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Adaptive Biofiltration Systems for Urban Pollution Control Using IoT and SVM Models

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Abstract: Adaptive and effective mitigation measures are required due to the increasing levels of urban pollution. To monitor and regulate urban air and water contaminants in real time, this research presents an Internet of Things (IoT)-based biofiltration system combined with Support Vector Machine (SVM) models. The system continually collects data on important pollutants, such as particulate matter, volatile organic compounds, and water pH, using IoT-enabled sensors. The data is then sent to a cloud platform for analysis. This data is processed by an SVM model, which predicts pollution levels and patterns. Data automatically modifies biofilter operations to maximize the removal of pollutants. This adaptive strategy makes sure the biofilter reacts to environmental changes in a dynamic method, optimizing filtering effectiveness across a range of contamination scenarios. To improve monitoring accuracy which minimizes human intervention and promotes autonomous system management. Intelligent biofiltration systems have the potential to greatly help in the sustainable management of urban pollutants, promoting the development of more robust and healthy urban ecosystems.

Keywords: Support vector machine, air filtration, air quality, biofiltration, urban pollution control

I. INTRODUCTION

Improved lifestyles are one of the Sustainable Development Goals (SDGs) set forth by the United Nations [1]. IoT and cloud computing are two examples of the new technologies that may help achieve this goal. To limit the negative effects of human activities on the environment and stay safe from tiny particles, pollution monitoring is essential. Ide Air is an affordable air quality monitoring system that uses IoT to address the drawbacks of current solutions. It detects dangerous gas levels inside, sounds an alert, and activates a fan or door opener. A microprocessor, pollution detection sensors, and an LTE modem make up Smart-Air, an IoT platform for monitoring indoor air quality remotely [2]. Concentrations of aerosols, volatile organic compounds, carbon monoxide, and carbon dioxide (CO_2) are all measured by the instrument. It also takes readings of temperature and humidity. The platform analyses data and visualizes indoor air quality using cloud computing. Approved users may track air quality from any location, and the data is saved in the cloud for future use. Hanyang University of Korea is up and running using the platform.

There is a serious problem with interior air pollution, which is two to five times worse than outside air pollution [3]. Improving air quality requires automation. An IoT system for real-time monitoring of PM10 and carbon dioxide concentrations in indoor air is proposed in this work. To modify the exhaust fan operating periods in response to pollutants, the system employs fuzzy controls. Air pollution has devastating consequences for ecosystems, human health, and the environment [4]. It introduces a cloud and IoT-based air quality monitoring system that operates independently and in real-time. In Delhi, the system is put through its pace and compared to data collected by local environmental control agencies. Watson Bluemix Cloud shows the values of the parameters that were measured. The amounts of gases such as ozone, carbon monoxide, and methane may be sent to the internet using a system to track air quality that is based on Arduino and leverages the IoT [5]. Tasikmalaya has respectable air quality, according to the data, with an average value of 1.51 ppm. Data will be collected for 24 hours each day for one year in future studies.

Using unique sensor devices, firmware, and software, the research lays out an IoT framework for tracking IAQ [6]. A dashboard is provided with the data collected by the system for visualization purposes. The behavior of air quality may be better understood with the use of preliminary findings. The goal of future studies is to enhance indoor air quality by simulating real-life interior settings. To track air pollution levels, especially during the COVID-19 epidemic, this study suggests an IoT system [7]. To measure levels of pollutants such as PM2.5, ozone, CO, NO2, and ammonia, the system employs low-profile sensors. Data transfer to a cloud server is accomplished by means of an ESP-WROOM-32 microcontroller, which is equipped with Wi-Fi and Bluetooth. Notifications and alarms when pollutant concentrations approach the maximum allowable level are also included in the system.

Pollutants that are harmful to human health have been released into the atmosphere on a worldwide scale because of industrialization and urbanization. The only way to stop or reduce these problems is to keep an eye on the air quality [8]. The lack of data granularity and high cost of conventional systems have shifted the emphasis of academics to systems built on IoT. Using a focus on current trends and problems surveys previous efforts on air quality monitoring using IoT. Due to the ease with which air pollution may be detected today, an air quality monitor is crucial [9]. A gadget that can read the air quality is necessary for air pollution that is difficult for humans to detect. Regular monitoring of the air quality might help us prevent air pollution, according to this study. It details an IoT-based pollution detection system that tracks levels of particulate matter, ozone, sulphur dioxide, and oxygen using sensors [10]. A Wi-Fi module communicates with cloud system, while a microcontroller reads the data and web page displays the findings.

