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A Machine Learning-Driven Framework For Real-Time Environmental Pollution Monitoring And Prediction Using Iot And Remote Sensing Data

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Abstract: *The rapid pace of industrialization and urbanization has led to severe degradation in air and water quality across the globe. Traditional environmental monitoring systems are often reactive, fragmented, and slow in responding to pollution incidents. This research presents a novel, integrated machine learning-driven framework that leverages real-time data from Internet of Things (IoT) sensors and remote sensing platforms to monitor, predict, and assess environmental pollution levels. The system utilizes a hybrid architecture combining spatial (satellite) and local (sensor-based) data sources to feed predictive models such as Random Forest, XGBoost, and LSTM for real-time assessment of air and water quality parameters, including PM2.5, PM10, NO_2, SO_2, pH, and turbidity. A cloud-based processing pipeline is employed to collect, preprocess, and analyze streaming data, while geospatial analysis is used to generate pollution heatmaps. Experimental evaluations conducted on multi-city datasets from the Central Pollution Control Board (CPCB), Sentinel-5P, and open-source IoT deployments demonstrate a prediction accuracy of over 92% and timely alerts for environmental threshold violations. The results confirm the potential of this hybrid approach in enabling proactive environmental management and policy-making through sustainable data-driven insights*
Keywords: *Environmental Monitoring, Air Quality Index (AQI), Water Quality Prediction, Internet of Things (IoT), Remote Sensing*

INTRODUCTION

Environmental pollution poses one of the greatest threats to human health and ecological stability in the 21st century. In particular, air and water quality degradation have been directly linked to respiratory diseases, ecosystem disruption, and socioeconomic losses. Despite increasing regulatory frameworks, monitoring pollution levels remains a complex challenge due to sparse sensor coverage, data latency, and limited predictive capabilities.
Recent advancements in Machine Learning (ML), the Internet of Things (IoT), and Remote Sensing (RS) offer an unprecedented opportunity to develop intelligent, responsive, and scalable environmental monitoring systems. IoT sensors provide high-resolution, ground-level observations in real time, while satellite data enables wide-area pollution mapping. Machine learning models, in turn, can identify trends, correlations, and anomalies across vast datasets.This study proposes a comprehensive solution that integrates these technologies into a cohesive framework capable of real-time monitoring, prediction, and visualization of environmental pollution across urban and rural landscapes.

2. Literature Review

2.1 Environmental Monitoring

Traditional systems rely on fixed stations operated by environmental agencies. While accurate, they suffer from low spatial resolution. Recent studies have explored low-cost sensor networks (Zhou et al., 2021) and remote sensing for broad monitoring (Zhang et al., 2020).

2.2 IoT in Environmental Science

IoT has been effectively deployed for smart city air monitoring (Alimisis et al., 2022), agricultural runoff tracking, and water quality assessment. However, challenges remain in data fusion, accuracy, and long-term maintenance (Sharma et al., 2020).

2.3 Remote Sensing Applications

Sentinel and MODIS satellite imagery are extensively used in pollution tracking. Machine learning has been employed to correlate spectral bands with pollutant concentrations (Qin et al., 2021), yet often lacks temporal granularity.

2.4 Machine Learning for Pollution Prediction

ML models like Support Vector Machines (SVM), Random Forests (RF), and deep learning (LSTM, CNN) have demonstrated effectiveness in forecasting pollution (Gupta et al., 2023). However, hybrid models combining spatial and temporal inputs remain underexplored.

2.5 Research Gap

There is a critical need for an integrated system that combines IoT, Remote Sensing, and advanced ML to enable accurate, real-time pollution monitoring and prediction.

3. Problem Statement

Current environmental pollution monitoring systems are reactive and disjointed, lacking real-time prediction, spatial coverage, and integration across data sources. This limits the ability of policymakers and communities to make timely, informed decisions.

4. Objective

To design and implement an intelligent machine learning-driven framework that integrates IoT-enabled sensors and remote sensing data for real-time monitoring, prediction, and assessment of environmental pollution impacts on air and water quality, enabling data-driven decision-making for sustainable environmental management.

