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IoT-ENABLED SMART AIR MONITORING SYSTEM FOR REAL-TIME SMOG DETECTION AND POLLUTION MITIGATION

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Abstract
Climate action, part of the Sustainable Development Goals (SDGs), targets solutions to combat climate change and its impacts. Urban air pollution and smog, as the prevalent threat to environmental sustainability and human health, have emerged due to rapid industrialization, vehicular emissions, and unrestrained urban growth. Prolonged exposure to air pollutants such as PM2.5, PM10, C, and NOx have been correlated directly with rising incidents of respiratory diseases, cardiovascular diseases, and diminution of life expectancy. Traditional static air quality monitoring systems are costly, have sparse spatial distributions, and provide no support for real-time decision-making systems. In response to the above limitations, this work intends to propose a novel IoT-based smart weather monitoring system for real-time smog detection and pollution mitigation. The system collects environmental and gas data using low-cost sensors. This data is analyzed using a fuzzy inference system (FIS), which applies predefined weather forecasting rules based on Air Quality Index (AQI)standards to support decision-making regarding smog levels. An IoT circuit connected to a mobile application enables real-time monitoring, classification, and visualization of smog levels. Laboratory testing under controlled conditions demonstrated that the system can reliably assess harmful gases and in real time to predict smog levels and issue timely alerts for mitigation actions. Affordable, scalable, and adaptable, the solution is ideal for deployment in low-resource urban environments. By combining real-time data collection, intelligent analysis, and a user-friendly design, it supports sustainable urban resilience and healthier living conditions.

1. Introduction

Pollution and smog have become significant threats to environmental health and human well-being in fast-growing urban settings. The problems result from rapid industrialization, uncontrolled development, vehicle emissions, and deforestation, among other things. Such factors keep increasing without considering sustainable human environmental practices. Over 99% of the human population in the world is breathing air that surpasses safety standards, according to the World Health Organization. This eventually expands the pollution-related diseases and premature deaths across the globe [1]. Such solid pollution makes a place like Lahore, Karachi, etc., frequently cross the limits for national standards, thus calling for an immediate action towards a sustainable monitoring and mitigation strategy [2]. Traditional air quality monitoring methods are based on static and centralized infrastructures, making them expensive, sparse, and inaccessible for capturing real-time dynamic changes in the environment [3].

The smog and pollution in the air do more than annoy a person temporarily: they cause considerable damage to the quality of life in cities and, in the long term, threaten sustainability. Exposure over a long period to PM2.5 and PM10 kinds of pollutants is known to increase the incidence rate of asthma, bronchitis, cardiovascular problems, and lower life expectancy [4]. Such pollutants also damage infrastructure and visibility and therefore affect the safety of transport while increasing the already stretched budgets of city maintenance [5].Urban agriculture and biodiversity are also subjected to negative effects, whereby the air pollution leads to plant growth, composition of the soil, and stability in the ecosystem [6].Vulnerable groups like children, elderly persons, and people with chronic illnesses suffer most under such conditions, further widening social inequalities associated with environmental degradation [7].

Air pollution directly impinges on health, while it turns into an indirect charge on people with regard to its cost in health services, increases energy consumption due to increased demand for air filtration, and reduces economic productivity, thereby hindering progress toward goal number 7 of sustainable development. The situation becomes much worse in highly populated areas, where often outdated or incomplete information stands in the way of timely and effective decision-making. Severe seasons with thick smog interruption of daily activity and school closures and restricts the transport in climate-sensitive regions, especially in South Asia [8]. Experts have stressed on the need for smarter and more intelligent solutions working in real-time and adapting rapidly to these dynamic urban systems [9]. Air quality monitoring now forms an important requirement for sustainable urban resilience compared to luxury.

Previous research has been instrumental in promoting the development of intelligent air quality monitoring systems. There is evidence that IoT-based networks will eventually cover environmental sensing to enable real-time monitoring of large areas [9]. Machine learning (ML) algorithms have also been applied to these data streams for identifying pollution trends and predicting smog-wrought events accurately [4]. Fuzzy inference systems (FISs) have been developed to handle this uncertainty in data by enabling human-like reasoning under conditions of ambiguity [10]. Structural measures, such as anti-smog towers and air purification systems, have appeared to treat local pollution levels and act as a data collection point at the same time [6]. Their major weakness is the lack of integration of those technologies into a single, sustainable, and real-time decision-support system. Although many researchers proposed solution for weather forecasting however given research gaps are major research motivations of proposed system.

·Minimizing the factors contributing to climate change and minimizing its effects is necessary to ensure that the world remains suitable for all living beings in the long run. Therefore, climate change in one of the Sustainable Development Goals (SDGs)
Research regarding the causes of climate change and the impact of smog is one of the critical issues that, over time, can severely damage the climate.

·Prior systems proposed weather monitoring frameworks, but they often ignored the smog variable. Given the prevalence of smog in certain regions, its accurate forecasting has become important.

There is a great demand for easy to use, regionally available software program to enable the public, especially those with limited understanding about smog and preventative measures, to receive timely information about smog and the need to adjust their behaviors during high concentration periods.

Proposed research aims to close this gap with the development of a robust intelligent system able to sense and predict pollution while also supporting mitigation with intelligent analysis, thus leading to more sustainable urban life and a healthier environment. The system includes real-time sniffing of the IoT sensors, fuzzy logic predictive analysis. It includes monitoring of PM2.5, PM10, NOx, CO2, humidity, and temperature and then processing and forecasting of smog level with advice for mitigating it on a user-friendly dashboard. The solution is cost-effective and scalable, and intelligent decisions are integrated; thus, it will contribute to the more extensive benefits of sustainable urban development.

