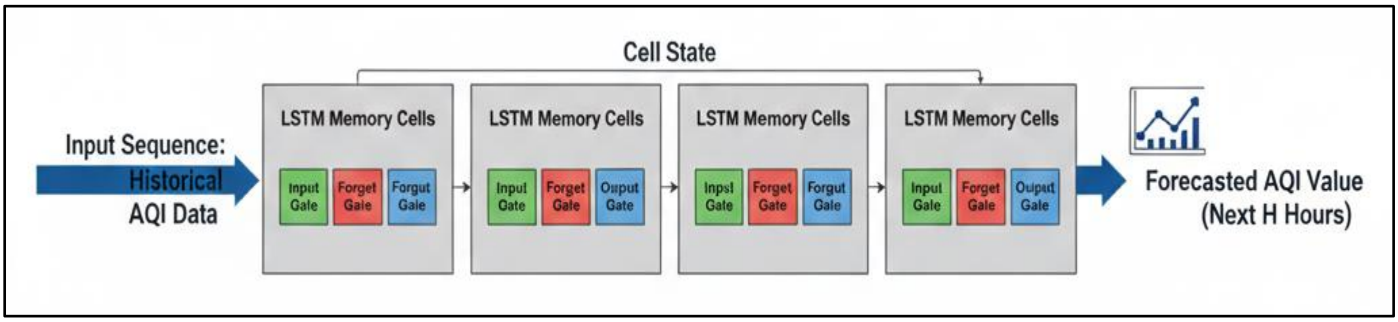

Fig 11 Architectural Framework of the LSTM-Based Time-Series AQI Prediction Model, Illustrating the Interaction of Input, Forget, and Output Gates for Capturing Temporal Pollution Dependencies

A conceptual comparison between actual and predicted AQI values over time is shown in Figure 12.

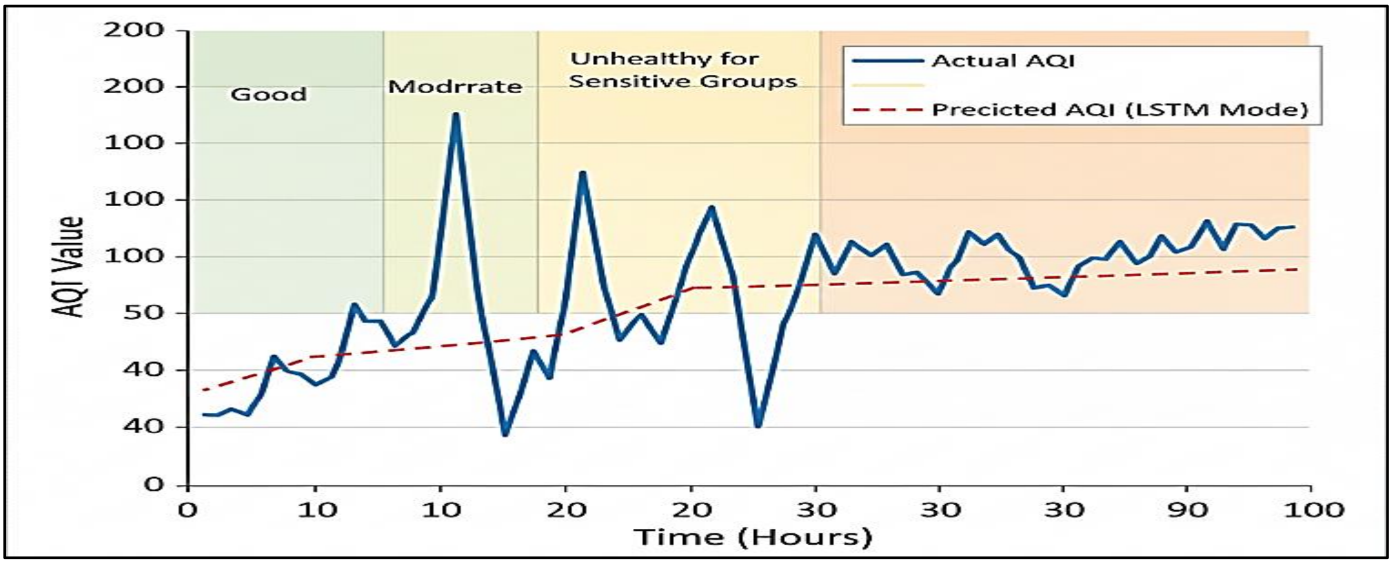

Fig 12 Comparison Graph of Actual vs. Predicted AQI Trends, Demonstrating the Model's Forecasting Accuracy and Temporal Alignment across the Evaluation Period.