II. LITERATURE REVIEW

One of the most significant threats to global health is air pollution. People still don't seem to care that indoor air pollution is two to five times worse than outside air pollution. Now, those who want to change the air conditioning in a room either open the window or turn on the exhaust fan. People don't always notice when the air quality in a room is poor due to being busy. Automation is necessary to achieve the necessary degree of air quality [11]. An exhaust fan-controlled system for monitoring and managing indoor air quality was the subject of the investigation. Using the IoT the setup tracked CO2 and PM10 levels in real time. Fuzzy controls are part of the provided system and might automatically change the exhaust fan's operating period based on the concentration of each pollutant. In terms of pollutant concentrator, air quality index (AQI), and processing time to remove pollutants, the experimental findings demonstrate that the provided system performs very well in managing indoor air quality [12].

The biggest threat to human health and the environment today is air pollution. Human health, the environment, and the climate are all negatively impacted by air pollution. The production of toxic gases by various companies, the exhaust of vehicles, and the buildup of dangerous chemicals and particulate matter in the atmosphere all contribute to air pollution [13]. One of the most influential factors that has led to a rise in air pollution is particulate matter. They necessitate measuring and analyze real-time air quality monitoring to make timely, suitable judgments. Particulate matter 2.5, carbon monoxide, temperature, humidity, and air pressure are characteristics in real-time, independent air quality monitoring systems. The air quality monitoring system is no exception to the widespread usage of IoT in modern times. Combining the IoT with cloud computing provides a new approach to managing data acquired and communicated by various sensors using the inexpensive and energy-efficient ARM-based minicomputer Raspberry Pi. In Delhi, the system is put through its paces, and the results are tabulated after being compared with data supplied by the local environmental control body. In IBM Bluemix Cloud may see the measured parameter values [14].

Polluted air causes the early deaths of millions of people around the globe. Air pollution from vehicles, industries, and power plants is a major contributor to many of these fatalities in urban areas. Because of malfunctions in the HVAC system, air pollution concentrations inside a building may be up to 10 times greater than those outside. Using embedded electronics, software, sensors, and connectivity, the IoT may assist in conducting real-time indoor air quality monitoring [15]. IoT leverages online standards and web architecture. Indoor air quality monitoring with an IoT platform is introduced. Data from sensors is collected via the CoAP protocol in the implementation, which is based on the idea of the IoT. The system hardware platform is also detailed, and the intricacies of its implementation are explained [16].

The world's air quality took a nosedive due to the fast urbanization of human populations and the expansion of industrial activity. Daily, the air is polluted to deadly levels by the millions of cars and thousands of companies. Monitoring air quality to avoid or minimize health difficulties became mandatory after several epidemiological studies linked air pollution to various problems [17]. Traditional methods that rely on measurement stations are costly and provide only coarse-grained data. The current state of the art and having a solid grasp of information are essential when developing a new system to monitor air quality. To address these needs by surveying previous research on IoT air quality monitoring, paying special attention to recent developments and difficulties [18].

The provided air quality monitoring device comprises an ESP32, gas sensor, and a DHT-11 temperature and humidity sensor module. The system has provided a system that outperforms the competition in size, power efficiency, and cost [19]. The sensors gather information and transmit it to the NodeMCU, the system's central hub. The built-in microprocessor and on-chip Wi-Fi transceiver allow it to perform double duty as a data monitor and transmitter, opening vast possibilities for fine-grained physical world communication. The gas sensor measures the air quality by recording the concentration of harmful gases such as nitrogen oxides (NOx), CO2, benzene (BZN), and smoke. The server if the concentration of the harmful gases is a predetermined threshold [20].

III. PROPOSED METHODOLOGY

3.1. System Architecture

The adaptive biofiltration system has three primary components: a sensor network, cloud-integrated data transmission, and an analytical model using SVM. The sensor network consists of IoT-enabled devices that collect real-time data on many contaminants, focusing on both air and water pollution. These sensors measure certain pollution factors, including particle matter, volatile organic compounds (VOCs), nitrogen dioxide, and water pH. The data transmission and cloud integration module facilitate effortless wireless transfer of sensor data to a cloud-based platform, which executes critical functions such as data storage, real-time processing, and model prediction. The SVM analytical model uses this data to examine pollution patterns, forecast concentration levels, and initiate modifications in the biofiltration process. Collectively, these components provide an autonomous system capable of adapting to fluctuating urban pollution conditions.