2. Literature Review

This paper provides a concentrated overview of the most important contributions to smart and scalable systems using the latest technologies, including Internet of Things (IoT), fuzzy logic, and machine learning. We also summarize the strengths, weaknesses, and future directions of these contributions. An IoT-based hybrid real-time air-quality monitoring system has been developed by Dutta et al. (2020) using fuzzy inference to accommodate uncertainties in sensor data [2]. This framework has the required flexibility to make decisions during varying environmental conditions and proved useful in interpreting incomplete data, even more reliable than threshold-based monitoring systems while lacking capabilities of prediction since fuzzy logic does not model temporal trends. In the future editions of the research, the authors envisaged integrating machine learning to give predictive intelligence to their fuzzy rule engine.

The cloud-IOT integrating monitoring system by Jamil et al. for centralized real time air quality information delivery is ideally developed through smart sensor networks [3]. This scheme comprised high-resolution data at the disposal of users and advanced portability and transparency. Although the addition of the capabilities of the model has included high data collection, analysis, and even greater value additions in forecast, it fails to address it. The subject authors suggested intelligent processing for data analytics methods like anomaly detection or ML algorithms to be included to provide actionable intelligence from these data collection.

Zhang et al. described an integrated IoT-and-ML framework, capable of supervised learning by means of Random Forest and Support Vector Machines for real-time smog prediction [4]. Their system predicted fog events and gave warnings to the public in a timely manner. Although it was an efficient tool where datasets were clean, its capability reduced dramatically under circumstances of incomplete or inconsistent sensor data. The authors considered a need to bring uncertainty into account, possibly through fuzzy logic, for future hybrid models.

Stanaszek-Tomal (2021) examined anti-smog towers as architectural solutions for local pollution control in urban regions [5]. These towers are an infrastructural relief feature, physically filtering the air plus serving as real monitoring stations for immediate air. They are costly to build and have to be static installations, although they have significant impacts within a local area at a time. The study concluded that the aforementioned towers can be made more versatile and cheaper in the future by combining them with portable or even networked smart sensor systems.

Woźniak et al. (2020) dealt with EU-funded energy and air quality policies-global, subsidized infrastructure and less-than-honest states in Europe, which made public funding for smart monitoring technologies work faster against pollution [6]. That would bring out in the utensil very good findings for centralized policy support to better air quality with cleaner technologies and monitoring networks but would do so heavily in terms of political will and budgetary allocations. In the future, the authors proposed decentralized planning.

A comprehensive hybrid approach through fuzzy inference and machine learning was thus introduced by Singh and Kumar (2022), and is viewed as well suited for intelligent environmental monitoring [10]. With this system, uncertainty was handled while learning from past data, inevitably combining flexibility and precision. Indeed, its strong impact was countered by the tremendous amount of data and computing resources it required, making real time applications tricky in low resource settings. They suggested future research work should focus on optimizing the computational load and automated rule tuning.

Finally, the World Health Organization (2021) has provided global standards of air quality monitoring owing to the severity attached to the impacts of air pollution on global health, thus emphasizing the necessity for real-time as well as scalable monitoring solutions [1]. However, no implementation frameworks were outlined in those guidelines hence leaving much space for an ingenious work in creation of smart, localized systems. Their findings further emphasized the need for such low-cost, intelligent systems that could support both public health and urban planning.

From reviewed literature, one sees that there has been significant advancement in intelligent environmental monitoring systems. IoT provided scalable data collection; machine learning was applied to enhance prediction accuracy; and fuzzy logic was essential for sustaining the resilience of systems under uncertainty. Nevertheless, we lack a single solution providing a comprehensive, inexpensive, real-time, and adaptive framework that could otherwise be fully scalable and deployable in developing urban environments. In most cases, systems are either heavily tilted towards data acquisition or prediction and rarely demonstrate a balanced integration of both along with decision support and public engagement. In the work by Alsamhi et al. (2022), a deep learning-based CNN model was integrated with IoT gas sensors for predicting air pollution levels in real time. This method showcased robust performance in forecasting, particularly when trained on large, well-labeled datasets. However, the reliance on computational power and extensive preprocessing remained a challenge in resource-constrained settings [11]. Meanwhile, Alyasseri et al. (2021) proposed a hybrid fuzzy logic and block chain-based IoT framework for smart monitoring systems. The integration of block chain added a layer of security and trust, addressing concerns of data tampering in air quality systems. Though promising in terms of decentralization and integrity, the added latency and system complexity made it less suitable for time-critical applications [12]. *Table* 1 presents a summary of the references in the literature review.

Table 1: ***State of The Art Work***

Ref.	Methodology Used	Sensors	Features	Research Gap
[2]	IoT with Fuzzy Inference System	Environmental sensors	Flexibility under variable conditions; interprets incomplete data better than threshold systems	No prediction capability; doesn't model temporal trends
[3]	Cloud-IoT based real-time monitoring	Smart sensor n etworks	High-resolution data; centralized real-time info delivery; transparent and portable	Lacks predictive intelligence; no anomaly detection or ML for analytics
[4]	IoT and ML (Random Forest, SVM) for smog prediction	Air quality sens ors	Real-time smog predliction; ti mely public warnings	Low performance with noisy/incomplete data; lacks uncertainty modeling

[5]	Architectural anti-smog towers	Onboard monitoring sensors	Physical air purification; real-time local monitoring	Expensive; static installations; limited coverage
[6]	Policy-driven smart infrastructure funded by EU for air/energy monitoring	Varied smart environmental sensors	Accelerated smart tech deployment through centralized policies	Dependent on political will and budget; less decentralized planning
[7]	Deep Learning (CNN) with IoT for intelligent air quality prediction	Low-cost gas sensors	High prediction accuracy; real-time forecasting; scalable solution	Requires high computational resources; challenges in training on heterogeneous data
[8]	Fuzzy Logic+ Blockchain-integrated IoT framework	Air quality and gas sensors	Enhanced data security; decentralized system; real-time trustworthy air quality monitoring	Increased system complexity; high latency due to blockchain integration

3. Smart Smog Detection Approach

The proposed system is design to monitor air for presence of harmful smog causing factors and detect smog levels in order to mitigate its harmful effects. The proposed system is using IoT based circuit for real-time monitoring of smog factors and incorporate decision making with help of efficiently designed Fuzzy Inference system (FIS). There are two major components of proposed system.

