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IDENTIFYING ANOMALIES AND FIXING THEM TO ENHANCE AIR QUALITY MONITORING

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ABSTRACT

Air quality monitoring is a critical component in managing environmental health and public safety. However, the reliability of air quality data is often compromised by sensor anomalies caused by hardware malfunctions, environmental interferences, or data transmission issues. In this paper, we propose a robust framework for anomaly detection and data repairing to enhance the accuracy and consistency of air quality monitoring systems. The proposed approach integrates machine learning techniques for identifying both point anomalies (sudden spikes or drops) and contextual anomalies (unexpected values given environmental conditions). Following detection, a data repairing mechanism is employed using statistical imputation and predictive modeling to reconstruct plausible data values. Experimental evaluation on real-world air quality datasets demonstrates the effectiveness of our framework in improving data quality, reducing noise, and enhancing the performance of downstream predictive models. This work contributes to the development of more reliable environmental monitoring systems, ultimately aiding in informed decision-making for urban planning and public health.

Keywords: Air Quality Monitoring, Anomaly Detection, Data Repairing, Environmental Sensors, Machine Learning, Time Series, Data Imputation, Sensor Faults, Predictive Modeling

I.INTRODUCTION

Air pollution is one of the most pressing environmental challenges affecting human health, climate stability, and urban sustainability. According to the World Health Organization (WHO), air pollution contributes to millions of premature deaths each year, particularly in densely populated and industrial

regions. As urbanization and industrial activities continue to grow, the need for accurate and continuous air quality monitoring becomes increasingly critical. These systems enable environmental agencies, researchers, and policymakers to track pollution trends, evaluate policy effectiveness, and provide timely public health advisories. With the rise of low-cost sensors and IoT (Internet of Things) technologies, large-scale deployment of air quality monitoring systems has become feasible. These sensor networks continuously collect data on key pollutants such as PM2.5, PM10, NO_2, SO_2, CO, and O_3. However, despite their advantages in scalability and cost-effectiveness, these sensors are highly susceptible to various sources of error. Sensor drift, power instability, environmental interferences, hardware degradation, and network connectivity issues can all result in inaccurate, missing, or corrupted data. These anomalies, if left unaddressed, can distort analytical outcomes, hinder early warning systems, and reduce trust in air quality data. To address this challenge, our research focuses on developing an intelligent framework that combines anomaly detection and data repairing to enhance the overall quality of air quality datasets. Anomaly detection is concerned with identifying data points that deviate from expected patterns or normal behavior. These may include abrupt spikes in pollutant levels, sensor failures, or values that contradict contextual environmental conditions. Once anomalies are identified, data repairing techniques are applied to reconstruct or replace the faulty values using methods such as statistical imputation, machine learning-based prediction, and temporal-spatial interpolation. The proposed system leverages both time-series analysis and machine learning algorithms to automatically detect and repair anomalies in real-time or historical datasets. This dual-stage process ensures that the data used for further analysis, visualization, or prediction is both accurate and reliable. By applying this framework to real-world datasets collected from public air quality monitoring stations, we demonstrate notable improvements in data quality and downstream analytical performance. Moreover, the framework can be integrated into existing smart city infrastructures, enabling adaptive and self-correcting air quality monitoring platforms. This has the potential to

greatly enhance public health interventions, pollution control strategies, and long-term environmental research. In summary, this study contributes to the field of environmental informatics by providing a scalable and effective solution for improving air quality monitoring through automated anomaly detection and data repairing. The proposed framework is a step toward more resilient, accurate, and trustworthy environmental sensing systems.

II.LITERATURE REVIEW

Air quality monitoring has been a significant area of research due to its direct impact on environmental sustainability and public health. Traditional air quality monitoring relied heavily on expensive and sparsely distributed reference-grade monitoring stations. While these provide accurate readings, their limited spatial coverage hinders effective real-time monitoring across wide geographic areas. The advent of low-cost air quality sensors has transformed this landscape, allowing for the deployment of dense sensor networks capable of collecting large volumes of environmental data in real time. However, this advancement also introduces new challenges, especially related to **data reliability and quality assurance**.