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➤ *GPS-Based Geofencing and Distance Computation*

The location-aware component of the system depends on GPS coordinates coming from both sensor nodes and user mobile devices. A virtual geo fence is established around polluted regions using predefined spatial boundaries coming from geographic coordinates. The Haversine formula is used to calculate the great-circle distance between the user and the pollution source:

$$D=2r\sin^{-1}\left(\sqrt{\sin^2\left(\frac{lat_2-lat_1}{2}\right)+\cos(\mathrm{lat}_1)\cos(\mathrm{lat}_2)\sin^2\left(\frac{lon_2-lon_1}{2}\right)}\right)$$

Enabling correct proximity calculation [8][17]. If the calculated distance is smaller than the specified geo fence boundary, then the user is identified as being in danger and relevant notifications are triggered.

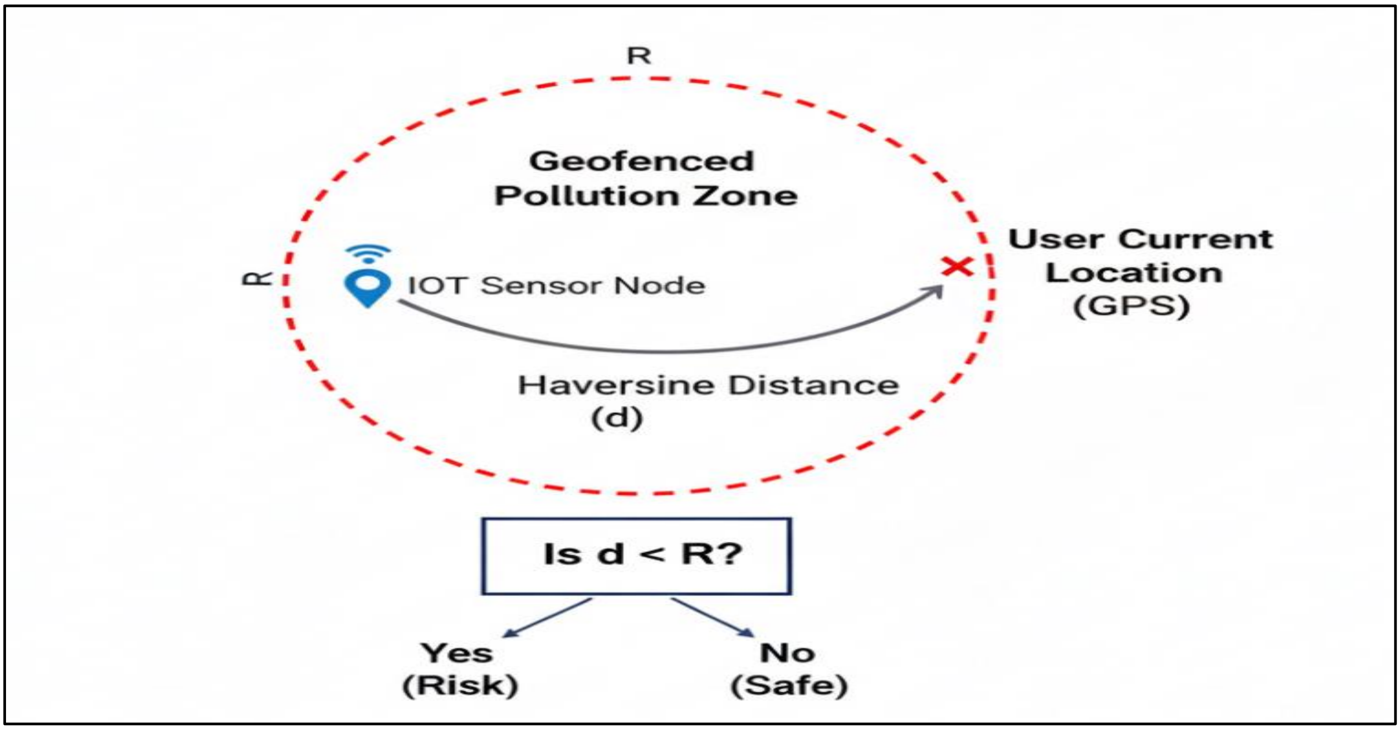

Fig 13 Spatial Mapping of the GPS-Based Geofencing Mechanism, Illustrating User Proximity Detection and the Calculation of Great-Circle Distance Relative to Polluted Zones.