1. Air Monitoring using IoT
2. Smog Detection using Fuzzy Inference System

The two parts are integrated via mobile application to provide easy GUI (graphical user interface). The app read real-time air factors (which are primary source of smog) and provide real-time input to internal FIS model. The internal FIS utilized its build-in rules to predict smog level and display them to user. The GUI also provides preventive measures and alerts. The block diagram of the proposed system architecture is shown in ***Figure*** 1.

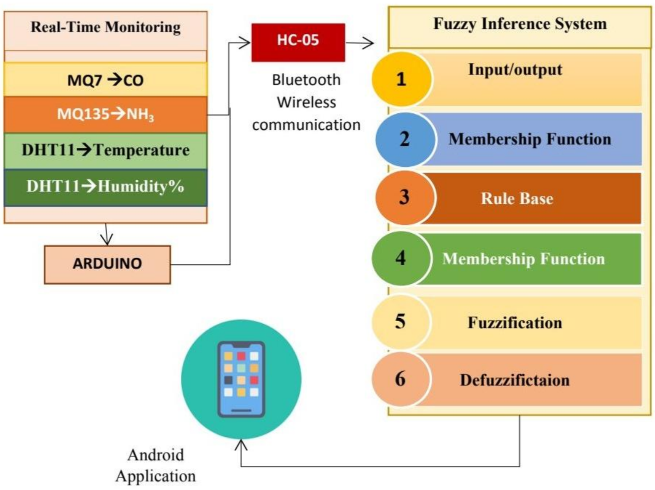

Figure 1. Framework of Proposed Methodology

3.1. Constructing IoT based Smog Detection Module

The system utilizes multiple gas and environmental sensors to monitor air pollutants and environmental factors. Each sensor was selected based on the sensitivity of its target gas, cost and reliability. The list of used sensor along with its description is listed below in ***Table*** 2.

Table 2: *Smog Detection IoT Module Components*

Used Sensor	Features	Figure
MQ-2 Sensor	MQ2 sensor can detect smoke, LPG(propane-butane), hydrogen (H2), and methane (CH4).The sensor has been included for monitoring smoke and flammable gases in the environment[21].	
MQ-7 Sensor	An MQ-7 sensor is used for denoting carbon monoxide (CO), which is a highly toxic air pollutant. It can function properly in the concentration range of 20-2000 ppm, being highly sensitive to CO at controlled heater voltages and timing cycles [20]	
MQ-135 Sensor	MQ-135 gas sensor is useful in the detection of a wide range of indoor air pollutants including ammonia (NH3), benzene(C_6H_6),alcohols, smoke, and carbon dioxide (CO2).This has been chosen for this system to monitor overall air quality and VOC (Volatile Organic Compounds) levels. It is also cost-effective and has a long operational lifespan [19]	
DHT11Sensor	It is a DHT11 sensor that senses environmental parameters, ie., temperature and relative humidity. These two parameters definitely influence the dispersion of gas and the accuracy of the sensors [22].	
Arduino Uno	The Arduino is a microcontroller board that interfaces with a large number of sensors. It is a simple very flexible board that can be applied in many solutions and different environments. It is power-efficient, and when used with expandable peripherals, this board can be achieved at a comparatively very low price [18].	
HC-05Bluetooth module	This low-cost HC-05 module is preferred over many other types due to small dimensions, easy availability, low power consumption, and stable working, besides easy pairing with compatible mobile devices or other microcontrollers and microprocessor platforms [23].	

3.2. Implemented IoT Circuit

The hardware employs an Arduino Uno R3 microcontroller, based on the ATmega328microcontroller, which allows real-time data acquisition from all sensor connections. The Arduino initially converts signals from analog to digital and does pre-processing. All this processed data is then relayed via Bluetooth module to an Android application for further processing and analysis. The IoT Module components explained above in ***Table*** 2 and final hardware IoT circuit setup is presented in ***Figure*** 2.

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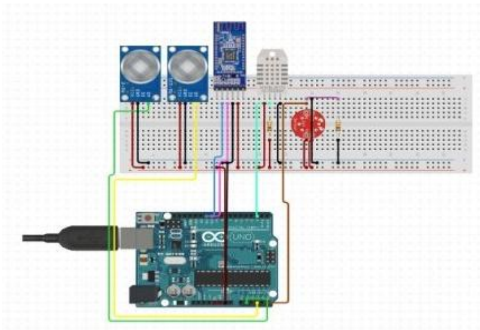

Figure 2. IoT Circuit Diagram

3.3. Fuzzy Logic Model Design

The real-time environmental sensor data were analyzed using fuzzy inference systems (FIS)and dynamically classified for air quality. As a type of soft computing technique, fuzzy logic aims at imprecise, vague, or incomplete reasoning. Thus, to a certain extent, allowing membership in multiple sets is a better representative of the environmental conditions than stark binary classifications. Fuzzy logic, therefore, finds its relevance in atmospheric monitoring due to, on the one hand, the nonlinear behavior of the interaction of pollutants and, on the other, and the uncertainty associated with low-cost sensor outputs. In effect, it mimics human decision-making under uncertainty by assigning the gas concentration and environmental parameters into linguistic categories: good, moderate, and high. The fuzzy inference system composed of three main layers, shown in ***Figure*** 3.