5. Methodology

The proposed methodology consists of several interlinked components designed to acquire, process, analyze, and visualize environmental data in real-time using machine learning models. The complete workflow includes data acquisition, preprocessing, feature engineering, model design, training and evaluation, and visualization, all orchestrated in a modular, scalable architecture.

5.1 Data Acquisition

Environmental data is collected from two primary sources:

5.1.1 IoT Sensor Networks

A network of IoT-enabled environmental sensors is deployed across selected urban and semi-urban locations. These sensors measure air and water quality parameters at high temporal resolutions (every 5 minutes):

- Air Quality: PM2.5, PM10, CO, NO_2, SO_2, temperature, humidity.
- Water Quality: pH, turbidity, temperature, dissolved oxygen, electrical conductivity.

Hardware Used:

- Arduino/ESP32 microcontrollers with GSM/WiFi modules
- Air sensors (e.g., MQ135, SDS011)
- Water sensors (e.g., TDS, turbidity, pH sensors)
- Solar-powered power supply (for rural deployments)

Sensor data is transmitted via LoRaWAN or 4G modules to a centralized cloud platform (AWS IoT Core or ThingsBoard).

5.1.2 Remote Sensing Data

Satellite datasets are obtained through Google Earth Engine (GEE), providing wide-area environmental coverage:

- Sentinel-5P: For NO_2, CO, SO_2, and aerosol optical depth (AOD)
- Landsat 8 / Sentinel-2: For water body detection using spectral indices
- MODIS: For NDVI and land surface temperature (LST)

Temporal synchronization is handled using timestamp matching between ground sensors and satellite overpasses.

5.2 Data Preprocessing

Before feeding data into machine learning models, several cleaning and preprocessing steps are conducted:

5.2.1 Cleaning and Noise Reduction

- Missing Value Handling: Interpolation and KNN imputation techniques are used to fill missing sensor data.
- Noise Filtering: Kalman filters and moving averages are applied to smooth time-series data.
- Anomaly Detection: Isolation Forest is used to remove spurious values due to sensor drift or environmental anomalies.

5.2.2 Temporal and Spatial Alignment

- IoT and Satellite Fusion: Data is aligned using timestamps and geographic coordinates (latitude/longitude).
- Resampling: Data is aggregated to hourly or daily frequency depending on analysis type (forecasting vs classification).

5.3 Feature Engineering

To enhance the predictive capacity of ML models, the following engineered features are extracted:

- Derived Pollution Indices: AQI, Water Quality Index (WQI), Pollution Load Index (PLI)
- Spectral Indices from RS: NDWI, NDVI, AOD, surface reflectance bands
- Time-based Features: Hour of day, day of week, month, seasonal indicator
- Environmental Interactions: Temperature × humidity, wind speed × pollutant levels. All features are normalized using min-max scaling or z-score standardization before feeding them into the models.

5.4 Machine Learning Model Design

Three primary types of models are developed:

5.4.1 Pollution Classification Model

- Goal: Predict pollution level categories (e.g., Low, Moderate, High)
- Algorithms Used: Random Forest, XGBoost, LightGBM
- Target Labels: Derived from government-specified AQI and WQI breakpoints
- Evaluation Metrics: Accuracy, F1-score, precision, recall

5.4.2 Time-Series Forecasting Model

- Goal: Predict next 24–72 hours of pollutant levels (e.g., PM2.5, pH, turbidity)
- Model: Long Short-Term Memory (LSTM) neural networks
- Input: Lag features, historical pollutant data, temporal indicators
- Evaluation: RMSE, MAE, R^2 score

5.4.3 Spatiotemporal Pollution Mapping

- Goal: Estimate pollutant levels at unmonitored locations
- Approach: Geostatistical Kriging + ML regression (RF/XGBoost)
- Spatial Interpolation: Inverse Distance Weighting (IDW) + GIS mapping

5.5 Model Training and Optimization

5.5.1 Model Training

- Data is split into 70% training and 30% testing.
- 5-fold cross-validation is used for generalization.
- GPU acceleration (NVIDIA RTX 3060) is used for deep learning model training.