➤ *Algorithm for Intelligent AQI Monitoring and Alert Generation*

- *Input*:

✓ Real-time sensor data from MQ-135 and PM2.5 sensors
✓ GPS coordinates of sensor nodes and mobile users

- *Output*:

✓ AQI classification label Predicted AQI value Location-based health alert
✓ Initialize IoT sensor nodes and establish cloud connectivity [3,4]
✓ While system is active do
✓ Acquire real-time pollutant data from MQ-135 and PM2.5 sensors [3,4]
✓ Perform data pre-processing:

▪ Noise filtering
▪ Normalization
▪ Missing value handling [10,11]

✓ Extract relevant features from pre-processed data
✓ Classify current AQI level using Random Forest classifier [5,13]
✓ Predict future AQI values using LSTM time-series model [6,15]
✓ Acquire GPS coordinates of users and sensor nodes [7,8]
✓ Compute distance using Haversine formula [17]
✓ If (user distance ≤ geo fence radius) AND (AQI ≥ threshold) then
✓ Trigger health alert via Firebase Cloud Messaging (FCM) [9]
✓ End If
✓ Store sensor readings, predictions, and alert logs in cloud database [4,14]
✓ End While

➤ *Alert Generation and Autonomous Health Intervention*

When the air quality index has been categorized as hazardous or exceeds the threshold level of safety, the system automatically produces health alerts [21][22]. The Firebase Cloud Messaging (FCM) service allows the system to relay push notifications in real-time [9].

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- *Alerts Include:*

✓ Health pointers that are contextual, such as:
✓ Use of protective masks
✓ Avoiding outdoor activities
✓ Moving from polluted areas
✓ Figure 14: Alert Delivery Mechanism

The alert delivery mechanism is demonstrated in Figure 14 and is based on typical mobile health notification systems [19][25].

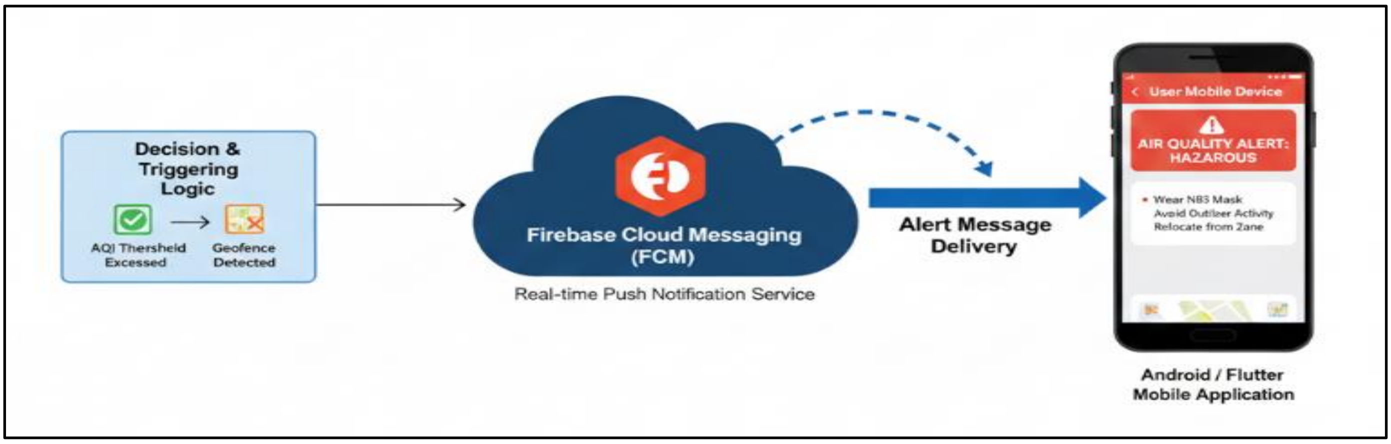

Fig 14 Cloud-to-Mobile Alert Dissemination Framework, Illustrating the Triggering of Context-Aware Health Notifications (FCM) Through the End-User's Mobile Application.

➢ *Visualization and User Interface*

For increasing user awareness, the mobile application uses Google Maps API or Mapbox services to display pollution hotspots and geo fenced risk zones [7][14]. Users can see their current location with reference to polluted zones; this is an important factor in increasing user awareness [8][17].

