Low-Cost IoT Platform for In-Cabin Air Quality Monitoring

Pilot Deployment and Machine Learning Feasibility Study

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Why In-Cabin Air Quality Matters

- Poor air quality affects health, comfort, and concentration
- Vehicles and closed spaces accumulate pollutants quickly
- Professional monitoring systems are expensive and static

Project Overview

- Low-cost IoT device for real-time air quality monitoring
- Live web platform for visualization
- Machine learning used for automatic air quality classification
- Pilot case study conducted in Almaty

System Architecture

- IoT sensor device (Tynys)
- Cloud database
- Web-based dashboard
- Machine learning inference layer

Measured Parameters

- CO_2
- $PM_{2.5}$
- PM_{10}
- PM_1
- Temperature
- Humidity
- VOC
- CO
- O_3
- NO_2
- CH_2O

Data Transmission Format

Sensor data is sent in JSON format:

```
{
 "device_id": "lab01",
 "site": "AGI_Lab",
 "pm25": 25.7,
 "pm10": 43.1,
 "co2": 412,
 "temp": 21.8,
 "hum": 46.2
}
```

Sampling and Noise Reduction

- Data sampled every 60 seconds
- 5-point moving average filter applied

$$y = \frac{x_1 + x_2 + x_3 + x_4 + x_5}{5}$$

Machine Learning Approach

The system automatically classifies air quality levels:

- Low / Moderate / High
- Safe / Unsafe

Algorithms Used

- Logistic Regression
- Decision Tree
- Random Forest
- XGBoost (main model)

Sensor Calibration

- Pre-deployment calibration conducted indoors
- Tynys device co-located with Qingping Air Monitor Gen 2
- One-hour synchronized measurement session
- Baseline offsets minimized

Reference Device Validation

- Qingping monitor evaluated by SCAQMD
- Compared against FEM-grade instruments
- $PM_{2.5}$ correlation: $R^2 = 0.89 – 0.95$
- High data recovery and low error

In-Cabin Validation

- Both devices installed inside a passenger cabin
- Measurements recorded simultaneously
- PM, CO_2, temperature, and humidity trends closely matched

Web-Based Dashboard

- Live visualization of sensor data
- Real-time air quality classification
- User-friendly interface for monitoring

Key Outcomes

- Reliable low-cost sensing performance
- Strong agreement with reference monitor
- Machine learning feasible for automatic classification
- Suitable for mobile and in-cabin environments

Future Improvements

- Larger dataset collection
- Long-term sensor drift analysis
- Advanced ML models
- Integration with alerts and recommendations

Conclusion

Low-cost IoT + Machine Learning

A practical solution for smart air quality monitoring