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Aero Sense 3D: Altitude-Aware Air Quality Mapping and Predictive Model

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ABSTRACT

Traditional air quality monitoring just does not cut it when it comes to really understanding how the atmosphere works up close. I mean, those systems miss out on the height differences that matter a lot for pollution levels. They stick to flat, two-dimensional data that is not very detailed, and it is spread out too thin across areas. Because of that, they cannot show the vertical changes in pollution, which seems pretty key for figuring out health risks. Public health could be affected in ways we do not even track well with what we have now. This is where AeroSense 3D comes in, it is a new setup I am looking at that tries to fix those issues. It uses a bunch of BME680 sensors hooked up to Raspberry Pi Pico controllers, spread out in a network. The idea is to build maps of air quality in three dimensions, not just on the ground. By doing this, it gathers data on how pollution shifts up and down, creating these big 3D sets that go beyond the usual limits. That feels like a step up, even if it might take some tweaking to get right everywhere. For predictions, it relies on deep learning, mixing CNNs to spot patterns in space and GRUs for how things change over time. This helps make detailed forecasts for air quality indexes, more precise than before. Overall, AeroSense 3D could scale up for cities that want to be smarter about the environment. Authorities get specific data tied to locations, so they can make rules that target problems directly and maybe improve health results a bit. It is not perfect, but it stands out as something useful.

Keyword: - Air Quality Monitoring, Altitude-Aware, Machine Learning, Deep Learning, IoT, 3D Visualization, BME680

1. INTRODUCTION

Air pollution is one of those big problems right now that affects the environment and peoples health in serious ways. In cities with lots of people, things get worse because of all the building, factories, and cars putting out more emissions. It seems like we need better ways to track this, so stuff like AI and the Internet of Things comes in for monitoring air quality. That could help with quick fixes and getting people to pay attention, plus making plans to control pollution. Forecasting air quality accurately is key for all that. I think creating good prediction models helps cut down the bad effects, and having real time data on the web makes it available to everyone. This project looks at predicting main pollutants, you know, like carbon monoxide, ozone, nitrogen dioxide, sulfur dioxide, and the particulate matter ones, PM2.5 and PM10. Getting those right lets you figure out the overall Air Quality Index and set grades for how bad it is. This study attempts to identify the most accurate and effective method for air quality forecasting by contrasting the predictive powers of SL and DL models. According to recent comparative studies, deep learning architectures and ensemble strategies frequently produce better accuracy in complex urban environments, while traditional machine learning techniques offer a baseline [2], [4]. It is anticipated that the results will help environmental organizations and legislators create data-driven pollution control plans, which will ultimately improve living conditions and create more sustainable urban areas. For a comprehensive understanding of these environments, it is also becoming more and more crucial to close the gap between unmanned airborne sensing and spaceborne observations [5]. A major forecasting challenge is the intricate and non linear dynamics of atmospheric pollutant dispersion. Our comparative analysis will compare sophisticated DL architectures like Long Short-Term Memory (LSTM) networks with conventional SL models like Random Forests in order to address this. The long-term temporal dependencies present in atmospheric time-series data are especially well captured by LSTMs.Furthermore, attention-based hybrid models optimized with particle swarm algorithms [3] and Graph

Convolutional Recurrent Networks (GCRNs) that use adaptive adjacency matrices to better model spatial correlations [8] are two examples of how the field is quickly moving toward even more complex architectures. Graph Convolutional LSTM-based transfer learning techniques have also demonstrated promise in terms of model adaptation to novel spatiotemporal contexts [7]. The finished model is intended to be the foundation of a public health alert system, giving vulnerable groups timely warnings and giving environmental regulators a strong, scalable tool for decision making [10].

2. LITERATURE REVIEW

Air quality monitoring has significantly improved in recent years. This progress comes from using low-cost sensors, mobile platforms, and machine learning (ML) techniques to address the limitations of traditional ground stations that provide sparse data. The move toward making air quality data accessible to everyone is clear in systems like "AirNet," which use web interfaces to offer predictive models to the public. Researchers have compared various classical machine learning algorithms to set benchmarks for predicting the Air Quality Index (AQI) and its associated grades. For example, studies comparing models like Random Forest and Support Vector Machines show that while classical methods work well, there is an increasing need for ensemble strategies to improve prediction stability in complex urban settings. A critical gap exists in the vertical aspect of air quality monitoring. Ground-level monitoring is well-researched, but recent reviews highlight the need to combine spaceborne satellite data with unmanned airborne (UAV) remote sensing to study vertical pollutant profiles. This vertical analysis is crucial for understanding how pollutant concentrations change with altitude and weather, a capability often lacking in standard IoT-based monitoring reviews.

