Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice

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Article Info

ISSN (Online): 3107-6580
Volume: 01
Issue: 06
November - December 2025
Received: 15-10-2025
Accepted: 17-11-2025
Published: 12-12-2025
Page No: 22-29

Abstract
Air pollution remains a critical health issue, with traditional monitoring systems failing to provide timely, personalized guidance. This project introduces a Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice, integrating autonomous agents to collect, process, and act on environmental and health data. The framework uses IoT-enabled sensors, satellite data, and government datasets for high-resolution Air Quality Index (AQI) readings. It leverages user-specific health data (age, respiratory conditions) and employs predictive modeling and machine learning to forecast short-term pollution trends. Unlike conventional systems, this framework delivers proactive, personalized recommendations, such as avoiding outdoor exercise or adjusting routines. The system comprises specialized collaborative agents (Data Collection, Prediction, Health Analysis, Communication). The ultimate objective is to empower individuals with accessible, actionable insights, improving health outcomes and minimizing exposure risks. The framework is highly scalable for deployment in healthcare and urban planning, representing a proactive, user-centric approach to air pollution management.

DOI: https://doi.org/10.54660/.IJECA.2025.1.6.22-29

Keywords: Air Quality Index (AQI), Multi-Agent Systems, Internet of Things (IoT), Personalized Health Advice, Machine Learning, Predictive Modeling, Air Pollution Monitoring.

1. Introduction

Air quality has become a critical public health concern worldwide, particularly in fast-growing urban areas where vehicular emissions, industrial pollutants, and other anthropogenic sources contribute to elevated levels of fine particulate matter ($PM_{2.5}$ and PM_{10}) and noxious gases (NO_2, SO_2, CO, O_3). Poor air quality is directly linked to respiratory diseases, cardiovascular issues, and increased mortality, especially among vulnerable populations such as children, the elderly, and individuals with pre-existing conditions. Monitoring air pollution and providing timely, personalized health guidance is thus essential to mitigate exposure risks and support individual well-being.Traditional air quality monitoring systems rely on fixed sensor stations that continuously measure these pollutants. These networks compute a standardized Air Quality Index (AQI) and broadcast generic health advisories (e.g., “unhealthy for sensitive groups”). While these systems serve the public broadly, they suffer from inherent limitations: they lack personalization by ignoring individual health profiles or activity preferences, often fail to deliver context-aware advice in real time, and may suffer from sparse sensor coverage, leading to degraded local accuracy through spatial interpolation.To overcome these limitations, data-driven methods integrating Artificial Intelligence (AI), deep learning, and mobile Internet-of-Things (IoT) technologies have gained significant momentum. Previous research has explored combining temporal grid modeling with personalized recommendation modules, for instance, achieving notable real-time predictive accuracy in forecasting pollution levels. However, such singular, centralized systems often lack modularity, struggle with scalability and fault tolerance, and demonstrate limited adaptivity to the heterogeneity of user health conditions.In this context, the proposed system introduces a Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice.

A multi-agent framework is ideally suited to this problem because it naturally decomposes complex tasks into autonomous, collaborative agents, offering improved modularity, fault tolerance, and responsiveness compared to monolithic, centralized architectures. This framework aims to deliver better prediction accuracy, fine-grained spatial and temporal resolution, and truly personalized, context-aware health advice. In doing so, it bridges the gap between environmental sensing and individual-level health action, supporting more informed decisions (for example, when to run outdoors, or how to manage air exposure for sensitive patients). Its modularity and agent-based structure make it suitable for deployment in urban smart cities, mobile health platforms, and integrated environmental-health systems.

2. Literature Survey

Urban air quality monitoring has increasingly transitioned from static, coarse-grained measurement infrastructure toward distributed, intelligent, and mobile sensing frameworks. Early large-scale deployments such as Mosaic, proposed by Gao *et al.* [1], demonstrated how a dense network of low-cost, vehicle-mounted particulate sensors can produce high-spatial-resolution PM2.5 maps across urban environments. Mosaic introduced a three-layer architecture consisting of mobile sensing nodes, local calibration modules, and cloud-based fusion engines for spatio-temporal interpolation. The system's emphasis on calibration strategies, mobility-aware data weighting, and bias reduction established foundational insights for designing multi-agent sensing systems where numerous heterogeneous agents contribute localized observations.