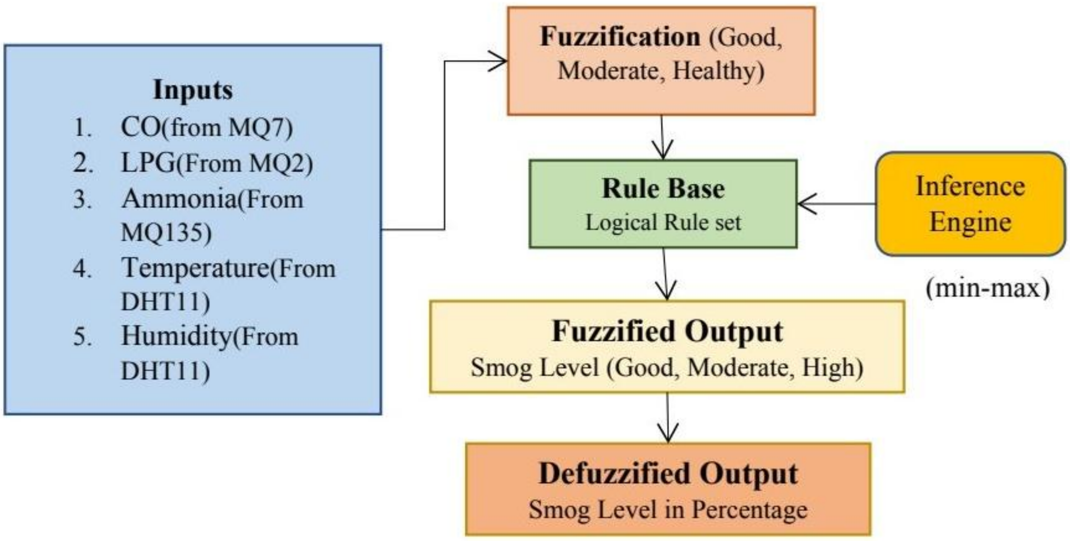

Figure 3. Fuzzy Inference Mechanism

1. **Fuzzification Layer**

First layer of proposed FIS converts crisp numerical sensor values into fuzzy linguistic variables using membership functions (MFs). Triangular membership functions (trimf) are used, defined in *Equation* 1.

$$\mu A(X)=\left\{\begin{array}{lll} \frac{x-a}{\frac{c-x}{c-b}} a^{0x\le a} \le b & & \\ \frac{c-x}{c-b} & a<x\le b & \\ \frac{c-b}{c} & 0 & x\le c \end{array}\right]$$

Where a, b, and c are parameters defining the shape of the triangle, and μA(X) is the degree of membership of x in the fuzzy set A.

2.Inference Engine

The next part of proposed FIS is inference engine, which play crucial part in decision making as all inference rules are part of this engine. The proposed fuzzy inference process uses Mamdani-type rules, which are of the form given in *Equation* 2.

$$IF A_1 AND A_2 AND \ldots\ldots A_n \boldsymbol{THEN\ B} \quad (2)$$

Where A_1 are fuzzy input terms (e.g., "CO is Unhealthy") and B is a fuzzy output (e.g., "Weather is Unhealthy"). Example rules of proposed system are given in ***Table*** 3.

Table 3: *Fuzzy Rules of System*

Rule No	Rule
1	IF CO IS good AND LPG IS safe AND Ammonia IS safe AND Temperature IS comfortable AND Humidity IS healthy THEN Smog Level IS good
2	IF CO IS moderate OR LPG IS moderate OR Ammonia IS high THEN Smog Level IS moder ate
3	IF CO IS unhealthy OR LPG IS dangerous OR Temperature IS uncomfortable OR Humidity IS unhealthy THEN Smog Level IS unhealthy

3.Defuzzification Layer

The final fuzzy output set is converted into a crisp value using the centroid method, defined as shown in *Equation 3*.

$$Z^* = \frac{\int z \cdot \mu B(z)dz}{\int \mu B(z)dz} \quad (3)$$

Where z* is the defuzzified output and μB(z) is the membership function of the output set B. The output value (0-100) is interpreted into qualitative categories:

- 0-30: **Clean**
- 31-70: **Moderate**
- 71-100: **Unhealthy**

This fuzzy-based classification ensures resilience to sensor noise, adaptability to different environmental conditions, and interpretability of results. Real-time sensor values are passed through this inference engine via a mobile application, offering users dynamic, and clear air quality assessments without requiring cloud-based processing.

3.4. Building and Deploying the Fuzzy Logic Model

The Proposed smog prediction system is based on FIS, which we deign and implemented in python using its native library scikit-fuzzy. The FIS follow given algorithm for its implementation in python.

1. START
2. DEFINE input variables of system i.e.CO, LPG, Ammonia, Temperature, and Humidity.
3. DEFINE output variable i.e. Smog Level (θ to 100%)
4. DEFINE membership functions for each input variable and output variable
5.DEFINE fuzzy rules:
6.Input Real-Time current sensor readings:
- Read values for CO, LPG, Ammonia, Temperature, Humidity
7.APPLY Fuzzification:
- Map crisp inputs into fuzzy sets using membership functions
8.APPLY inference:
- Evaluate all rules based on fuzzy inputs
- Combine results using fuzzy logic (e.g., max-min or weighted average)
9. APPLY Defuzzification:
- Convert fuzzy output set (SmogLevel) into crisp output value
10. DISPLAY result:
- Output SmogLevel percentage and corresponding Label (good, Moderate, High)
11. END

We define five input variable and one output variable in proposed FIS. The input variables are CO, LPG, ammonia, temperature and Humidity and output variable is smog. The membership function of proposed system with numerical ranges are listed in ***Table*** 4. The membership function graph of proposed FIS shown in ***Figure*** 4.