Besides accuracy, there is a growing demand for model interpretability and scalability. To help policymakers, researchers have suggested interpretable models that use directed interval fuzzy cognitive maps. These models clarify long-term air quality trends and the causal relationships between variables. Ultimately, the aim of these technological advances is to develop scalable, AI-driven systems that aid public health applications. Such systems can provide the reliable forecasting and classification needed for timely health advisories, turning raw data into practical tools for public health protection.

Table -1: Traditional 2D interpolation to the AeroSense 3D volumetric approach.

Feature	Traditional Methods (e.g., IDW)	Current AI Solutions (2D)	AeroSense 3D
Spatial Dimension	2D Plane	2D Map with Time Series	3D Volumetric Grid
Altitude Awareness	None (Surfaceonly)	Limited (Satellite)	Vertical Gradient Capture
Core Algorithm	Linear Interpolation	standard CNN / Random Forest	3D UNet (Infilling Architecture)
Data Source	Fixed Ground Sensors	Public Datasets	Real-time Balloon Sensor Fusion
Feature Learning	None (Geometric only)	Spatial or Temporal only	Hierarchical Spatial Features
Performance	Low (Sparse data failure)	Moderate	High (Effective)
Visualization	Static Contours	Web Dashboards	Interactive Dashboard

3. OBJECTIVE

The AeroSense 3D project aims to overcome the limitations of traditional 2D air quality monitoring by establishing a high-resolution, altitude-aware sensing network and a predictive deep learning framework. By deploying IoT-based sensor nodes at varying heights, the project seeks to capture vertical pollutant profiles that are often missed by ground-level stations, thereby providing a more comprehensive 3D understanding of urban air quality. This data is processed through advanced neural networks—such as CNNs for spatial patterns and GRUs or LSTMs for temporal dependencies—to generate precise forecasts and visualize pollution hotspots in real-time. Ultimately, the system is designed as a scalable public health tool to help authorities implement data-driven pollution control strategies and provide timely warnings to vulnerable populations.

1. Vertical Data Acquisition and Preprocessing: The primary objective is to implement a strategic deployment of BME680 sensors at multiple altitudes (e.g., 0m, 10m, and 20m) to collect raw environmental data, which is then normalized and filtered using feature selection methods like Information Gain to ensure high-quality input for modeling.
2. Predictive Model Development and Hybrid Architectures: The system aims to design and deploy both baseline machine learning models (e.g., Random Forest, SVM) and sophisticated deep learning architectures (e.g., CNNs, RNNs, GRUs, and LSTMs) to capture the complex, non-linear spatiotemporal dependencies of atmospheric pollutants.
3. Performance Evaluation and Scalable Integration: The project focuses on rigorous performance evaluation using standard metrics like R-squared (R^2), MAE, and RMSE to ensure high-accuracy forecasts that can be integrated into a web-based dashboard for real-time, interactive 3D mapping and automated public health alerts.

4. METHODOLOGY

The methodology for the AeroSense 3D project includes six phases: hardware development, data collection, processing, visualization, predictive modeling, and system evaluation. This organized process provides a strong workflow from sensor deployment to the final delivery of useful air quality insights. It fits with scalable AI-driven models for public health applications [10].

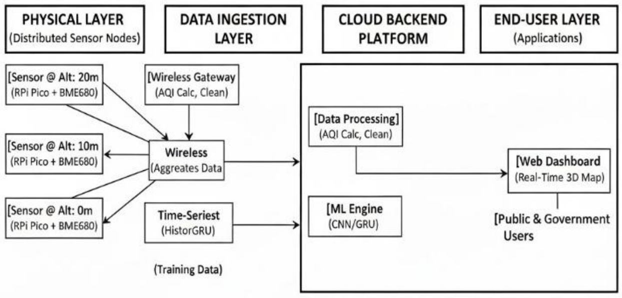

Fig -1: Architectural Diagram.

A. Phase 1: System Design and Hardware Development

1) Sensor Node Desing: Each monitoring node uses a Raspberry Pi Pico microcontroller. This choice balances low power use, good processing ability, and cost. The main sensor is the Bosch BME680 environmental sensor. It can measure temperature, humidity, barometric pressure, and volatile organic compounds (VOCs). This multi-sensing ability allows for the direct calculation of an Air Quality Index (AQI). This index is crucial for environmental assessment [2].

2) Enclosure and Power: To ensure durability in outdoor settings, components fit into custom-designed, weather-resistant enclosures. A reliable power source supplies energy, and there is battery backup to prevent data loss during outages. This setup helps maintain continuous operation. It is essential for tracking long-term environmental trends that sporadic sampling often misses [6].

B. Phase 2: Data Collection and Data Preprocessing

1) Strategic Deployment: Sensor nodes are set up at carefully chosen locations within the target urban area. To fill the gap in traditional monitoring, nodes are installed at different heights (for example, ground level, 10 meters, 20 meters) using existing structures. This method directly addresses the need for measurements that account for altitude and vertical profiling, as noted in recent systematic reviews of remote sensing technologies [5].