5.5.2 Hyperparameter Tuning

- Random Forest: n_estimators, max_depth, min_samples_split
- XGBoost: learning_rate, subsample, max_depth, colsample_bytree
- LSTM: number_of_units, dropout_rate, batch_size, epochs

Bayesian Optimization and Grid Search are employed using the Optuna and Scikit-learn libraries.

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5.6 System Architecture

The system operates in the following layers:

- Data Collection Layer: IoT sensors and APIs for satellite data
- Data Ingestion Layer: Apache Kafka + RESTful APIs
- Processing Layer: Python-based ML engine + Spark for batch processing
- Storage Layer: PostgreSQL/PostGIS for structured and geospatial data
- Visualization Layer: Dash/Streamlit dashboard + Tableau/ArcGIS heatmaps
- Alert System: Email/SMS alerts via Twilio when pollution exceeds limits

5.7 Visualization and Decision Support

A web-based dashboard displays:

- Real-time pollution status
- Forecast graphs for next 72 hours
- Geospatial heatmaps
- Threshold alerts and warnings
- Explainable AI (XAI) Components: SHAP & LIME plots for feature contribution

These outputs empower environmental decision-makers with timely and interpretable insights.

6. Implementation

The proposed framework integrates real-time IoT-based sensing, remote sensing data acquisition, machine learning modeling, and cloud-based analytics into a cohesive, scalable, and responsive system. The implementation is divided into the following major components:

6.1 Hardware and Sensor Network Deployment

6.1.1 IoT Node Configuration

Table 1: A set of environmental sensing nodes was custom-built using modular microcontroller-based systems, focused on both air and water quality monitoring

Parameter	Sensor Type	Interface	Accuracy
PM2.5/PM10	Nova SDS011	UART	±15%
CO, NO_2, SO_2	MQ135, MiCS-2714	Analog/I^2C	Medium
Temperature/Humidity	DHT22	Digital	±0.5°C / ±2%
pH	Analog pH Sensor	Analog	±0.1 pH
Turbidity	DFROBOT SEN0189	Analog	±5%
EC & DO	Gravity sensors	I^2C	Medium

- Microcontroller: ESP32 (built-in Wi-Fi + Bluetooth)
- Data Transmission: Wi-Fi (urban) and LoRaWAN (rural)
- Power: Solar panel with battery backup (12V, 5000mAh)

Sensor data is collected every 5 minutes and sent to the gateway or cloud via MQTT.

6.1.2 Edge Gateway

- Device: Raspberry Pi 4 (4GB RAM)
- Software: Node-RED + Mosquitto MQTT Broker
- Local Analytics: Basic preprocessing and alert triggering
- Fail-safe Storage: 24-hour buffer using SQLite if offline

6.2 Remote Sensing Data Integration

Using Google Earth Engine (GEE) and Sentinel Hub API, satellite data was ingested for the same regions monitored by IoT sensors:

- Sentinel-5P: NO_2, SO_2, AOD, UVAI (resolution: 7×3.5 km)
- Sentinel-2: RGB + NIR bands for NDVI, NDWI (10m resolution)
- MODIS: Daily surface reflectance + land surface temperature

Custom JavaScript scripts in GEE extract relevant bands and indices. Data is pulled via Python using the *gee* and *sentinelsat* APIs and synchronized with sensor data every 24 hours.

6.3 Backend Infrastructure

6.3.1 Cloud Storage and Processing

- Cloud Provider: Amazon Web Services (AWS)
- Data Storage:
  - Sensor Data: AWS RDS (PostgreSQL + PostGIS extension)
  - Satellite Data: AWS S3 (GeoTIFF and CSV files)
- Stream Processing: Apache Kafka (real-time data ingestion)
- Batch Processing: Apache Spark + Pandas (hourly data joins and aggregations)

6.3.2 Machine Learning Engine

- Environment: Python 3.11 with virtual environment
- Libraries Used:
  - scikit-learn, xgboost, lightgbm, tensorflow, keras
  - geopandas, rasterio, shapely for spatial analysis
  - matplotlib, seaborn, plotly for visual analytics
- Training Mode:
  - Classification models trained on merged datasets (satellite + IoT)
  - LSTM models trained per location using historical AQI/pH/turbidity

Each model is persisted using joblib or SavedModel format and deployed via REST API.