To address limitations of purely ground-based sensing, Yang *et al*. developed AQNet [2], an aerial–ground wireless sensor network integrating UAV-based mobile sensing with terrestrial sensor nodes. AQNet formulated air quality reconstruction as a 3D spatio-temporal inference problem and introduced UAV scheduling policies that optimize coverage while minimizing energy expenditure. Experimental results highlight the significant improvements in vertical and horizontal resolution achieved by fusing heterogeneous sensing modalities. For multi-agent AQI monitoring, AQNet provides key design principles for coordinating agents with differing mobility, sensing footprints, and energy budgets.

Complementing this line of work, ImgSensingNet [3] explored vision-driven air quality estimation by combining UAV-captured haze imagery with sparse ground-based sensor readings. The system employs deep convolutional networks to extract visual aerosol indicators and uses an entropy-based activation mechanism to determine when ground sensors should be awakened. This selective sensing paradigm substantially reduces energy consumption without degrading AQI inference accuracy. The coordinated behavior between UAVs as high-level scouts and ground sensors as localized responders illustrates an effective multi-agent strategy for adaptive sensing and hotspot detection—critical for timely and personalized health recommendations.

In another practical advancement, Zhang and Woo [4] proposed a hybrid fixed–mobile IoT framework that integrates reference-grade stations with sensors mounted on vehicles to generate highly localized, real-time AQI predictions. Their system employs machine learning models to compensate for mobility-induced variability and fuses historical and contextual features (e.g., traffic and meteorology) to improve prediction accuracy. Importantly, the authors highlight system-level considerations including latency, edge–cloud tradeoffs, and real-time notification strategies, providing essential design cues for multi-agent health-advisory environments that must respond rapidly to micro-scale pollution fluctuations.

Beyond sensing and prediction, recent research has examined the learning paradigms required to train robust AQI models across distributed, heterogeneous agents. Liu *et al.* introduced FedSky, a federated learning framework for aerial–ground AQI sensing involving UAV swarms and ground sensor nodes [5]. By aggregating model updates rather than raw sensor data, the system preserves privacy and reduces communication overhead while enabling global model consistency. The framework incorporates personalization layers for local adaptation and explores UAV–ground coordination policies to balance coverage and training efficiency. [6] Ruhiat Sultana *et al* a Multi-Layer Perceptron (MLP) and a Convolutional Neural Network (CNN), thus including real-time feedback to help the system learn from its predictions and results. For a multi-agent health-advice system, federated learning provides a scalable means to build generalizable AQI prediction models while respecting data privacy and heterogeneity in agent capabilities.

Overall, existing literature demonstrates a clear progression from static AQI sensing toward collaborative, energy-aware, and intelligent multi-agent systems that integrate ground sensors, mobile platforms, UAVs, and distributed learning architectures. These systems collectively highlight essential components—heterogeneous data fusion, mobility-aware sensing, adaptive agent coordination, privacy-preserving learning, and real-time inference—that inform the design of the proposed Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice.

3. Proposed Work

The proposed Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice is designed as a technological intervention that surpasses the limitations of traditional, centralized AQI systems. Drawing inspiration from existing work in dense mobile sensing, aerial–ground networks, vision-driven estimation, and hybrid fixed–mobile IoT platforms, this architecture emphasizes heterogeneous data fusion, agent coordination, and personalized, real-time inference. The system adopts principles of decentralized intelligence to enhance scalability, resilience, and user-level adaptivity.