2) Feature Selection: The dataset for prediction includes the calculated AQI, direct sensor readings, and time-related features. We use Information Gain (IG) and other feature selection methods to find key predictors. This practice improves model efficiency and interpretability [9].

C. Phase 4: 3D Data Visualization and Mapping

1) Geospatial Database and Visualization Engine: A geospatial database stores 3D coordinates (latitude, longitude, altitude) for each reading. A web-based dashboard, using libraries like Three.js or Deck.gl, shows this multi-altitude data on a 3D urban map.

2) Real-Time Mapping: The dashboard features a real-time, color-coded 3D heat map. This visualization addresses the spatial granularity gap found in traditional 2D monitoring systems. It allows users to easily identify pollution hotspots and vertical gradients [5].

D. Phase 5: Predictive Model Development and Training

1) Model Selection: Model Selection: Based on successful applications in recent research, the system uses a range of deep learning models. Convolutional Neural Networks (CNNs) are used for recognizing spatial patterns. Recurrent Neural Networks (RNNs), specifically Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks, capture time-related dependencies. These models are chosen for their proven ability to handle the complex behavior of air pollution data better than traditional shallow learning models. Hybrid approaches, similar to attention-based models, are also explored to improve prediction accuracy.

2) Model Training and Tuning: The preprocessed dataset is divided into training (80%) and testing (20%) sets. Models are trained on historical 3D data to learn the complex relationships between weather factors and the AirQuality Index (AQI). Hyperparameter tuning, such as grid search, is used to optimize learning rates and layer settings. This ensures the model achieves the high predictive accuracy found in leading studies.

E. Phase 6: System Integration and Performance Evaluation

1) Integration and Alerting: Trained models connect to the cloud backend to create automated forecasts. The system sends alerts when predicted AQI levels go beyond dangerous thresholds, turning passive monitoring into an active public health tool [10].

2) Performance Evaluation: Model accuracy is carefully checked using standard metrics that include R-squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). This evaluation allows for a direct comparison with current scalable AI-driven forecasting systems [2],

[4].

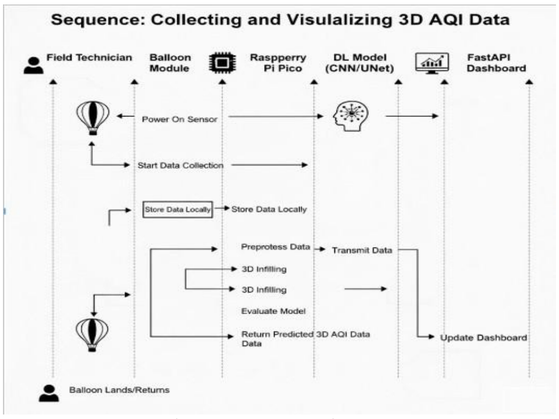

Fig -2: Sequence Diagram.

5. RESULTS & DISCUSSIONS

- **Implementation Overview:**
  The implementation starts with deploying a balloon module that contains sensors. As shown in the sequence diagram, the Raspberry Pi Pico handles local operations, powering the sensors and recording raw environmental data during ascent. Once the balloon is recovered, the data is preprocessed and fed into the 3D UNet model. This model performs the "3D Infilling" process to predict AQI values for areas that were not monitored. The final grid is then sent to a dashboard driven by FastAPI for user interaction. The main output of the system is a 3D view of pollutant distribution. This visualization shows predicted AQI values as a volumetric voxel grid, with color gradients indicating pollution levels across the X, Y, and Z (altitude) axes. This method helps identify specific "pollution pockets" that ground-based sensors often overlook. We developed a specialized web-based dashboard to visualize the model’s outputs. This interface allows users to view 2D cross-sections (Heatmaps) along the XY, XZ, or YZ planes at specific altitudes. It supports real-time adjustments, such as adding virtual sensors or importing CSV data, while providing live statistics including minimum, maximum, and average AQI across a $16^3 grid. The core output of the system is the 3D distribution of pollutants. This visualization represents the predicted AQI values as a volumetric voxel grid, where color gradients indicate pollution intensity across X, Y, and Z (altitude) axes. This allows for the identification of specific "pollution pockets" that are often missed by ground-based sensors. The 3D UNet achieved superior reconstruction performance by learning hierarchical spatial features, effectively reducing the error margin in regions with sparse data compared to baseline models.