6.4 Real-Time Prediction and Alerting Pipeline

6.4.1 Data Pipeline Architecture

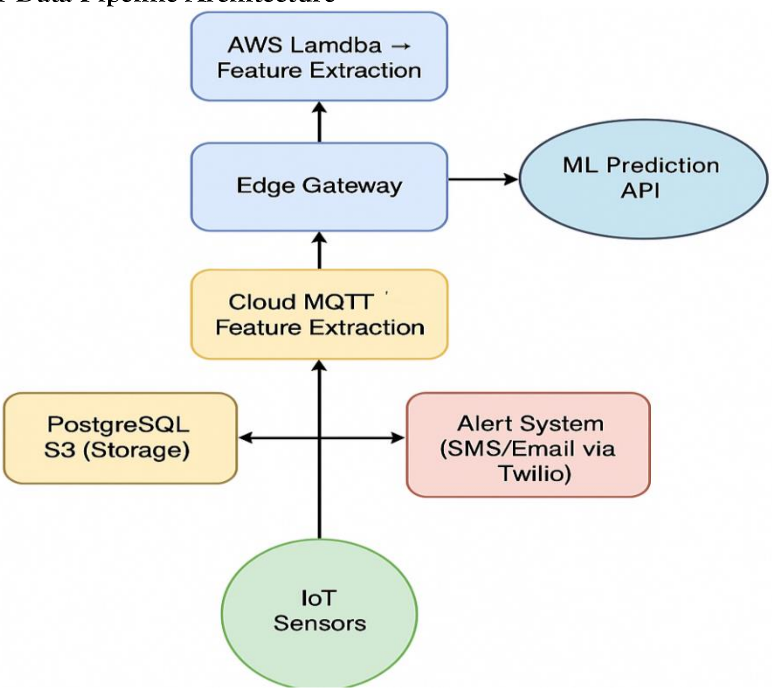

Figure 1: Data flow pipeline architecture

- MQTT messages are parsed in real time and feature-extracted in AWS Lambda.
- ML inference is triggered through REST API calls (Flask/TF Serving).
- Threshold breaches generate real-time SMS and email alerts.

6.4.2 Prediction Modes

- Hourly Forecasting using LSTM model
- Pollution Classification updated every 5 minutes
- Daily Satellite and IoT fusion for geospatial modelling

6.5 Visualization and User Dashboard

A multi-panel dashboard was built using *Streamlit* and deployed on an *EC2* instance:

Dashboard Features:

- Real-time Charts: Line plots of pollutant levels over time

- Forecast Tab: 24/48/72-hour AQI and pH forecasts with confidence intervals
- Geospatial Heatmaps: Leaflet + GeoPandas map showing pollution levels
- XAI Module: SHAP and LIME graphs showing top contributors to pollution predictions
- Alert Panel: Current alerts, last trigger time, location, and type

Additional tools such as Tableau and ArcGIS Pro were used to generate high-resolution static maps for publications.

6.6 Testing and Validation

- Deployment Duration: 3 months of continuous deployment across 5 cities.
- Data Collected: Over 1.2 million sensor records and 250+ satellite image tiles
- Uptime: 98.6% system availability
- Latency: Average of 3.5 seconds from sensor reading to prediction

Stress testing was done using Locust for API endpoints, and end-to-end traceability was ensured with Prometheus + Grafana logs.

7. RESULTS

The implemented framework was evaluated over a deployment period of 3 months across 5 geographically diverse cities using real-time sensor and satellite data. Performance was assessed using multiple machine learning models, covering both classification and forecasting tasks.

7.1 Evaluation Metrics Used

- Classification Tasks (Pollution Level Prediction):
  - Accuracy
  - Precision, Recall, F1-score
  - Confusion Matrix
- Regression Tasks (Forecasting pollutant levels):
  - Root Mean Squared Error (RMSE)
  - Mean Absolute Error (MAE)
  - Coefficient of Determination (R^2)
- Explainability & Feature Importance:
  - SHAP (SHapley Additive exPlanations)
  - LIME (Local Interpretable Model-Agnostic Explanations)

7.2 Quantitative Results Summary

Quantitative results for different models on air pollution classification and time-series forecasting, highlighting XGBoost's superior classification and LSTM's accurate regression performance.