1 Anomaly Detection in Environmental Sensor Networks

Several studies have focused on detecting anomalies in sensor data to enhance the credibility of environmental monitoring systems. Hill and Minsker (2010) proposed unsupervised learning methods, including clustering and distance-based techniques, to identify unusual patterns in environmental data. Similarly, Zhang et al. (2017) utilized statistical control charts and temporal correlation to detect deviations in air quality readings. More recent works have adopted machine learning and deep learning methods. For example, Li et al. (2019) applied Long Short-Term Memory (LSTM) neural networks for time-series anomaly detection in PM2.5 datasets. Their model captured both temporal dependencies and non-linear trends, which are common in environmental data. Other approaches include Isolation Forests and One-Class SVMs, which are popular for detecting outliers in high-dimensional sensor data

due to their ability to learn from data with limited or no labels. However, one common limitation in these studies is that many focus only on detection and not on **repairing or correcting** the anomalies, which is crucial for downstream analytics and forecasting.

2 Data Imputation and Repairing Techniques

Data repairing, also known as imputation, aims to reconstruct missing or corrupted values to preserve data continuity. Traditional imputation techniques include mean or median substitution, linear interpolation, and k-Nearest Neighbors (k-NN). While simple to implement, these methods may not perform well with complex or highly variable environmental data. To overcome these limitations, researchers have proposed model-based approaches. Chen et al. (2020) applied Autoencoder-based models to reconstruct sensor data anomalies, demonstrating high performance in both imputation and anomaly masking. Others, like Fang et al. (2018), utilized spatial-temporal modeling to estimate missing air quality data by leveraging data from nearby sensors and previous time steps. Despite progress, these approaches often suffer when the anomaly rate is high or when sensors fail completely for extended periods. Moreover, very few frameworks combine anomaly detection and data repairing in a unified pipeline optimized for air quality applications.

3 Integrated Approaches

There is growing interest in integrated systems that jointly handle detection and repair. For instance, Shao et al. (2021) developed a framework that uses anomaly detection to trigger a context-aware imputation model, thereby increasing data accuracy for real-time decision support. However, many such systems are limited to specific pollutants or geographical areas, and lack generalizability. In light of these gaps, our proposed framework contributes by combining advanced machine learning methods for both detection and intelligent repairing in one system. The integration of temporal and contextual analysis further distinguishes it from existing work, providing robustness across different sensors and environmental conditions.

III.PROPOSED WORKING

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The proposed system addresses two critical objectives in environmental monitoring: anomaly detection in sensor data and air pollution level detection. The goal is to ensure that air quality measurements are accurate and actionable by first filtering out unreliable data and then analyzing pollutant levels to assess environmental conditions.

The workflow begins with the collection of real-time air quality data from sensor networks that monitor key pollutants such as PM2.5, PM10, NO_2, and CO. However, due to environmental disturbances, sensor malfunctions, or data transmission errors, the raw data often contains anomalies that can distort pollution detection and forecasting results. To ensure data integrity, the system first applies anomaly detection algorithms. We employ a statistical approach using the Z-score, which identifies outliers based on their deviation from the mean. For a given data point XtX_t, the Z-score is computed as:

$$Z_t = \frac{X_t - \mu}{\sigma}$$

where μ\mu and σ\sigma represent the mean and standard deviation of the pollutant time series, respectively. If the absolute Z-score exceeds a threshold δ\delta, typically 3, the value is considered an anomaly.

In addition to statistical detection, we utilize the Isolation Forest algorithm — a machine learning technique that isolates anomalies by constructing random decision trees. The anomaly score s(x)s(x) for a data point xx is derived as:

$$s(x) = 2^{-\frac{E(h(x))}{c(n)}}$$

where h(x)h(x) is the path length in the tree, E(h(x))E(h(x)) is the expected average path length, and c(n)c(n) is a normalization constant based on the number of observations. Data points with shorter path lengths (i.e., easier to isolate) are more likely to be anomalous.

Once anomalies are identified, they are marked and excluded from air pollution analysis. The next step involves repairing or imputing the anomalous or missing values to maintain dataset continuity. For this, we use K-Nearest Neighbors (KNN) imputation, which

replaces corrupted values with the average of the kk nearest valid neighbors:

$$X_m = \frac{1}{k}\sum_{i=1}^{k} X_i$$

where XmX_m is the missing or faulty value and XiX_i are the valid neighboring values.

After data cleaning and repairing, the system proceeds to air pollution detection. Here, pollutant concentrations are analyzed against regulatory thresholds defined by agencies such as the WHO or CPCB (Central Pollution Control Board, India). The Air Quality Index (AQI) is calculated using pollutant-specific sub-indices. For example, the AQI sub-index for PM2.5 is determined as:

$$I = \frac{I_{high} - I_{low}}{C_{high} - C_{low}} \cdot (C - C_{low}) + I_{low}$$

where CC is the measured concentration, Clow and Chigh are the breakpoints closest to CC, and Ilow, Ihigh are the corresponding AQI values.