Table 4: *Fuzzy Input and output Variables and Membership Categories*

Variable	Type	Linguistic Terms	Range/Unit
Smoke	Input	Good, Moderate, Unhealthy	0-500 µg/m3
CO	Input	Good, Moderate, Unhealthy	0-50 ppm
H2	Input	Safe, High	0-500 ppm
LPG	Input	Safe, Moderate, Dangerous	0-10,000 ppm
Temperature	Input	Comfortable, Uncomfortable	0-50℃
Humidity	Input	Healthy, Unhealthy	0-100%RH
Weather Status	Output	Clean, Moderate, Unhealthy	0-100

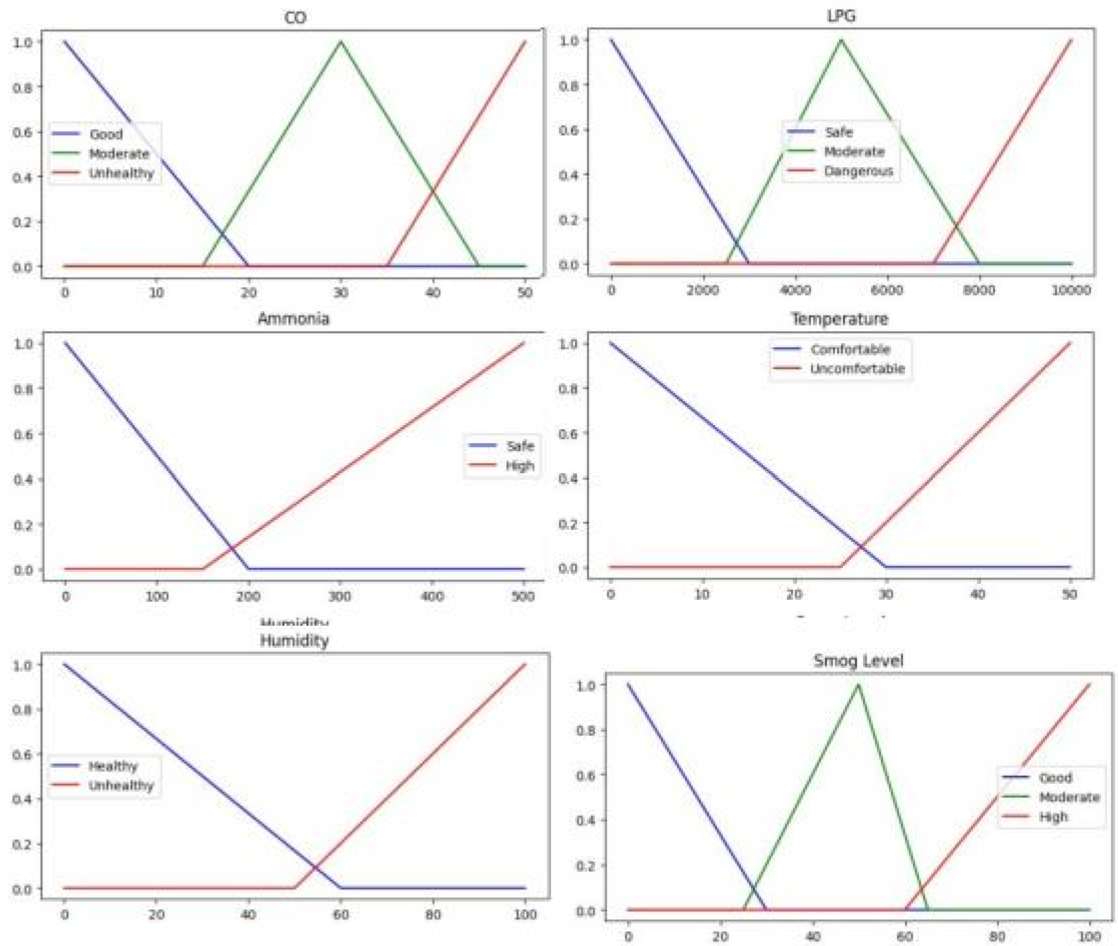

Figure 4. Membership functions of input and output variables

The smog level of proposed FIS is based on all five input variables i.e. normal ranges of each input variable proportional to normal smog level whereas abnormal ranges of input variables ultimately give rise to smog level. This relationship of one input variable CO with output variable smog level is depicted in ***Figure 5*** i.e. CO is map against Smog level by giving three different ranges of CO normal, moderate and high. Graph showing that normal range of CO predicting normal smog and vice versa.