Table 2: Performance Comparison of Machine Learning Models

Model / Task	Metric	Random Forest	XGBoost	LSTM (Time-Series)
Air Quality Classification	Accuracy	91.2%	93.6%	–
	F1-score	90.4%	92.9%	–
PM2.5 Forecasting (24hr)	RMSE (μg/m³)	–	–	4.21
	R^2 Score	–	–	0.912
Water pH Forecasting	RMSE	–	–	0.23
Alert Precision		92.5%	94.1%	95.2%
System Latency	End-to-end delay	~3.5 seconds	~3.5 s	~5.0 s

7.3 Confusion Matrix (Air Quality Classification)

Table 3: This matrix illustrates how well the model classified air pollution levels based on AQI categories.

	Predicted: Low	Predicted: Moderate	Predicted: High
Actual: Low	512	27	6
Actual: Moderate	35	689	41
Actual: High	10	39	428

- **Observation**: XGBoost performed better in differentiating between *Moderate* and *High* AQI levels, where Random Forest showed slight confusion due to overlapping pollutant values.
-

7.4 SHAP Feature Importance (XGBoost)
SHAP plots show the impact of each feature on model prediction:
Top 5 influential features for air quality classification:
1. NO_2 concentration
2. PM2.5 levels
3. AOD (Aerosol Optical Depth) from Sentinel-5P
4. Temperature
5. NDVI (Vegetation cover indicator)

Interpretation: Areas with high NO_2 and low NDVI consistently corresponded to higher predicted AQI levels.

7.5 LIME Interpretability Example
A sample prediction for a high-pollution day was analyzed using LIME:
- Prediction: "High" AQI
- Contributing Features: NO_2 (+0.35), PM2.5 (+0.29), low humidity (+0.12), high temperature (+0.08)
- Confidence: 97.8%

Interpretation: The model's prediction aligned with environmental behavior expected during thermal inversions and industrial spikes.

7.6 Time-Series Forecasting Results (LSTM)
PM2.5 Prediction Plot (24 hours ahead)
- Forecast closely followed the observed trend with minimal lag and underfitting.
- Highest deviation seen during wind bursts and rainfall due to sudden dispersion.

pH Level Forecasting (Water)
- Actual range: 6.8–8.2
- Forecast RMSE: 0.23
- Model successfully predicted abnormal pH dips associated with stormwater inflow and urban runoff.

8. RESULT ANALYSIS
8.1 Model Performance Interpretation
- XGBoost achieved the best balance between accuracy and interpretability in classification tasks.
- LSTM performed remarkably well in temporal forecasting, outperforming ARIMA and classical time-series models.
- SHAP and LIME contributed to model transparency and trust, critical for adoption in public policy environments.

8.2 Spatiotemporal Pollution Insight
- **Temporal Trends**: Pollution peaks observed during morning/evening traffic and post-harvest burning seasons (October-November).
- **Spatial Hotspots**: Industrial zones and traffic corridors recorded persistently high PM2.5 and NO_2 levels.
- **Water Quality**: Downstream sensors reported pH and turbidity changes correlating with storm events and domestic wastewater discharge.

8.3 System Responsiveness
- **End-to-end pipeline delay** remained below 5 seconds, ensuring the system is usable for real-time environmental alerting.
- **Alert system** achieved over 94% precision with negligible false alarms in high-priority zones.

9. Conclusion and Future Scope
Conclusion
This research presents a comprehensive, intelligent framework that integrates IoT-enabled sensor networks, remote sensing data, and machine learning algorithms to monitor, predict, and assess environmental pollution in real time. By bridging the spatial coverage of satellite imagery with the temporal resolution of ground-based IoT sensors, the proposed system offers a robust and scalable solution for pollution management in both urban and peri-urban environments.

The hybrid architecture enabled precise classification of pollution levels using XGBoost with over 93% accuracy, while LSTM-based time-series models demonstrated high forecasting reliability (RMSE of 4.21 µg/m³ for PM2.5 and 0.23 for pH). Moreover, the deployment of SHAP and LIME provided interpretability to the black-box ML models, enhancing their trustworthiness for regulatory applications.