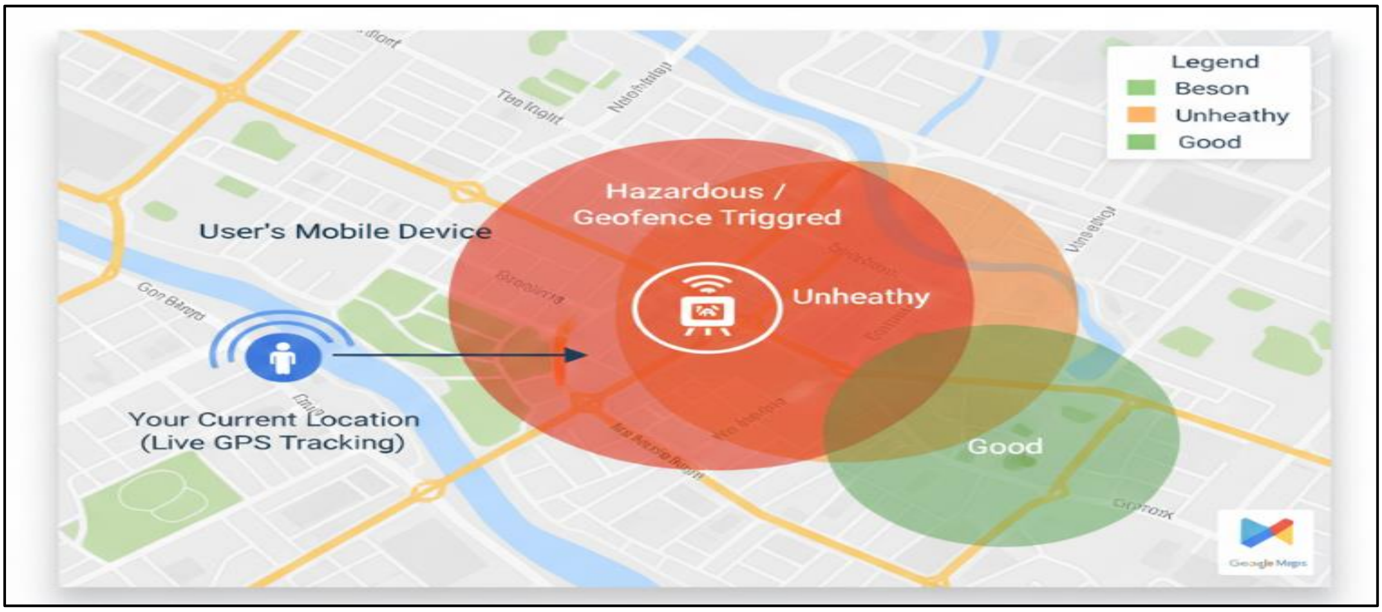

Fig 15 Map-Based Visualization Interface, Demonstrating the Integration of Geospatial APIs for Real-Time Tracking of Pollution Hotspots and Geo Fenced Risk Zones.

➢ *Mathematical Modelling*

AQI Classifications Functions (Random Forest):

$$\text{AQI}_{\text{class}} = \arg \max_{c} \sum_{i=0}^{n} T_{\text{i}}(x)$$

Where T_{i} represents the decision of the i^{th} tree.

LSTM-Based AQI Prediction:

$$\text{AQI}_{t+1} = f\ \text{LSTM}(\text{AQI}_{t-n+1}, \text{AQI}_{t-n+2}, \ldots, \text{AQIt})$$

Geofensing Distance (Haversine):

$$d = 2r \sin^{-1}$$

$$\left(\sqrt{\sin^2\left(\frac{lat_2 - lat_1}{2}\right) + \cos(\text{lat}_1)\cos(\text{lat}_2)\sin^2\left(\frac{lon_2 - lon_1}{2}\right)}\right)$$

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Where

- D = distance between two geographical points
- R = radius of the Earth
- Lat_1, lat_2 = latitudes of two locations
- Lon_1, lon_2= longitudes of two locations

IV. RESULT AND DISCUSSION

Table 2 AQI Classification Performance

Model	Accuracy (%)	Precision	Recall	F1-score
Decision Tree	85.2	0.84	0.83	0.83
SVM	91.3	0.90	0.91	0.90
Random Forest	**94.8**	**0.95**	**0.94**	**0.94**

Table 3 AQI Prediction Error

Model	MAE	RMSE
ARIMA	14.6	18.9
Linear Regression	12.1	15.4
LSTM	**6.3**	**8.1**

V. FUTURE DIRECTIONS

The proposed Intelligent Geo fenced Air Quality Monitoring System establishes a robust foundation in real-time AQI detection, predictive analytics, and autonomous location-based health intervention. Building upon the present system design and experimental outcomes, a few potential areas of future research are identified to further improve system intelligence, scalability, and relevance to society.