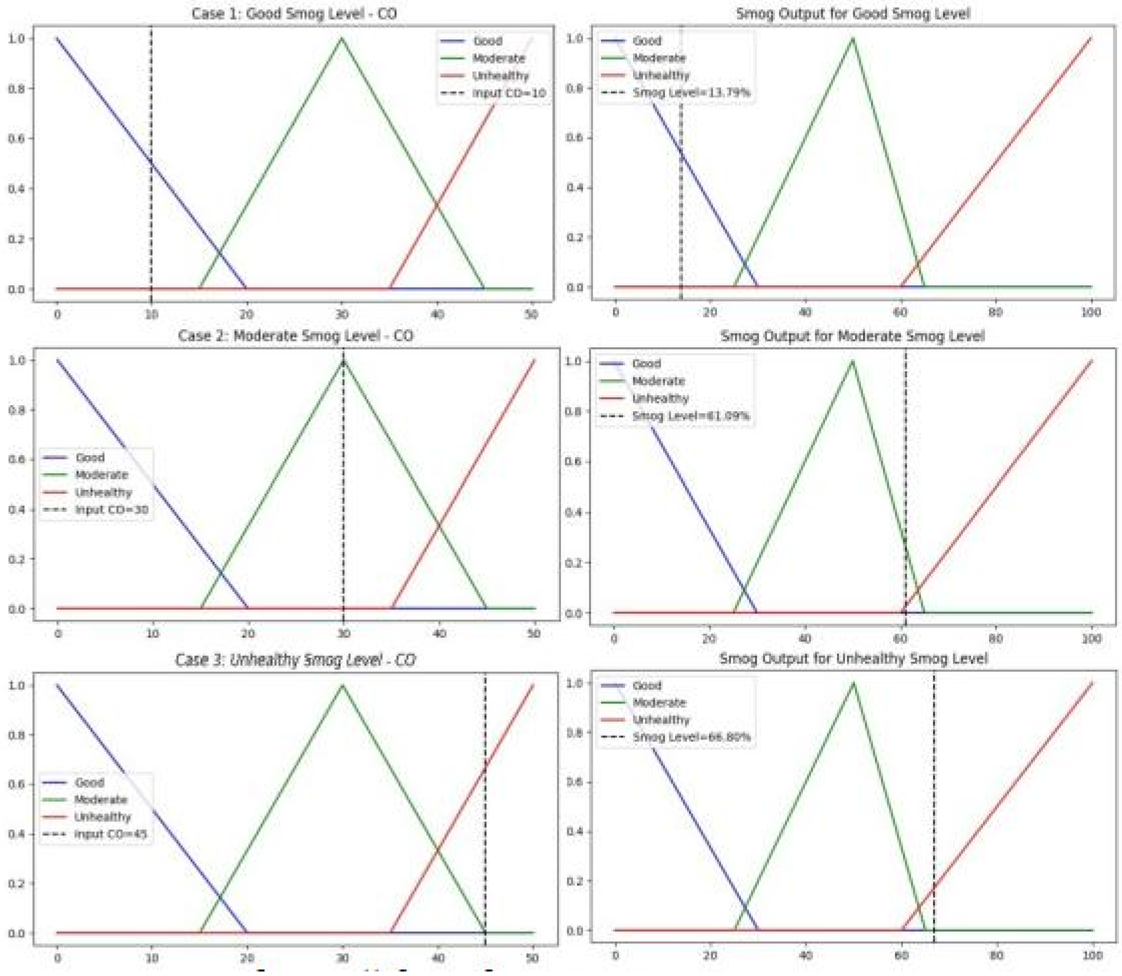

Figure 5: CO mapping with Smog Level

The graph between input variables and predicted output is shown in ***Figure*** 6, this shows how the normalized input parameters relate to predicted smog level via the fuzzy inference system. All five inputs.CO, LPG, Ammonia, Temperature, and Humidity are mapped to a common range of 1-100 so they can be compared on the same axis, and the smog level is shown as a percentage from 0% (Good) to 100% (Unhealthy). Every curve illustrates the impact on smog level when one input parameters varied while the others remain constant at the mid-range values. The results suggest that CO, LPG, and Ammonia and induce a greater effect on smog level, with increased values resulting in a sharp increase towards the unhealthy region, while Temperature and Humidity demonstrate relatively moderate impact. This plot illustrates there pensiveness soft he fuzzy system to each environmental parameter and thee effect of rising pollutant levels and playing and major role in smog creation polluted environments.

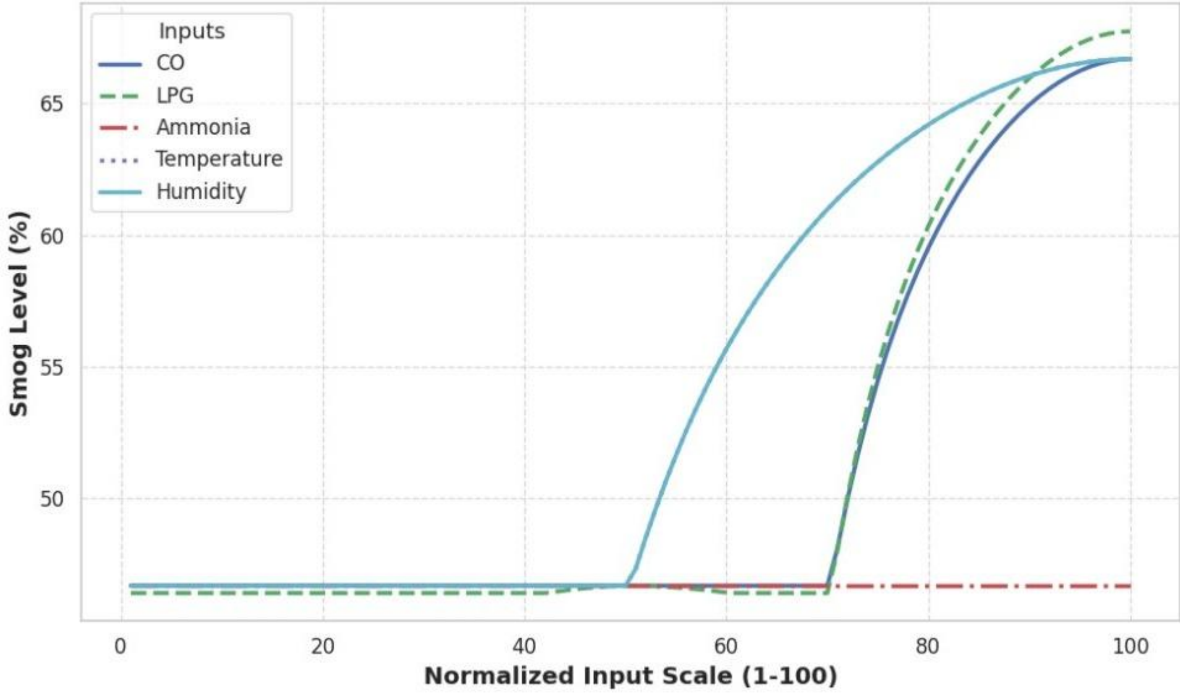

Figure 6. Membership functions of input and output variables

The implemented FIS is than integrated in to GUI based on android application which received sensor data from the IoT circuit via Bluetooth communication. The application has embedded fuzzy inference logic to predict smog levels on the mobile device itself without any cloud connectivity.