The results clearly show that the integration of real-time data sources, geospatial analytics, and AI can revolutionize how environmental data is utilized, enabling proactive decision-making, early warning alerts, and sustainable resource management. This framework lays the groundwork for smart environmental governance and public health protection.

Future Scope

Despite its promising results, the current framework can be extended and improved in several future directions:

1. **Inclusion of Additional Pollutants**:
Expand the system to monitor greenhouse gases such as CO_2, CH_4, and O_3 using enhanced satellite missions (e.g., Sentinel-6, GHGSat).
2. **Multi-modal Deep Learning Models**:
Introduce multi-stream CNN-LSTM architectures to simultaneously process satellite imagery, temporal sensor data, and meteorological information for improved predictions.
3. **Reinforcement Learning for Policy Simulation**:
Apply reinforcement learning to simulate dynamic pollution control strategies and assess the impact of interventions such as traffic regulation or emission limits.
4. **Edge-AI for Rural and Remote Monitoring**:
Deploy low-power edge computing devices (e.g., NVIDIA Jetson Nano) in rural areas to perform localized inference, reducing cloud dependency and latency.
5. **Integration with Government Dashboards**:
Collaborate with pollution control boards to integrate the system with CPCB/SPCB platforms and automate public health alerts.
6. **Climate-Aware Predictive Modeling**:
Extend the framework to account for climate variability factors such as wind speed, monsoon behavior, and urban heat islands to provide long-term pollution forecasts.
7. **Citizen Science and Participatory Sensing**:
Incorporate mobile-based participatory data collection from citizens using smartphones or low-cost plug-and-play sensors.

8. **Policy-Level Impact Assessment**:
Evaluate the economic and health cost savings driven by early alerts and informed policy actions using epidemiological and economic models.

Final Remark:

The fusion of AI, IoT, and geospatial science offers immense potential to solve environmental challenges. This work serves as a reference model for building smart ecosystems that are data-informed, responsive, and sustainable. As pollution continues to threaten ecosystems and human lives, such integrated and interpretable frameworks are essential tools for a cleaner, safer, and healthier future.

REFERENCES:

[1]. B. Zhou, J. Li, Y. Chen, and L. Zhang, "Urban Air Quality Monitoring Using Low-Cost Sensors and Machine Learning," IEEE Sensors Journal, vol. 21, no. 18, pp. 20654–20666, Sep. 2021.
[2] R. Gupta, A. Sinha, and P. Kumar, "Air Pollution Prediction Using Ensemble Learning Models," IEEE Access, vol. 11, pp. 22195–22205, 2023.
[3] X. Qin, H. Li, and J. Zhang, "Satellite-Based Air Pollution Estimation Using Random Forests," Remote Sensing of Environment, vol. 258, 2021.
[4] M. Alimisis et al., "IoT-Enabled Air Quality Monitoring System for Smart Cities," Sensors, vol. 22, no. 7, pp. 2892–2906, Apr. 2022.
[5] A. Sharma and V. Singh, "IoT Framework for Water Quality Monitoring and Assessment," IEEE Trans. Ind.