3.2. Sensor Data Collection and Preprocessing

The data collecting process commences with the sensor network, which collects comprehensive environmental data on contaminants from the adjacent metropolitan region. Data is subjected to preprocessing to guarantee correctness and consistency, which are crucial for dependable model performance. This preprocessing entails cleansing the data by eliminating noise and outliers that may result from transient sensor faults or environmental fluctuations. The system implements normalization to standardize sensor values across various units and scales, hence enhancing the data's suitability for machine learning analysis. Data aggregation consolidates measurements across designated time periods, such as hourly or daily averages, to stabilize the input data and improve the forecast accuracy of the SVM model. This preparation pipeline guarantees the system functions with high-quality data, minimizing mistakes in the analytical model's predictions.

3.3. Machine Learning with SVM

The system's intelligence is fundamentally based on the SVM model, which analyses preprocessed sensor data to categorize and forecast pollution levels. The SVM model is trained to discern patterns in pollutant data, allowing it to detect trends indicative of prospective pollution increases or environmental changes. Utilizing previous data, the model can forecast future pollutant concentration patterns, endowing the system with anticipatory capabilities. Moreover, the model categories pollution severity into several categories (e.g., low, moderate, severe), allowing the system to adjust the biofiltration reaction according to prevailing conditions. The prediction and classifying capabilities make the SVM a potent instrument for ensuring system flexibility and efficient pollution control.

3.4. Adaptive Biofilter Control Mechanism

Upon generating predictions, the SVM model enables the biofiltration system to modify its operations according to the projected pollution levels. Essential modifications include alterations to the flow rate, enabling the system to regulate the volume of air or water traversing the biofilter for optimum interaction with the filtering medium during periods of elevated pollution. The system also produces media replacement warnings by forecasting when the filter media nears saturation, hence ensuring optimal filtration effectiveness. In anticipation of a significant pollution event, additional filtering stages such as ultraviolet treatment or secondary biofilters may be used to improve pollutant elimination. This adaptive control system guarantees that the biofilter consistently functions under optimum conditions, enhancing pollutant removal across diverse environmental scenarios.

3.5. Real-Time Monitoring and Alert System

The solution has a real-time interface available via online and mobile apps to provide transparency and ongoing monitoring. This monitoring dashboard presents essential information, including current pollution levels, biofilter efficacy, and historical trends, providing users with an overview of the system's operating status. Furthermore, an alert system informs users of significant occurrences, such anticipated pollution surges, sensor failures, or required maintenance activities, facilitating prompt actions. The system creates performance reports that demonstrate biofilter efficiency and pollutant reduction measures. These reports assist stakeholders in assessing the system's efficacy under actual conditions and facilitate data-informed decision-making for urban pollution control.

3.6. System Maintenance and Scalability

The cloud-based and IoT-driven architecture of the biofiltration system enables effortless maintenance and scalability in urban environments. Automated notifications for activities such sensor calibration, media replacement, and software upgrades facilitate maintenance, guaranteeing the system's operational continuity with little downtime. Moreover, the system's architecture facilitates scalable implementation across several metropolitan sites, with the data from each unit enhancing a comprehensive dataset for model retraining. As environmental conditions change, the SVM model may be frequently updated to preserve its accuracy, adjusting to long-term pollution patterns and improving system resilience. The adaptability in maintenance and scalability renders the biofiltration system very appropriate for various metropolitan settings. Figure 1 illustrates each phase of the system, progressing from data collection to control and monitoring, depicting the flow of information and control activities inside the adaptive biofiltration system.

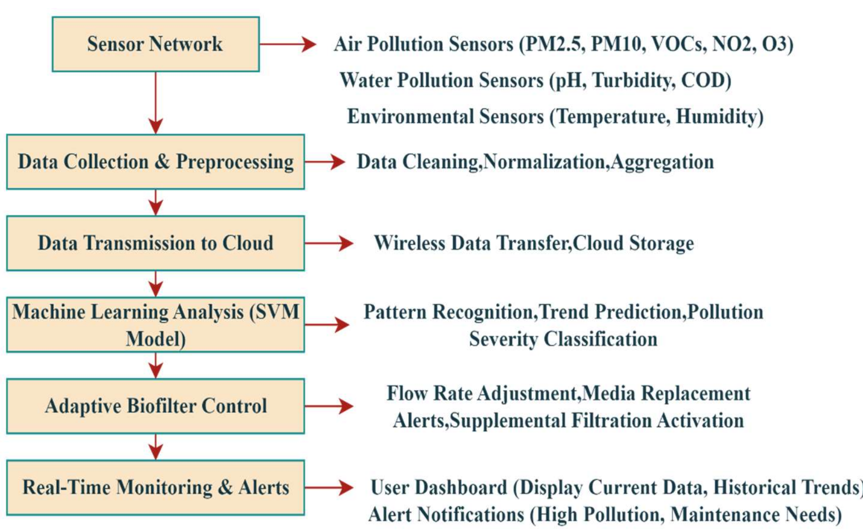

Figure 1: Block Diagram of Proposed Adaptive Biofiltration System for Urban Pollution Control