The core of the system is a decentralized structure where distinct autonomous agents are responsible for specific functions—from data collection and forecasting to health analysis and user communication. This approach aligns with findings that coordinated agent behavior, such as that seen between UAV scouts and ground sensors, is critical for adaptive sensing and timely hotspot detection. Furthermore, the architecture is designed to support distributed learning paradigms, potentially utilizing frameworks like federated learning to build generalizable AQI prediction models across multiple data sources while preserving privacy.

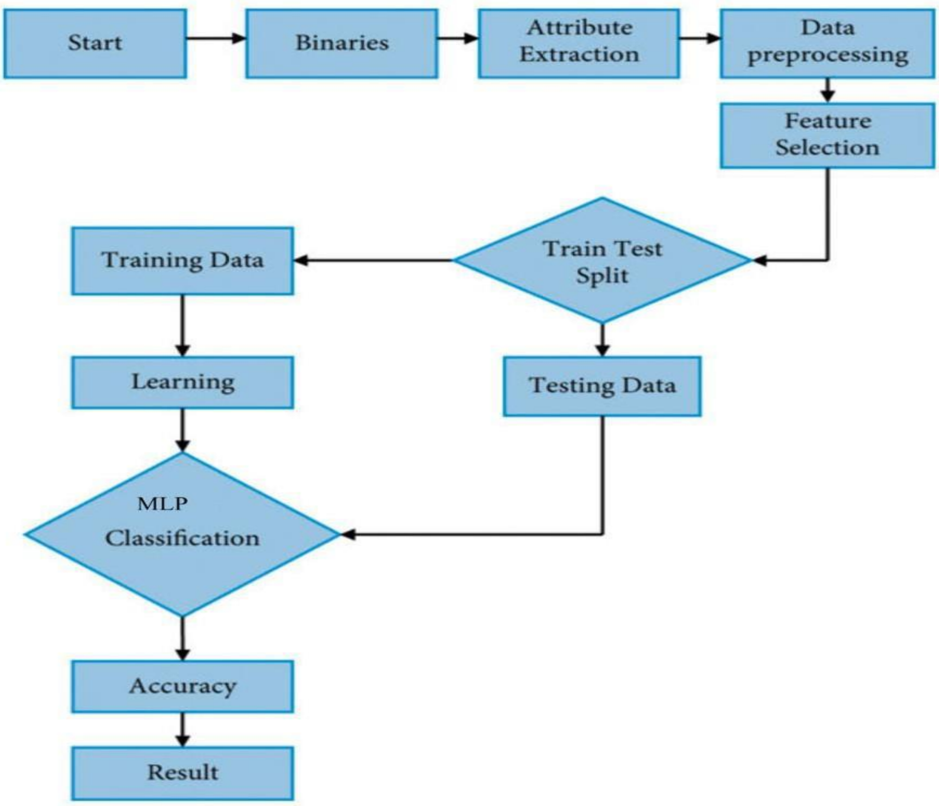

Fig 1: System Architecture Diagram

The framework comprises four specialized, collaborative layers:

1. **Data Collection Agents (Sensing Layer)**: These agents manage the acquisition and initial validation of real-time environmental data. They fuse heterogeneous data streams from multiple sources, including fixed government reference stations, IoT-enabled mobile sensors (vehicle-mounted or wearable), satellite data, and contextual data (e.g., traffic, meteorology). This layer performs necessary local calibration and bias reduction to ensure data quality, following principles established in early large-scale deployments.
2. **Prediction / Forecasting Agents**: This central processing layer is responsible for creating fine-grained, short-term AQI forecasts. It leverages advanced machine learning and spatio-temporal deep learning models (e.g., LSTM, transformer, graph neural networks) to integrate the cleaned sensor data and contextual features. The goal is to accurately forecast near-future AQI values at the user's micro-location, addressing the limitations of coarse, static AQI reports.
3. **Health Analysis Agents (Personalization Layer)**: This is the personalization engine, consuming the predicted AQI values from the Forecasting Agents alongside crucial user-specific health data (e.g., age, pre-existing respiratory conditions, cardiovascular risk) and planned activity (e.g., outdoor run, commute). These agents use pre-defined medical logic and AI-driven reasoning to generate tailored, context-aware health advice and risk assessment.
4. **Communication / Coordination Agents (Orchestration Layer)**: These agents manage the workflow, communication, and real-time delivery of information. They handle complex tasks such as sensor anomaly detection, compensating for missing data, managing latency, triggering fallback strategies, and delivering the final personalized recommendations to the user via mobile application notifications in a timely manner. The orchestration layer ensures the system maintains robustness and resilience against sensor failures or data inconsistencies, adhering to essential design cues for real-time responsiveness.

