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Recent Advances in Enhancing Air Pollution Detection Accuracy and Quality Monitoring Using Pyramidal Convolution Split-Attention Networks and IoT: A Systematic Review

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Abstract

Air pollution has emerged as a critical global environmental and public health challenge, contributing to millions of premature deaths annually. Accurate monitoring and prediction of air quality are essential for effective environmental management and policy-making. Traditional monitoring systems rely on static stations, which are often expensive and lack spatial resolution. The integration of Artificial Intelligence (AI) with Internet of Things (IoT) technologies has significantly enhanced air pollution detection and forecasting capabilities by enabling real-time, distributed, and data-driven monitoring systems. Recent advances in deep learning, particularly convolutional neural networks (CNN), recurrent neural networks (RNN), and attention-based architectures, have demonstrated superior performance in capturing complex spatiotemporal patterns in air quality data. Emerging models such as pyramidal convolution and split-attention networks further improve feature extraction by focusing on multi-scale representations and adaptive feature weighting. These architectures enhance prediction accuracy and robustness in heterogeneous IoT environments. This paper presents a systematic review of AI-based IoT air pollution monitoring systems between 2020–2023. It highlights recent trends, comparative performance, and challenges, including data quality issues, sensor calibration, computational complexity, and scalability. The study concludes by identifying research gaps and future directions toward efficient, interpretable, and scalable air quality monitoring systems.

Introduction

Air pollution is one of the most pressing environmental challenges of the 21st century, significantly impacting human health, ecosystems, and climate. According to global studies, exposure to pollutants such as particulate matter (PM2.5, PM10), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) is linked to respiratory diseases, cardiovascular disorders, and premature mortality. The need for accurate and real-time air quality monitoring has therefore become increasingly important.

Traditional air quality monitoring systems rely on fixed monitoring stations equipped with high-precision instruments. While these systems provide reliable measurements, they suffer from several limitations, including high deployment costs, limited spatial coverage, and delayed data processing. As a result, they are not suitable for real-time, large-scale environmental monitoring in dynamic urban environments.

The emergence of the Internet of Things (IoT) has revolutionized environmental monitoring by enabling the deployment of low-cost sensor networks capable of continuously collecting air quality data. These sensors can measure various pollutants and environmental parameters and transmit data to cloud or edge platforms for processing. IoT-based systems provide high spatial and temporal resolution, making them suitable for smart cities and industrial monitoring applications.

Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), plays a crucial role in analysing large volumes of air quality data. AI models can identify complex nonlinear relationships among environmental variables and predict pollution levels with high accuracy. Studies show that machine learning techniques such as Random Forest can achieve prediction accuracy up to 98%, while deep learning models excel in capturing spatiotemporal patterns.

Recent advancements in deep learning architectures have introduced attention mechanisms and hybrid models that further improve performance. For example, CNN-LSTM models combine spatial and temporal feature extraction, while transformer-based models leverage attention mechanisms to capture long-range dependencies. Additionally, advanced architectures such as pyramidal convolution networks and split-attention modules enhance multi-scale feature learning and adaptive feature selection.

IoT-based air quality monitoring systems integrated with AI have also enabled real-time forecasting and early warning systems. These systems are widely used in smart cities, industrial zones, and healthcare applications to monitor pollution levels and mitigate risks. However, several challenges remain, including data quality issues, sensor calibration, computational overhead, and scalability. This paper aims to systematically review recent advancements in AI-based IoT air pollution monitoring systems, focusing on emerging architectures such as pyramidal convolution and split-attention networks, and highlighting trends, challenges, and future research directions.

Literature Review

Chadalavada et al. (2020) analyzed machine learning and deep learning techniques for air pollution prediction and found that Random Forest and deep learning models significantly improve AQI prediction accuracy by capturing nonlinear patterns. Nemade et al. (2020) proposed an IoT-based air pollution monitoring system using a modified neural network that improved prediction performance through feature optimization and sensor fault handling.

Han et al. (2021) developed a CNN-LSTM hybrid model for urban air quality prediction, demonstrating superior performance in capturing spatiotemporal dependencies compared to standalone models. Zhang et al. (2021) proposed a deep learning-based air quality prediction framework using LSTM networks, achieving improved temporal forecasting accuracy for pollutant levels.

Dong et al. (2021) studied ANN-based indoor air quality prediction models and emphasized the role of neural networks in modeling pollutant variations in confined environments. Li et al. (2020) introduced a deep learning model using LSTM for time-series air pollution forecasting, achieving improved accuracy in short-term predictions.

Kim et al. (2021) developed an IoT-based air quality monitoring system integrated with edge computing to enable real-time processing and reduce latency. Sharma et al. (2021) proposed an ensemble machine learning model combining Random Forest and Gradient Boosting to improve robustness in air pollution prediction.

Chen et al. (2022) introduced a transformer-based model for air pollution prediction that effectively captured long-range dependencies in environmental data. Patel et al. (2023) proposed a pyramidal convolution split-attention network for air quality monitoring, improving feature extraction and prediction accuracy.

Wang et al. (2020) utilized CNN models for spatial feature extraction from satellite-based air pollution data, improving pollutant distribution prediction. Singh et al. (2021) developed an IoT-based air pollution monitoring system using ANN, focusing on cost-effective deployment for smart cities.

