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AI-Driven Personal Air Quality Monitoring System

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ABSTRACT :

Air pollution remains a critical global issue, contributing to millions of premature deaths annually. Traditional air quality monitoring systems are often expensive, stationary, and lack real-time personalization. This project introduces an AI-driven portable air quality monitoring system that leverages the ESP32 microcontroller, MQ135 gas sensor (for CO_2 and VOCs), and a PM2.5 particulate matter sensor to provide hyper-local pollution tracking. The system processes data at the edge using TinyML , ensuring low latency and offline functionality. Real-time air quality metrics are transmitted via Wi-Fi to a cloud-based dashboard and mobile app, enabling users to receive instant alerts and historical trends. With a prediction accuracy of 92% and a production cost of under $50 , this solution offers an accessible and scalable approach to personal air quality monitoring. Air pollution continues to pose significant challenges in both urban and suburban environments. Traditional fixed air monitoring systems lack the spatial granularity required for hyperlocal analysis. This paper presents a portable air quality mapping device integrated with embedded artificial intelligence (AI) for detecting real-time environmental anomalies. The system incorporates multiple gas and particulate sensors, GPS tracking, and on-device machine learning capabilities to identify sudden changes in pollution levels. Logged data can be visualized using a mobile or web dashboard, enabling users to track pollution hotspots. The developed solution is compact, battery-powered, and suitable for applications in personal exposure monitoring, environmental research, and smart city planning.

Keywords: Air pollution, anomaly detection, embedded AI, GPS mapping, hyperlocal monitoring, IoT, portable air quality device, TinyML

Introduction

Air pollution poses severe health risks, with studies linking prolonged exposure to respiratory diseases, cardiovascular conditions, and reduced life expectancy. While government-operated air quality stations provide regional data, their sparse distribution and delayed reporting limit their usefulness for individuals seeking real-time, location-specific insights. Additionally, commercial wearable air quality monitors are often prohibitively expensive for widespread adoption.

To address these challenges, this project develops a low-cost, portable air quality monitoring system powered by ESP32, MQ135, and PM2.5 sensors . The ESP32 serves as the central processing unit, collecting data from the MQ135 (which detects CO_2, ammonia, benzene, and other harmful gases) and the PM2.5 sensor (which measures fine particulate matter). A machine learning model deployed on the edge (TinyML) analyzes sensor data to predict the Air Quality Index (AQI) in real time. The system transmits this data to a cloud server (Firebase) and a mobile app (Blynk) , where users can view trends, set pollution alerts, and make informed decisions about outdoor activities.

This project bridges the gap between stationary monitoring systems and personalized health insights , offering a scalable solution for individuals, urban planners, and health researchers.

Air quality is a critical component of environmental health, directly affecting human well-being and ecosystems. In many countries, including India, rapid industrialization and urban traffic have exacerbated pollution levels. Existing environmental monitoring systems are typically centralized, expensive, and unable to provide high-resolution spatial data at the neighborhood or street level.

This research proposes a compact and low-cost device that uses embedded intelligence to detect pollution anomalies in real time. By combining gas sensors, GPS modules, and edge-based machine learning, the system delivers location-specific insights into air quality conditions. Such data is essential for both public awareness and informed policy decisions.

Literature Survey

Existing air quality monitoring solutions face several limitations. Government-operated AQI stations, while accurate, are sparsely distributed and provide delayed updates. Satellite-based monitoring systems offer broad coverage but lack granularity for micro-environments. Commercial wearables, such as Atmotube and Plume Labs, provide real-time tracking but are costly and rely heavily on cloud processing, which introduces latency.

Recent advancements in edge AI and TinyML have enabled low-power, real-time sensor data analysis. Studies by Zhang et al. (2022) demonstrated the effectiveness of XGBoost and LSTM models in predicting AQI from multi-sensor inputs. However, most implementations require expensive hardware or cloud dependencies. This project builds upon these findings by integrating ESP32-based edge computing , ensuring affordability and offline functionality.

Air quality monitoring has been a subject of extensive research due to its direct impact on public health and environmental policy. Traditional air quality monitoring systems deployed by government agencies typically involve fixed-location stations equipped with expensive, high-precision instruments. While these systems provide accurate measurements, their sparse spatial distribution limits the resolution and coverage, especially in rural and semi-urban areas.

Recent advancements in low-cost sensors and Internet of Things (IoT) technology have enabled the development of portable and scalable air quality monitoring solutions. Researchers have demonstrated the feasibility of using mobile platforms such as vehicles, bicycles, and handheld devices to collect real-time pollution data. These approaches significantly improve spatial resolution and enable dynamic mapping of pollution sources. However, the challenge of ensuring data accuracy, sensor calibration, and anomaly detection remains prevalent in these systems.

To address the limitations of static data processing, studies have explored the integration of machine learning techniques into environmental sensing. Unsupervised learning methods, such as clustering and autoencoders, have been used to detect abnormal pollution events without the need for labeled data. Edge computing and TinyML have further enabled the deployment of AI models directly on microcontrollers, reducing latency and dependence on cloud infrastructure. This shift towards on-device intelligence aligns with the growing need for real-time, energy-efficient, and privacy-preserving environmental monitoring systems.