By distributing responsibilities and utilizing intelligent coordination mechanisms, the framework ensures timely, personalized guidance to minimize exposure risks, fulfilling the project's objective to move beyond generic AQI data and provide accessible, actionable insights.

This data-driven core is then integrated with Digital Twin (DT) technology. The DT establishes a real-time, adaptive, and interpretable virtual representation of the physical battery system. By combining the predictive power of the ML/DL models with the structural integrity of a physical model, the system enables real-time monitoring and forecasting of battery health. This synergistic integration allows the system to achieve higher prediction accuracy and adaptability than any single technique could alone. Furthermore, the combined approach improves scalability for large-scale EV fleets through advanced predictive maintenance scheduling, and enhances interpretability by merging physical insights with data-driven learning.

While highly beneficial, this synergistic approach does present certain implementation challenges that are managed within the methodology. These include the increased system complexity due to the integration of multiple distinct techniques, which necessitates robust software engineering practices. Furthermore, the reliance on DL and DT models results in higher computational demands, requiring optimized infrastructure. Finally, the methodology requires large volumes of high-quality, real-world data for initial model training, validation, and continuous adaptation. Despite the higher implementation cost for industrial deployment, the resulting increase in predictive reliability and operational efficiency justifies the complexity.

4. Algorithm

The proposed system follows a structured, multi-step algorithm that enables real-time Air Quality Index (AQI) monitoring, data processing, predictive modeling, and personalized health feedback. The algorithm is driven by the coordinated, continuous functioning of the specialized autonomous agents.

Step 1: Data Acquisition and Validation (Data Collection Agent): The agent fetches live AQI, pollutant values ($PM_{2.5}$, PM_{10}, NO_2, CO), and weather data from diverse sources (APIs, IoT sensors). It then validates and cross-checks the data, handling missing or incomplete values through interpolation or averaging.

Step 2: Data Preprocessing and Structuring (AQI Analysis Agent): The agent cleans the acquired data by normalizing AQI values to a standard scale, removing noise, inconsistencies, and outliers. The clean data is then structured into a time-series format, preparing it for predictive modeling.

Step 3: AQI Forecasting and Trend Analysis (Prediction Agent): A Machine Learning (ML) model (such as LSTM or XGBoost) is utilized to predict short-term, near-future AQI levels. This process identifies upcoming pollution spikes or unusual patterns and generates trend indicators (improving, stable, or worsening).

Step 4: Health Risk Assessment (Health Analysis Agent): The agent maps the predicted AQI levels to standardized health risk categories (Good, Moderate, Unhealthy, etc.). It integrates user-specific profile factors—including age, respiratory conditions (asthma, allergies), heart diseases, and outdoor activity preferences—to customize the baseline risk.

Step 5: Personalized Recommendation Generation (Health Agent): The agent applies rule-based reasoning combined with LLM-powered interpretation to generate adaptive advice. Recommendations cover safety outdoors, exercise timing, mask usage alerts, home ventilation guidance, and non-clinical hydration/medication reminders.