4. Experiments and Results

The experimental activities were spread over five months, from October 2024 up to February 2025. Measurements were obtained at different times of the day (morning, afternoon, and evening) for assessment of variation due to environmental and pollutant exposure conditions. Experimental measurements in an indoor environment at the university campus. Data were recorded in the morning, afternoon, and evening sessions, with care taken to account for natural variations of the pollutant concentration. Real-time measurements would be transmitted from the Arduino setup to the mobile device via Bluetooth, where they will be processed on-device by the fuzzy inference engine, and displayed live within the application.

4.1 Experimental Data Collection

Experimental setup consists of MQ-2, MQ-7, MQ-135 and DHT11 sensor connected through AT-Mega 328-based Arduino Uno microcontroller for exact and real time monitoring of various gases like carbon monoxide, smoke, liquefied petroleum gases and hydrogen, along with temperature and humidity values. The readings obtained by Arduino from the sensors were transmitted to a custom-built Android application using HC-05 Bluetooth module. The Android application which was developed in Android Studio had embedded fuzzy inference engine for classifying air quality dynamically based on incoming data. The entire system was operated on USB or battery of 9 volts and it was tested indoor during several sessions a day during October 2024 through February 2025 subjected under varying environmental conditions. Performance evaluation of real-time air quality classification system was done under various indoor conditions during the trial period of October 2024 to February 2025 show in ***Table*** 5. Throughout the day, sensors picked up concentration levels of pollutants, and the Android application processed the readings using a fuzzy inference engine. Then from experimental data collection we pick suitable sample data for evaluation of system performance. We applied precision, recall and accuracy to compute performance of proposed system. The sample data and evaluation is listed in ***Table*** 5.The computation of precision, recall and accuracy based on given parameters.

TP=Good and Predicted as good
TN=High and predicted as high
FP=High and Predicted as good
FN=Nothing but Predicted as high

Table 5: ***Rea-Time Air Quality Classification Based on Sensor Data and Fuzzy Inference Outputs during Indoor Trials (October 2024-February 2025***

Duration	Time	Sample from Collected instances	TP	FP	TN	FN	Precision $TP/TP+FP$	Recall $TP/TP+FN$	Accuracy $TP+TN/TP+TN+FP+FN$
February 2022-50	Morning	150	139	2	10	1	98%	99%	99%
	Afternoon	150	138	2	2	10	98%	93%	98%
	Night	150	137	2	2	11	98%	92%	98%

4.2 Smog Prediction App Results

The collected data as than passed to proposed android application for prediction of smog. The Android application received real-time sensor data that were integrated with fuzzy logic rules to determine the Smog level in real-time. As an example, the category may have been "Good," "Moderate," or "Unhealthy." These outputs were visually displayed on the application interface through text labels and color indicators shown in ***Figure*** 7. The application also recorded the historical trends of various pollutants to allow for analysis of the changing state of air quality during the day. Alerts were triggered if the smog level is "Unhealthy" and worse categories so as to demonstrate the dynamic adaptability of the system to environmental changes.

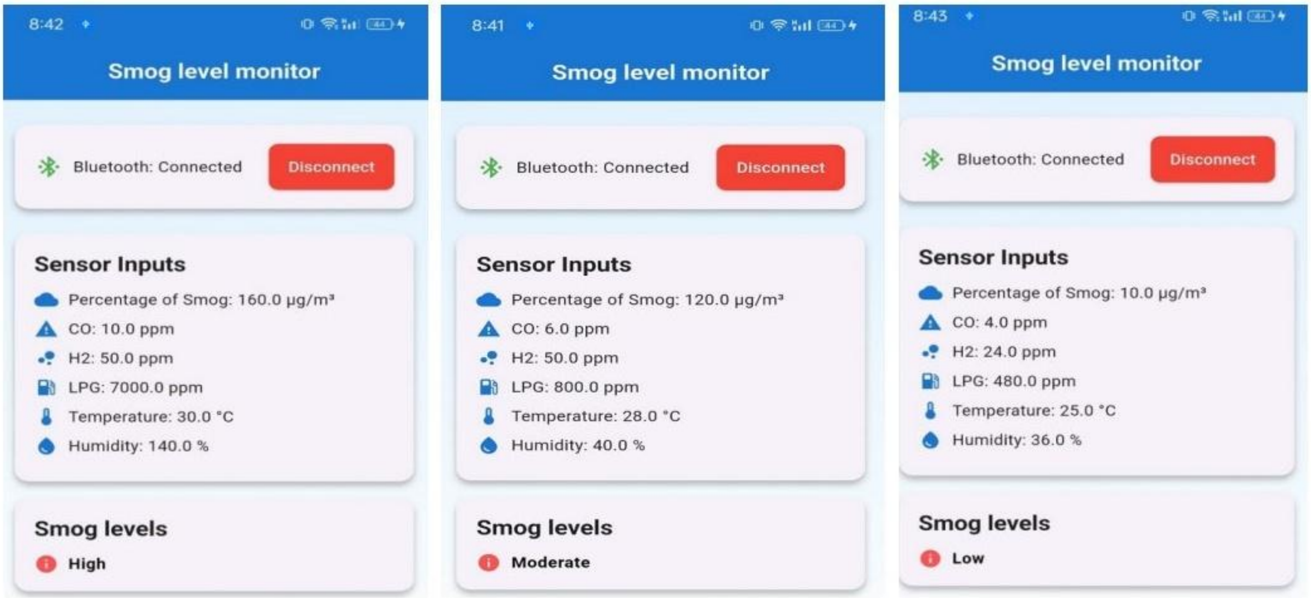

Figure 7. Real Time Smog Prediction on Android App

The unification of fuzzy logic with the real-time sensing and visualization on mobile phones proffer a solution for air quality monitoring that is responsive, portable, and low-cost in comparison to traditional AQI measurement systems. The real-time alerts generated by the app are particularly helpful with early warnings in places where dangerous gases can build up unnoticed. The output graph of experiments results is shown in ***Figure 8.***