System Design

A) Hardware Configuration

1.Sensor Array:

- PM2.5 sensor (for particulate matter detection)
- CO_2 sensor (to monitor carbon dioxide levels)
- VOC sensor (to detect organic chemical compounds)

2.GPS Module:

A GPS receiver is used to record geographic coordinates for every data sample, allowing spatial mapping of environmental conditions.

3.ESP32 Microcontroller:

chosen for its dual-core processing, Wi-Fi/Bluetooth connectivity, and low power consumption

4.Power Supply:

The system is powered by a 18650 lithium-ion battery , ensuring 8+ hours of operation.

B) Software Architecture

The software system is designed for real-time air quality analysis, cloud integration, and user-friendly mobile visualization. It comprises four main modules: edge AI inference, IoT cloud communication, cloud storage, and mobile interface, as outlined below:

1. Edge AI Processing

At the core of the system, the ESP32 microcontroller handles real-time data acquisition and AI-based prediction. A lightweight TensorFlow Lite model is deployed directly on the ESP32 to predict the Air Quality Index (AQI) using sensor inputs such as PM2.5, CO_2, VOCs, temperature, and humidity. The model runs inference locally to detect pollution spikes and estimate AQI with minimal latency and no dependence on external servers.

2. IoT Communication via Blynk

The ESP32 connects to the Blynk IoT platform over Wi-Fi, enabling seamless transmission of processed AQI data to the cloud. Blynk's lightweight protocol ensures efficient communication, real-time data synchronization, and remote device management.

3. Cloud Data Management

All transmitted AQI data is stored in Firebase Realtime Database, which supports fast read/write operations and structured storage. Firebase enables historical trend analysis, user-specific data filtering, and the generation of notifications or health warnings based on defined thresholds.

4. Mobile Application (Flutter)

A cross-platform mobile application is developed using Flutter, providing a clean and responsive user interface. Key features include:

- Live AQI display with location context
- Historical data graphs for pollution trends
- Personalized health recommendations based on AQI levels and user profiles
- Push alerts for anomaly or high-pollution events

Methodology

1.Data Collection and Preprocessing

To ensure comprehensive model training and evaluation, data was collected from diverse geographic zones including urban streets, suburban residential areas, and industrial sectors. Over 10,000 sensor readings were recorded, each consisting of five environmental parameters: PM2.5, CO_2, VOCs, temperature, and humidity.

To normalize the data and reduce variability caused by changing weather or environmental conditions, Min-Max scaling was applied to all sensor features. This step ensured consistent input values within the range of 0 to 1, facilitating stable model convergence.

2.Machine Learning Model

A hybrid approach was adopted for AQI prediction by combining XGBoost and LSTM (Long Short-Term Memory) networks:

- XGBoost was used for feature importance ranking, identifying which environmental variables most influenced AQI levels.
- LSTM, a recurrent neural network, was selected to model temporal dependencies across 24-hour sequences of sensor data**.**

The model input consisted of 24-hour historical data windows with 5 features (PM2.5, CO_2, VOCs, temperature, humidity). The final architecture is described below:

python

```
model = Sequential()
model.add(LSTM(64, input_shape=(24, 5)))  # 24-hour history, 5 input features
model.add(Dense(1, activation='linear'))  # AQI output
```

Performance Metrics:

- Accuracy: 92%
- Mean Absolute Error (MAE): 4.2 AQI points

3.Edge Deployment

To enable on-device inference using the ESP32 microcontroller, the trained model was quantized and converted using TensorFlow Lite. The final model size was reduced to under 50 KB, making it suitable for deployment within the limited flash memory and compute capabilities of the ESP32 platform. The quantized model was integrated with the sensor data pipeline to deliver real-time AQI predictions at the edge.

Results & Discussion

The proposed air quality monitoring system was rigorously tested in real-world conditions to evaluate its performance in predicting AQI and delivering actionable insights to users.

1.Real-Time Prediction Performance

The system achieved real-time AQI predictions with latency consistently under one second. This ensures timely feedback for users and makes the solution viable for continuous, mobile use.

2.Accuracy and Correlation

To validate prediction reliability, results from the system were compared with nearby government-operated reference air quality stations. The model output showed a strong correlation coefficient ($R^2 = 0.91$), indicating high alignment with ground-truth AQI values.

3.Personalized User Alerts

The Flutter-based mobile application was able to provide users with dynamic, personalized alerts based on detected environmental conditions. Example messages included:

- "High PM2.5 detected! Avoid outdoor exercise."
- "CO_2 levels elevated—consider ventilation."

Applications

- **Health Monitoring**: Supports individuals with respiratory conditions.
- **Smart Cities**: Complements fixed monitoring stations for urban planning.
- **Research and Education**: Provides data for academic and citizen science projects.
- **Disaster Response**: Rapid deployment during fires or chemical leaks.

Conclusion & Future Work

This project successfully developed a low-cost, AI-driven air quality monitor that provides real-time, personalized pollution tracking. The approach provides hyperlocal pollution tracking with spatial tagging and embedded intelligence, representing a step forward in personal environmental sensing. Future enhancements include:

- Solar-powered operation for extended battery life
- Integration with smart city infrastructures
- Federated learning for crowd-sourced model improvements

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