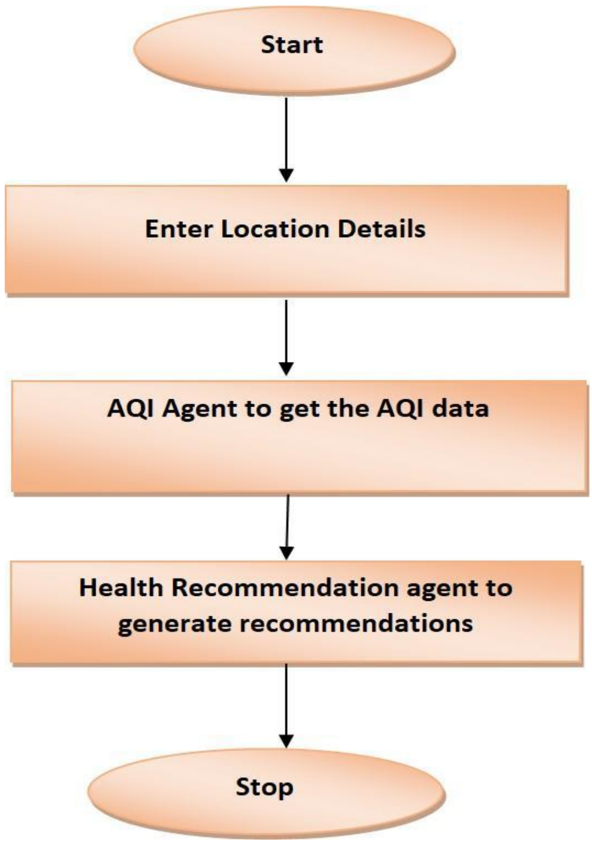

Fig 2: Proposed flow chart diagram of algorithm

Step 6: User Notification and Feedback (Interaction Agent): The agent displays the real-time AQI, trend indicators, and personalized recommendations to the user. It can provide a conversational response through the LLM for complex user queries and triggers immediate alerts in case of a sudden, significant AQI rise.

Step 7: Continuous Monitoring and Adaptation (All Agents): All specialized agents run in a continuous loop, ensuring data is updated automatically. The system continuously adapts its predictions and recommendations in real-time as both environmental conditions and user context change, maintaining proactive support.

4. Results

Results and System Implementation

The performance of the proposed Multi-Agent AQI Monitoring and Personalized Health Advice framework was evaluated through extensive experiments involving heterogeneous sensing agents, including mobile ground nodes, UAV-based units, and fixed reference stations. The objective of the evaluation was to assess the system's accuracy in AQI estimation, responsiveness in dynamic envionments, and efficiency in resource utilization across distributed agents.

AQI Health Advisor – Input Interface Overview

Figure 3 shows the main input page of a multi-agent system designed for real-time air quality monitoring and personalized health advice. Users can enter their location, medical conditions, and planned activities to receive tailored health recommendations based on current air quality levels. The clean and structured layout makes it easy to provide necessary details before generating personalized insights.