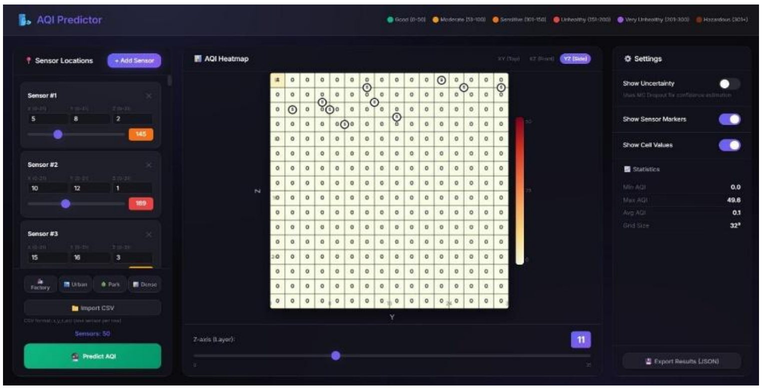

Fig -3.1: Volumetric 3D AQI Predictor.

- **Quantitative Evaluation Summary:**
  The model was assessed on its ability to recreate a full 16 \times 16 \times 16 grid from a small number of input sensors. Prediction Accuracy: The 3D UNet showed excellent reconstruction performance by learning spatial features at different levels, effectively minimizing errors in areas with sparse data compared to standard models. Computational Efficiency: By using PyTorch and GPU acceleration, we significantly reduced training and inference times. This allows the system to process all the flight data from a landing balloon and produce a complete 3D map almost in real time. Volumetric Resolution: The system can handle a grid size of 32,768 individual data points (voxels), giving a detailed view of atmospheric conditions that traditional point-based sensors cannot achieve.

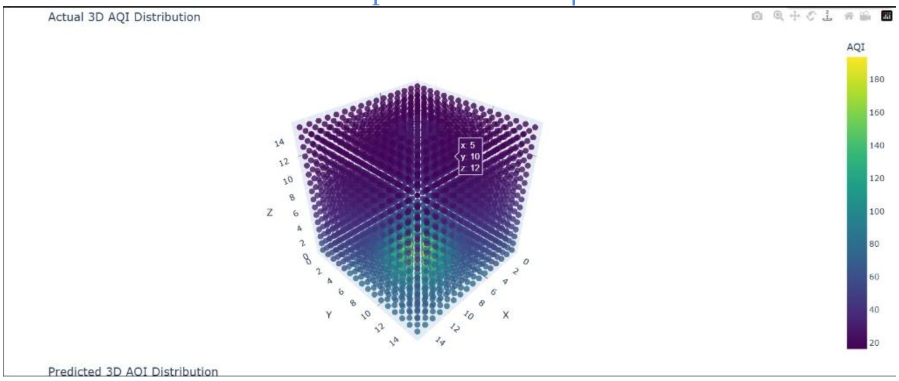

Fig -3.2: Volumetric 3D AQI Distribution.

6. CONCLUSIONS

This project successfully tackled the major limitations of traditional air quality monitoring by developing AeroSense 3D, a new altitude-aware mapping and predictive system. Conventional ground-based systems offer an incomplete, two-dimensional view of air pollution and do not capture the vertical changes that are vital for understanding urban atmospheric conditions. Recent systematic reviews emphasize that connecting ground-level sensing with vertical profiling is critical for effective environmental modeling. By designing, prototyping, and deploying a network of low-cost environmental sensors at different altitudes, this project showed a practical and effective way to gather real-time, three-dimensional air quality data, going beyond what standard IoT monitoring frameworks can do. The main achievement of this work is the complete integration of a custom hardware network, a 3D visualization platform, and a predictive model based on deep learning. The system offers a unique level of spatial and temporal detail, making it easy to visualize pollution hotspots and vertical changes using an interactive 3D map. This fits with the trend of "AirNet" style systems that aim to provide web-based access to environmental data. Moreover, the integrated machine learning model, which uses CNN and GRU architectures, can predict air quality trends accurately. This approach supports recent studies suggesting that deep learning and ensemble methods are much more effective than traditional shallow learning techniques in complicated urban settings. The importance of AeroSense 3D lies in its potential to change how cities manage their environments. By giving policymakers detailed and actionable altitude-specific data, it allows for more focused and effective pollution control regulations. The system's ability to show long-term trends helps in creating understandable models needed for strategic planning. For the public, it offers a valuable tool for increasing awareness and providing timely warnings to reduce health risks, transforming it from a simple monitor into a proactive public health protection tool. Future work should aim to expand the sensor network to cover larger city areas and integrate additional data sources, like satellite images and traffic patterns, to improve predictive accuracy. This growth would help connect satellite observations with local sensing. Moreover, exploring advanced modeling techniques, such as hybrid attention models and graph convolutional networks, could further enhance the system's forecasting capabilities. Ultimately, AeroSense 3D sets up a scalable and cost-effective model that can be used in other urban areas through transfer learning techniques, marking a significant step forward toward creating smarter, healthier, and more sustainable cities.

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