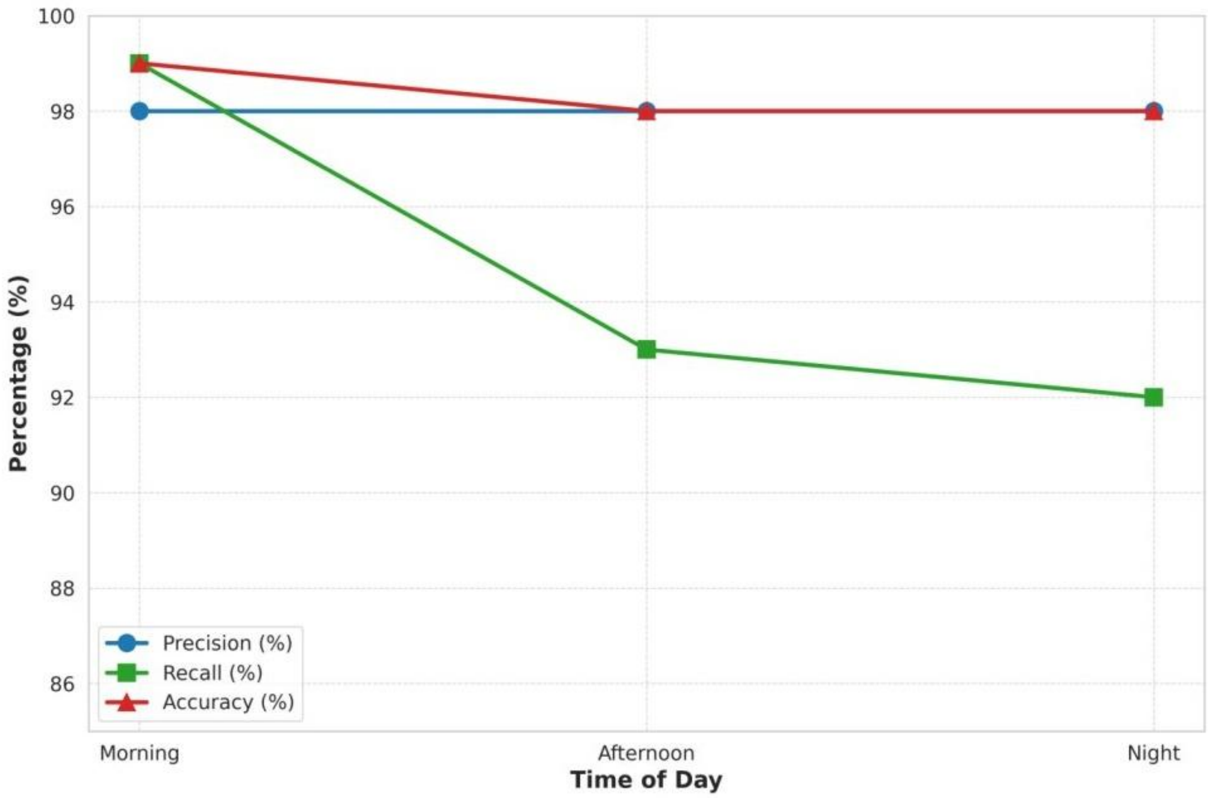

Figure 8.Performance of proposed system

4.3. Limitations and Future Work

However, the implemented system has certain shortcomings:

1. **Limited detection ranges of gases by sensors:** The deployed sensors failed to detect indoor air quality-affecting gases such as ozone, Sulphur dioxide, or formaldehyde.
2. **Calibration dependent:** Gas sensors associated with different MQ-series always require calibration from some time to maintain accuracy but difficult for general purposes.
3. **Budget:** The experiments were conducted with cheap sensors due to budget issues which are sensitive to some parameters.
4. **Bluetooth range constraint**: Such communication would thus be limited to 10meters or so, which means the monitoring of mobile devices would be up to a distance of 10 meters from the module.

Some future modifications made on this system:

1. The system integrates GPS-based location tracking which allows it to correlate pollution levels in terms of AQI index with some geographic data for pollution mapping.
2. Inclusion of more specialist gas sensors-such as ni trogen dioxide((NO_2)and ozone (O_3),,particulates (PM2.5/PM10)-increases the coverage of pollutants.
3. Cloud storage and analytics capacity for detailed trend analysis and long-term storage of the data, while also availing access to AQI data on multiple devices.
4. Voice notifications and accessibility features for better usability for elderly or sight-impaired users.
5. Creation of machine-learning-based classification models from datasets collected to supplement or reinforce fuzzy logic performance.

5. Conclusion

Real-time affordable and scalable smog detection is demonstrated through the environmental components coupled with fuzzy inference and mobile integration. The system addresses the shortcomings of air quality monitoring in near real-time using smart IoT technology. It does an excellent job of presenting alerts and feedback to the end user through a mobile app, which allows the user to act in terms of personal health and safety based on real-time information sent from the sensors about air quality conditions. The results of the experimentation confirm the reliability of the system in varied indoor settings, thus proving the quality of dynamic assessment and accurate measurement regarding air quality. While portability and user friendliness are huge advantages, further enhancements in its effectiveness will need to be made by addressing the drawbacks arising from sensor calibration, limited detection range of the pollutants, and Bluetooth communication. Future work will ensure GPS mapping, enhanced cloud analytics, and more sensor integration, which will make the system smarter and more comprehensive for environmental monitoring. In a nutshell, the system serves as a practically and adaptive good tool for near-real-time detection of smog and pollution mitigation, thereby greatly impacting urban health and sustainability.

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Data Availability: The data used to support the findings of the study are available from the corresponding author upon request.

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