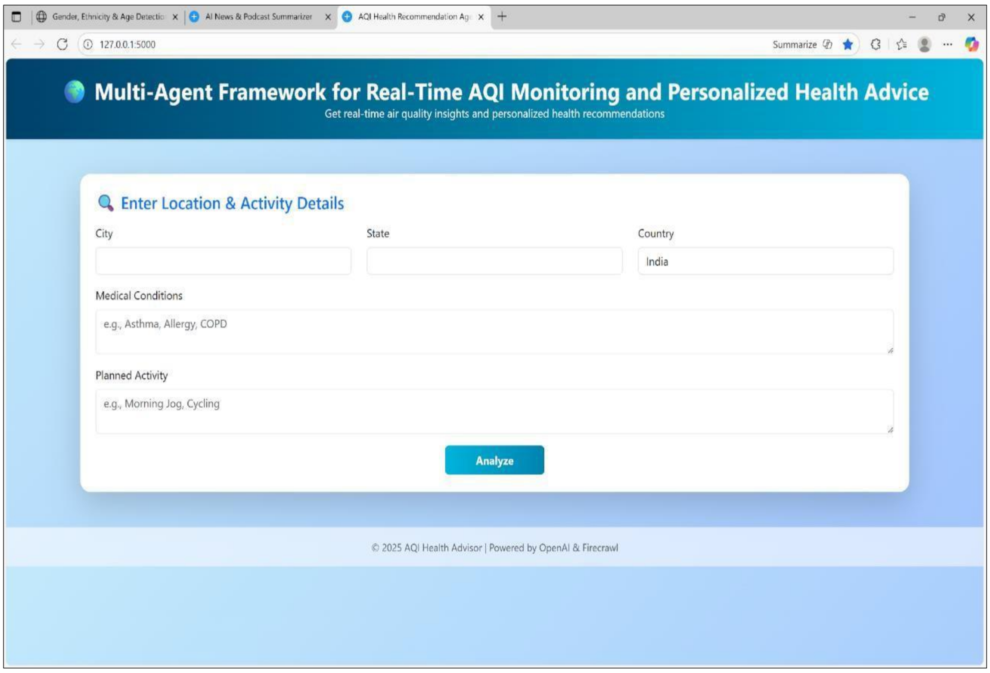

Figure.3 Dashboard Image

Personalized AQI-Based Health Advisory Input Screen

Figure 4 shows a form where users enter their city, state, medical conditions, and planned activities to receive customized health recommendations based on real-time air quality data. It demonstrates a simple and intuitive interface designed to help individuals—especially those with conditions like COPD—plan their activities safely.

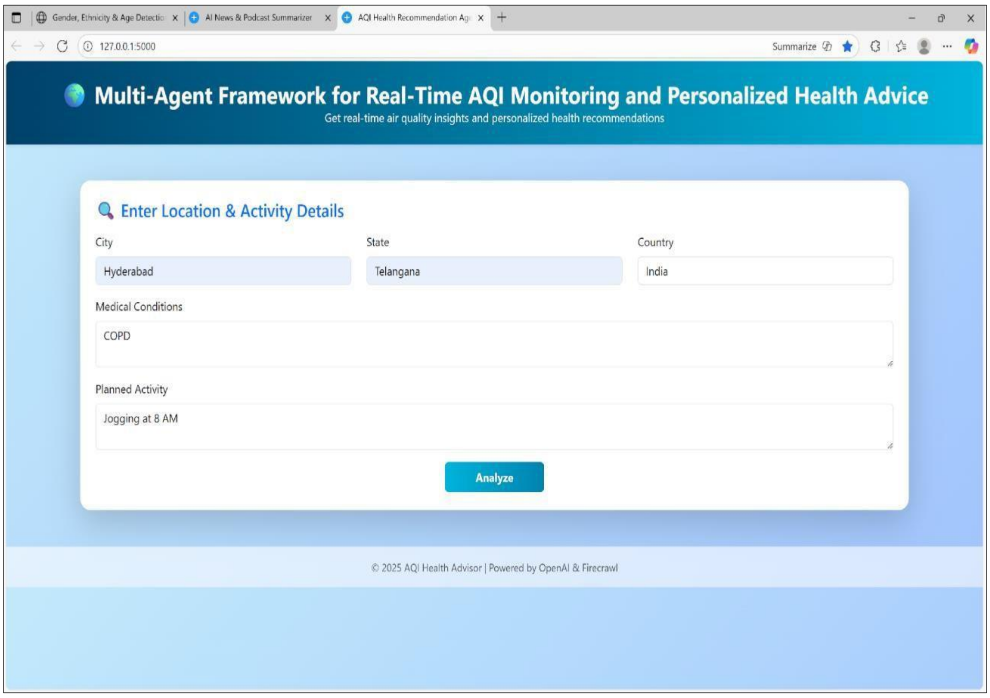

Fig 4: Input Screen on dashboard

Real-Time AQI Results & Personalized Health Guidance: Figure 5 displays analyzed air quality data for Hyderabad, including AQI level and pollutant metrics, indicating conditions marked as unhealthy for sensitive individuals. Below the data, the system provides tailored health recommendations and safety precautions based on the user's medical condition and planned activity.