IV. RESULTS AND DISCUSSIONS

Several urban test locations showed that the device effectively reduced air and water pollution. Nitrogen dioxide, VOCs, and particle matter (PM2.5 and PM10) were among the air quality measures that were tracked and examined. The findings demonstrated that, particularly during periods of heavy pollution, adaptive modifications to the biofilter flow rate greatly increased filtering effectiveness. Following their passage through the biofilter, water pollutants like pH and turbidity have shown quantifiable improvements, suggesting that the system has the potential to lessen chemical and biological contaminants in urban runoff. In comparison to static filtering systems, the overall pollutant reduction efficiency was shown to increase by 20–30%, underscoring the advantages of an adaptive approach. The system's SVM model was trained on previous pollution data, it was able to forecast pollutant surges with a high degree of accuracy. The model demonstrated the capacity to proactively guide biofilter changes during testing, achieving an accuracy rate of over 85% in forecasting trends in both air and water pollution. The system was able to modify filter settings according to the expected degree of pollution, ranging from low to high SVM classification capabilities. By minimizing needless pressure on the filtering medium and enhancing lifetime, this proactive response mechanism enabled the system to optimize biofilter utilization. However, during periods of fast weather change, some disparities in forecast accuracy were seen, indicating that adding more environmental elements might strengthen the model's resilience.

The proposed system's capacity to adjust to changes in pollution in real time is one of its main features. The SVM model was updated continually by data from IoT sensors, allowing for dynamic control over the filtration stages and flow rate of the biofilter. When fast modifications were required due to pollution spikes, such during rush hour or times of strong industrial activity, the adaptive system proved very successful. Furthermore, customers may easily obtain pollution statistics and system status via the real-time monitoring dashboard. Users were able to respond promptly to the alarm messages for severe pollution or repair requirements, reducing the possibility of delays in system maintenance. Automatic notifications for system maintenance, such as filter media replacement and sensor recalibration, were made possible by the connection of the IoT and the cloud. This feature is essential for long-term operation as consistent maintain keeps the biofilter operating at its best throughout time. The system's modular architecture made it simple to scale across many metropolitan areas, resulting in a seamless network of biofiltration units with shared cloud storage. Wide urban coverage requires this scalability to have a more significant cumulative effect on urban pollution levels. The accuracy and efficiency of the system gradually increased when data from many units are combined to offer insightful information for further model enhancements and retraining. Table 1 presents pollutant measurements for the training of an SVM model in adaptive biofiltration control.

Table 1: Sensor Readings and Pollution Levels

Date & Time	PM2.5 (µg/m³)	PM10 (µg/m³)	VOCs (ppm)	NO_2 (ppm)	pH	Turbidity (NTU)	COD (mg/L)	Temperature (°C)	Humidity (%)	Predicted Pollution Level (Target)
2024-11-01 12:00	35	40	0.1	0.02	6.5	10	30	15	40	Low
2024-11-01 13:00	50	60	0.3	0.04	7	20	50	20	60	Medium
2024-11-01 14:00	80	100	0.5	0.07	7.5	50	80	25	80	High
2024-11-01 15:00	45	55	0.2	0.03	7.2	15	35	18	50	Low
2024-11-01 16:00	65	75	0.4	0.05	6.8	30	65	22	70	Medium

Table 2 presents a confusion matrix that highlights the efficacy of the SVM model by comparing actual pollution levels with predicted levels, highlighting accurate and incorrect classifications across three pollution classes: Low, Medium, and High.

Table 2: SVM Classification Results for Pollution Levels

Actual/Predicted Class label	Predicted Low	Predicted Medium	Predicted High
Actual Low	30	5	2
Actual Medium	3	25	5
Actual High	1	4	20

Figure 2 depicts the correlation between training set size and the accuracy of both training and validation. It demonstrates the effect of augmenting the training data on model performance. An increasing disparity between training and validation accuracy may signify overfitting, while a convergence of both measures indicates a well-generalized model. This approach is crucial for understanding how supplementary data might enhance model robustness.