- *Expansion of Sensing Capabilities*

Future research activities can include the expansion of the sensor layer by incorporating other pollutant and environmental sensors, such as the ones corresponding to the following pollutants/parameters: nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), temperature, and humidity. These sensors will increase the accuracy of AQI measurements and, in turn, enhance health risk analysis.

- *Adoption of Advanced and Hybrid Machine Learning Models*

Even though the performance of the Random Forest model and the LSTM model is quite robust, in the future, one can explore other architectures that involve hybrid learning and deep learning techniques such as CNN-LSTM networks, time series prediction using the Transformer architecture, and ensemble learning techniques. This will help in predicting the patterns of pollutant diffusion in the spatial-temporal domain in a more accurate manner using the distributed sensors.

- *Edge Computing and Distributed Intelligence*

In the future, edge computing techniques could be used in these systems to reduce dependence on cloud infrastructures and latency. Usage of lightweight machine learning inferences on microcontrollers or edge devices like ESP32 or Raspberry Pi for deployment would facilitate quicker decision-making without disturbance when the network is interrupted, hence improving the reliability of the system in field deployments.

- *Large Scale and Smart City Integration*

One major future direction that needs to be addressed is the scaling of the system to be implemented at the level of cities. Implementation of the system with smart city platforms, traffic management systems, and public health dashboards can facilitate the monitoring management of the environment by the concerned authority by providing environmental analysis at an aggregated level of air quality indices.

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➢ *Customized and Context-Aware Health Advisory Services*

Such research in the future may be directed toward delivery of personalized health recommendations based on individual exposure patterns, location history, and vulnerability factors. Adaptive alert mechanisms could be developed using reinforcement learning to dynamically adapt the notifications and preventive guidance in order to more effectively engage users and improve their health outcomes.

➢ *Integration with Healthcare and Wearable Systems*

The system could also be improved by making use of wearable health technologies and digital health platforms. It would be possible to raise an alarm for health dangers posed by air pollution by correlating the data on AQI exposure with physiological data like respiration rate and oxygen saturation levels.

➢ *Long-Term Environmental Analytics & Policy Support*

Data produced on AQI on a longitudinal basis by the system could be used to analyze long-term trends and predict policies with respect to the environment. All this could help to assist researchers and policymakers in understanding pollution and effects of climate change.

VI. CONCLUSION

The research essay covered an Intelligent Geo fenced Air Quality Monitoring System by merging IoT Environmental Systems, ML Analysis, GPS geofencing, and AH Mobile Intervention to successfully meet the rising issues posed by air pollution in urban settings. The essay utilized low-cost sensors like MQ-135 and PM2.5 modules connected to a Node MCU and Arduino to perform a continued and real-time capture of air quality data with even granular data points in space.

The inclusion of machine learning models greatly boosts analytical intelligence over traditional monitoring methods. The Random Forest Classifier offers accurate real-time classification of air quality status itself, whereas the time series prediction model using the LSTM network successfully extracts the dynamics of the variations exhibited by the pollution level over time to predict the trends of the AQI status for the coming periods.

A critical strength of the proposed framework is its intelligence that is location-aware. GPS geofencing and Haversine distance calculations allow the system to dynamically identify user presence in polluted regions. Moreover, Firebase Messaging ensures that messages are delivered instantly with no delay in applications running in the background. More specifically, this functionality is used in sending personalized health messages.

Experimental analysis results prove that the proposed solution can be scaled, have low energy costs, and be economically viable to implement and integrate within large-scale smart city environments. In contrast to the installed air quality monitoring infrastructure, the solution breaks the boundaries of passive observation and begins to engage and predict in addition to observing and responding to information. In summary, the proposed Intelligent Geo fenced Air Quality Monitoring System provides a comprehensive and feasible platform geared towards effective living environment surveillance and health preservation in real time. The integration of IOT sensing, machine learning algorithms, geo-intelligence, and mobile communications in a novel architecture represents an integral addition to innovative advancements in smart living environment surveillance systems in this research. Despite its efficiency, it should be noted that its efficacy relies on sensor calibration precision and density within a local setting, which may be rectified in future deployments of a similar scope.

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