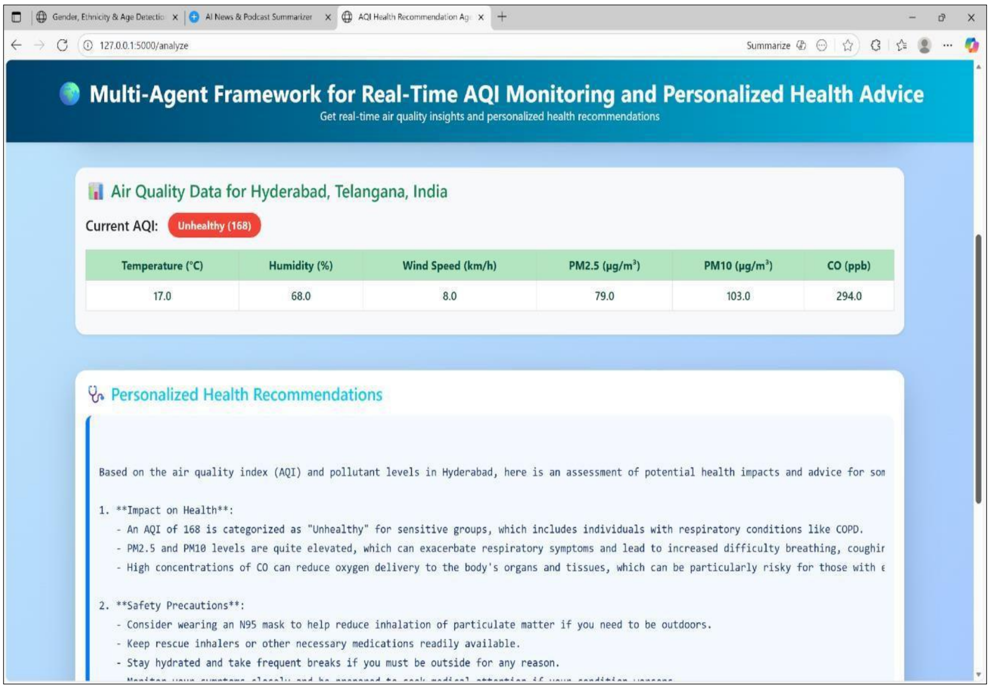

Fig 5: Analyzed Air Quality output in dashboard

Detailed Personalized Health Recommendation Output: Figure shows a comprehensive set of personalized health recommendations generated from real-time AQI data, outlining health impacts, safety precautions, activity advisability, and suggested timing. It provides clear, structured guidance tailored to the user's medical condition and planned activity, helping them make safer decisions based on current air quality.