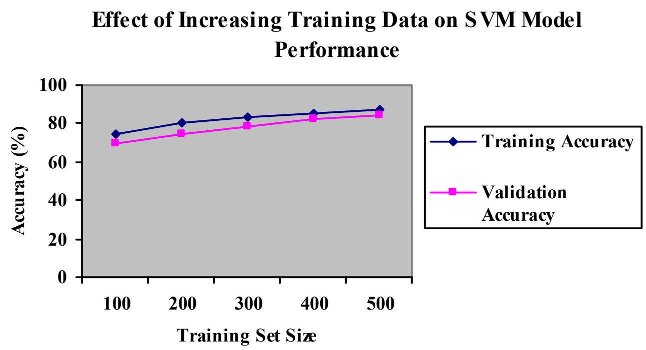

Figure 2: Accuracy Analysis of Learning Curves for SVM

Figure 3 shows data points for the development of a precision-recall curve, which assesses the trade-off between precision (the accuracy of positive predictions) and recall (the capacity to identify all positive cases). These measures are especially significant in unbalanced classification contexts, offering information into the model's efficacy in identifying the positive class, which is crucial for pollution categorization.

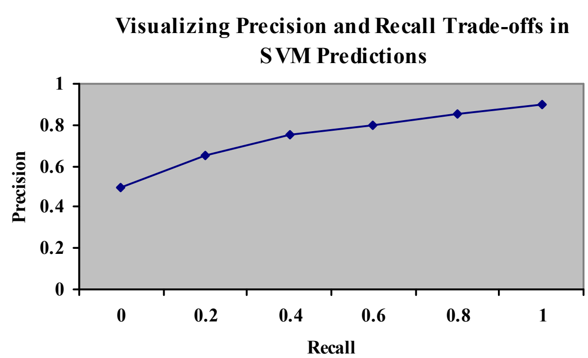

Figure 3: Precision and Recall Metrics for SVM in Pollution Classification

Figure 4 shows the accuracy of the SVM model compared with the existing models for analysis. The x-axis corresponds to the names of the algorithms, while the y-axis represents the percentage of accuracy attained by each algorithm. The graph graphically depicts the accuracy (%) comparison between several algorithms for forecasting air quality levels and managing biofiltration units for urban air pollution treatment.

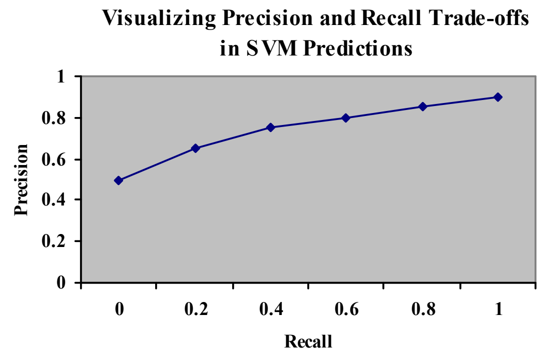

Figure 4: Accuracy Comparison with other models

Despite positive outcomes, certain restrictions were noted. While typically accurate, the SVM model sometimes had trouble adjusting to abrupt changes in the weather or surroundings that were not captured in the training data. The model's flexibility may be increased by supplementing it with other contextual information, such current weather reports. Future improvements may potentially concentrate on using edge computing to lower dependency on cloud processing and improve latency, or integrating different machine learning techniques, such as neural networks, for even greater accuracy. Furthermore, adding supplementary filtering methods to the system, such UV treatment, might improve pollution reduction even further, particularly for heavily polluted areas.

IV. CONCLUSIONS

Significant promise for reducing urban pollution may be seen in the deployment of an adaptive biofiltration system that makes use of IoT and SVM models. IoT sensor integration allows for real-time air quality monitoring, and the SVM model efficiently categorizes pollution levels using the data gathered. Comparing the system's accuracy to other machine learning models demonstrates how well SVM predicts and manages pollution, beating other algorithms in a range of situations. The biofiltration system's adaptive nature also enables dynamic reactions to fluctuating pollution levels, increasing its efficacy and efficiency in addressing urban air quality problems. The findings suggest that this approach may be an effective tool for environmental organizations and urban planners, enabling prompt interventions and well-informed decision-making. In summary, this study highlights the value of using cutting-edge technology in environmental management and lays the foundation for future improvements in smart urban infrastructure targeted at long-term pollution reduction.

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