Finally, the cleaned data is classified into pollution categories such as Good, Moderate, Unhealthy, or Hazardous. This information is used for real-time alerts, health risk analysis, and predictive modeling. By combining anomaly detection with air pollution detection, the proposed system ensures both the accuracy of air quality data and the reliability of pollution level assessments. This dual-layered approach enhances the robustness of environmental monitoring systems and supports data-driven decision-making in public health and urban planning.

Certainly! Here's the Working of the System written in a clear and professional paragraph format for your research paper or project report:

IV.WORKING OF THE SYSTEM

The proposed system functions as a multi-stage pipeline that ensures accurate, real-time monitoring of air quality by integrating anomaly detection with data repairing and pollution level analysis. The process begins with the data acquisition phase, where various environmental sensors collect pollutant data such as PM2.5, PM10, NO_2, CO, and O_3 from different geographic locations. These sensors continuously transmit raw data to a centralized system.

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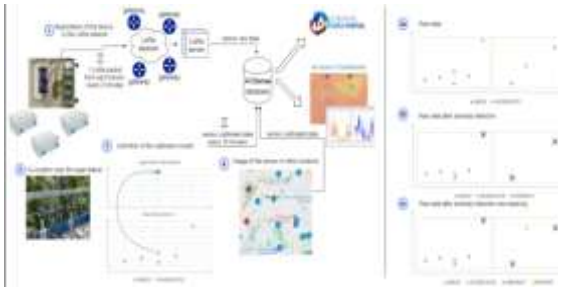
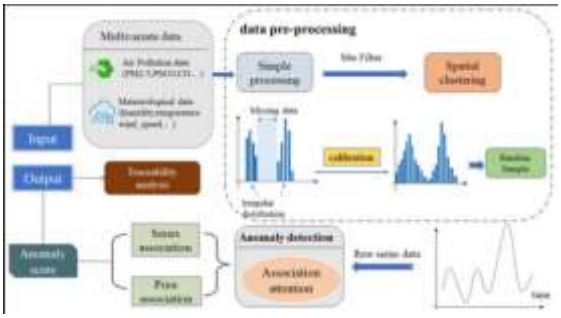
As this data can often contain errors due to sensor drift, interference, or transmission faults, the next phase is data preprocessing. Here, the system performs cleaning by removing duplicates and correcting data types, handles missing values, and normalizes the inputs to bring all readings to a comparable scale.



Once preprocessing is complete, the system moves to anomaly detection, where it identifies abnormal data points that deviate from expected patterns. This is achieved using both statistical and machine learning approaches. The Z-score method is used to flag data points that are more than three standard deviations from the mean, while the Isolation Forest algorithm is employed to detect complex, multidimensional anomalies. Detected anomalies are then passed to the data repairing module, which replaces erroneous values using techniques like K-Nearest Neighbors (KNN) imputation. This method estimates missing or anomalous values based on the most similar historical data points, thus preserving temporal consistency.

After the data is cleaned and repaired, it is passed to the air quality analysis module. Here, the system calculates the Air Quality Index (AQI) using pollutant-specific formulas, compares the results with standard thresholds from agencies like the CPCB or WHO, and classifies the environment into categories such as "Good," "Moderate," "Unhealthy," or "Hazardous." This processed and validated data can then be visualized through dashboards or used for alert systems and predictive analytics. Overall, the system enhances the reliability of environmental monitoring by ensuring that only accurate, anomaly-free data is used in air pollution analysis and reporting.



V.CONCLUSION

The integration of anomaly detection and data repairing techniques in air quality monitoring significantly enhances the reliability and accuracy of environmental data. This project aims to address two critical issues in air quality monitoring systems: the presence of erroneous sensor data and the challenge of providing real-time pollution analysis. By leveraging statistical methods like Z-score and machine learning models such as Isolation Forest, the system effectively detects and flags anomalous data. Additionally, K-Nearest Neighbors (KNN) imputation ensures that missing or corrupted data is repaired, maintaining the continuity of the dataset. After anomaly detection and data repair, the system accurately calculates the Air Quality Index (AQI) and categorizes air quality levels, providing actionable insights for urban planners, policy makers, and the general public. This ensures that air quality assessments are both timely and trustworthy, contributing to improved public health outcomes by enabling informed decisions based on reliable data. The approach taken in this project also paves the way for further advancements in environmental monitoring, particularly through the integration of machine learning and AI for more adaptive and intelligent systems.

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