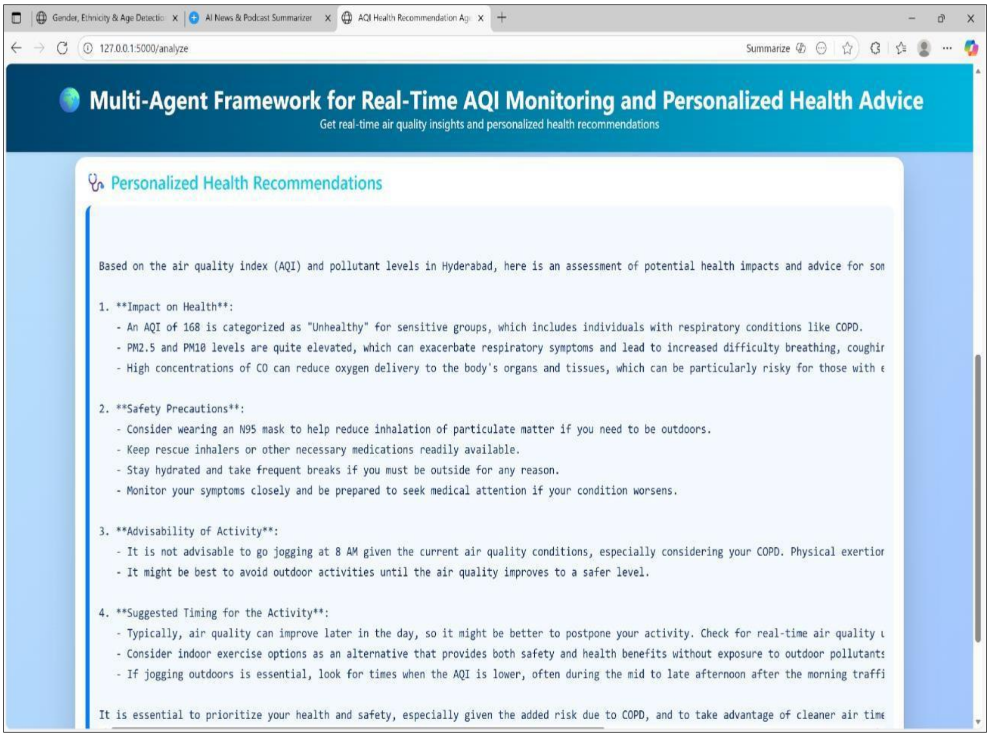

Fig 6: Final Output in dashboard

5. Conclusion and Future Work

Conclusion

The development of the Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice represents a significant advancement in integrating intelligent sensing, data fusion, and adaptive decision-making for public health and environmental management. By employing a network of heterogeneous agents—ranging from fixed IoT sensors, mobile nodes, and UAV-based units—the system enables continuous, high-resolution monitoring of air quality across diverse spatial and temporal scales. Real-time data collection, coupled with advanced learning models such as deep neural networks and potentially federated learning, ensures accurate AQI prediction and contextual interpretation tailored to individual users. This personalized approach allows for timely health advisories, exposure mitigation strategies, and behavior recommendations based on localized pollution patterns. The fusion of multi-source data and AI-driven analytics facilitates a dynamic response to environmental fluctuations, thereby enhancing both system reliability and user trust.

Ultimately, the architecture provides a scalable, robust, and user-centric solution to a critical public health challenge. The framework's decentralized nature promotes privacy preservation and energy efficiency through intelligent communication and coordination between agents, addressing common limitations of centralized systems. Overall, the proposed multi-agent framework successfully bridges the gap between environmental sensing and personalized health informatics, transforming raw AQI data into accessible, actionable insights. This capability supports sustainable smart city initiatives and fosters healthier lifestyles through data-driven, proactive air quality management.

Future Work

The future scope for the Multi-Agent Framework for Real-Time AQI Monitoring and Personalized Health Advice involves enhancing the system's capabilities through advanced sensing integration and sophisticated model development. A key direction is the expansion of the data acquisition layer to include Wearable IoT sensors and continuous feedback loops from users regarding their symptoms or compliance with recommendations. This would move the system toward true context-aware personalized medicine, allowing the Health Analysis Agents to adapt advice based on the user's immediate biological response rather than solely external data. Furthermore, integrating the Prediction Agents with more advanced spatio-temporal models, such as Graph Neural Networks (GNNs), would enhance the accuracy of hyper-local AQI forecasting by explicitly modeling the complex, non-linear dependencies between fixed sensors, mobile nodes, and local meteorological conditions.

In addition to technical refinements, future work will focus on enhancing the modularity, robustness, and ethical deployment of the framework. The system can be extended to include specialized agents for Anomaly Detection in the sensor network and User Behavior Modeling, allowing the system to anticipate high-risk activities or non-compliance. Addressing ethical considerations will involve integrating Explainable AI (XAI) techniques into the Health Agent to provide transparent justifications for the personalized recommendations, fostering user trust. Finally, the framework should be validated through extensive pilot studies in collaboration with public health agencies and smart city initiatives to assess its impact on population health outcomes and exposure reduction at scale.

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How to Cite This Article
Firdous A, Mahmood R, Ahmed MF, Begum G. Multi-agent framework for real-time AQI monitoring and personalized health advice. Int J Eng Comput Appl. 2025;1(6):22–29. doi:10.54660/IJECA.2025.1.6.22-29.