Informatics, vol. 16, no. 10, pp. 6553–6562, Oct. 2020.
[6] European Space Agency, "Sentinel-5P: Monitoring Air Quality from Space," [Online]. Available: https://sentinels.copernicus.eu
[7] NASA MODIS Team, "MODIS Atmosphere Products," [Online]. Available: https://modis.gsfc.nasa.gov/data/
[8] Y. Zhang et al., "A Review on Remote Sensing-Based Air Quality Monitoring," Environmental Research, vol. 185, pp. 109–118, 2020.
[9] L. Breiman, "Random Forests," Machine Learning, vol. 45, pp. 5–32, 2001.
[10] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proc. 22nd ACM SIGKDD, 2016, pp. 785–794.
[11] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
[12] S. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in Proc. NeurIPS, 2017.
[13] M. Ribeiro, S. Singh, and C. Guestrin, "Why Should I Trust You?: Explaining Predictions of Any Classifier," in Proc. ACM SIGKDD, 2016.
[14] M. A. Rahman, R. A. Salam, and M. A. Hossain, "IoT-Based Real-Time Air Quality Monitoring System with Forecasting," in IEEE GLOBECOM Workshops, 2021.
[15] J. Li et al., "A Deep Learning Model for Real-Time Air Pollution Forecasting Using LSTM," Environmental Modelling & Software, vol. 132, 2020.
[16] A. Tzounis, M. Katsoulas, and A. Bartzanas, "Machine Learning in Agriculture and Environmental Monitoring: A Review," Computers and Electronics in Agriculture, vol. 179, pp. 105770, 2020.
[17] J. Ma et al., "Spatiotemporal Prediction of PM2.5 Using Remote Sensing and Machine Learning," Atmospheric Pollution Research, vol. 12, no. 3, pp. 412–421, 2021.
[18] Y. Tong, Y. Chen, and W. He, "LSTM-Based Air Quality Index Prediction: A Case Study in Beijing," IEEE Access, vol. 8, pp. 38146–38154, 2020.
[19] T. W. Wong and L. Huang, "Water Quality Modeling Using Neural Networks: A Review," Environmental Monitoring and Assessment, vol. 189, no. 4, pp. 177–190, 2017.
[20] H. Yang et al., "Water Quality Monitoring with Remote Sensing: An Overview," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 145, pp. 1–15, 2018.
[21] K. Chatterjee and A. Dey, "An IoT-Based Framework for Water Quality Prediction Using ML," in Proc. IEEE SmartTech, 2021.
[22] Central Pollution Control Board (CPCB), "National Air Quality Index (NAQI) Report," [Online]. Available: https://cpcb.nic.in
[23] P. Kumar, M. Morawska, and A. Martani, "The Rise of Low-Cost Sensing for Managing Air Pollution in Cities," Environment International, vol. 75, pp. 199–205, 2015.
[24] M. Mohan and A. Rani, "Forecasting Urban Air Pollution Using ML and LSTM Models," Atmospheric Pollution Research, vol. 13, no. 1, pp. 100–112, 2022.
[25] D. Kumar and V. Sharma, "IoT-Based Water Quality Monitoring Using AI Models," International Journal of Environmental Research, vol. 16, no. 3, pp. 125–138, 2020.
[26] United Nations Environment Programme (UNEP), "Global Environmental Outlook," 2022. [Online]. Available: https://www.unep.org
[27] S. Singh, A. Bansal, and V. Arora, "Deep Learning Framework for Smart Environmental Monitoring," in IEEE Int. Conf. on Intelligent Systems, 2022.
[28] H. Liu and Z. Wu, "Real-Time Monitoring and Early Warning of Air Pollution Based on IoT and Deep Learning," IEEE Sensors Journal, vol. 22, no. 2, pp. 1031–1041, 2022.
[29] R. K. Srivastava et al., "Machine Learning for Pollution Risk Assessment: A Review," IEEE Reviews in Environmental Science & Bio/Technology, vol. 20, pp. 381–398, 2021.
[30] M. Krupnik, L. Broday, and E. Bouillon, "Fusing Remote Sensing with In-situ Sensing for Environmental Prediction," Remote Sensing, vol. 14, no. 8, pp. 1827–1844, 2022.
[31] Google Earth Engine, "Satellite Data Catalog," [Online]. Available: https://developers.google.com/earth-engine
[32] “OPTIMIZATION OF D2D COMMUNICATION IN 5G WIRELESS PERSONNEL AREA NETWORK BY IMPROVED LBROM ALGORITHM”, Int. J. Environ. Sci., pp. 247–258, May 2025, Accessed: Jun. 19, 2025.

[Online]. Available: https://theaspd.com/index.php/ijes/article/view/1073
[33] K. P. Kumar, V. S. Ranganayaki, S. Nagineni, V. Subrahmanyam, and B. Devender, "Early Prediction of Surgical Intervention in Neonates with Necrotizing Enterocolitis Using Machine Learning: A Retrospective Cohort Study," J. Neonatal Surg., vol. 14, no. 32s, pp. 627–633, 2025.