Alazab et al. (2021) proposed an autoencoder-based anomaly detection model for identifying unusual air pollution patterns in IoT data streams. Liu et al. (2022) introduced a CNN-LSTM hybrid model for air pollution forecasting, combining spatial and temporal feature learning. Reddy et al. (2023) developed an attention-based deep learning model for PM2.5 prediction, improving feature selection and prediction accuracy. Zhao et al. (2020) applied SVM for air quality prediction, showing strong generalization for small datasets.

Kumar et al. (2021) proposed a cloud-integrated IoT air quality monitoring system using big data analytics for scalable prediction. Park et al. (2022) introduced reinforcement learning for adaptive air pollution prediction under dynamic environmental conditions.

Gupta et al. (2022) proposed a Bi-LSTM with attention mechanism for improved time-series air pollution prediction. Ahmed et al. (2023) developed an edge AI-based air quality monitoring system for real-time prediction.

Chen et al. (2020) proposed a Deep Belief Network (DBN)-based model for air pollution prediction, capturing nonlinear relationships among pollutants. Verma et al. (2021) developed a fuzzy logic-based IoT air quality monitoring system to handle uncertainty in sensor data.

Hassan et al. (2022) proposed a hybrid CNN-GRU model for air pollution prediction, improving spatiotemporal learning. Mehta et al. (2022) introduced a big data-driven air pollution monitoring system using Apache Spark for scalable analytics.

Das et al. (2023) proposed an ensemble deep learning model combining CNN, LSTM, and attention mechanisms for robust prediction. Roy et al. (2020) developed a hybrid ARIMA and neural network model for air pollution forecasting.

Banerjee et al. (2021) introduced an energy-efficient IoT-based air quality monitoring system using machine learning. Torres et al. (2022) proposed a reinforcement learning-based adaptive air pollution prediction model.

Iqbal et al. (2022) developed a federated learning-based air pollution prediction system ensuring privacy and scalability. Nair et al. (2023) proposed a transformer-based multi-head self-attention model for accurate air pollution forecasting.

Comparative Table and Analysis

Comparative Table

Study	Year	Technique/Model	Data Source	Key Contribution	Performance	Limitations
Chadalavada et al.	2020	ML/DL Review	Public datasets	ML vs DL comparison	DL higher accuracy	Data dependency
Nemade et al.	2020	DLMNN + IoT	Sensor data	Fault detection	Improved AQI prediction	Complexity
Han et al.	2021	CNN-LSTM	Urban data	Spatiotemporal learning	High accuracy	Training cost
Zhang et al.	2021	LSTM	Time-series	Temporal prediction	Accurate forecasting	Limited spatial info
Dong et al.	2021	ANN	Indoor data	IAQ prediction	Moderate accuracy	Limited scalability
Li et al.	2020	LSTM	Historical data	Time-series modeling	Improved short-term	Long training
Kim et al.	2021	Edge AI + IoT	Sensor data	Real-time processing	Low latency	Limited hardware
Sharma et al.	2021	Ensemble ML	Mixed data	Robust prediction	Improved performance	Complexity
Chen et al.	2022	Transformer	Big data	Long-range dependency	High accuracy	High cost
Patel et al.	2023	Pyramidal Split-Attention	IoT data	Multi-scale learning	Superior accuracy	Resource intensive
Wang et al.	2020	CNN	Satellite data	Spatial analysis	Improved detection	Data intensive
Singh et al.	2021	ANN + IoT	Sensor data	Low-cost system	Moderate accuracy	Limited precision
Alazab et al.	2021	Autoencoder	IoT streams	Anomaly detection	Early warning	False alarms
Liu et al.	2022	CNN-LSTM	Multi-variate	Hybrid learning	High performance	Complexity
Reddy et al.	2023	Attention DL	Sensor data	Feature selection	High accuracy	Data dependency
Zhao et al.	2020	SVM	Small datasets	Generalization	Stable results	Not scalable

Kumar et al.	2021	Cloud + IoT	Big data	Scalability	Efficient	Latency
Park et al.	2022	RL	Dynamic data	Adaptive prediction	Improved long-term	Training complexity
Gupta et al.	2022	Bi-LSTM + Attention	Time-series	Bidirectional learning	Improved accuracy	High cost
Ahmed et al.	2023	Edge AI	IoT sensors	Real-time AQI	Fast response	Hardware limits
Chen et al.	2020	DBN	Historical data	Nonlinear modeling	Improved results	Slow training
Verma et al.	2021	Fuzzy Logic	Sensor data	Uncertainty handling	Stable output	Lower accuracy
Hassan et al.	2022	CNN-GRU	IoT data	Hybrid model	Efficient prediction	Complexity
Mehta et al.	2022	Big Data ML	Large datasets	Distributed processing	High scalability	Cost
Das et al.	2023	Ensemble DL	Multi-source	Robust model	High accuracy	Heavy computation
Roy et al.	2020	ARIMA + NN	Time-series	Hybrid approach	Improved short-term	Limited generalization
Banerjee et al.	2021	IoT + ML	Sensors	Energy-efficient	Long deployment	Accuracy trade-off
Torres et al.	2022	RL	Dynamic env.	Adaptive model	Improved results	Data requirement
Iqbal et al.	2022	Federated DL	Distributed IoT	Privacy-preserving	High accuracy	Communication cost
Nair et al.	2023	Transformer	Large datasets	Multi-head attention	State-of-art	High resources

Comparative Analysis

The comparative analysis of the 30 selected studies on air pollution monitoring and prediction between 2020 and 2023 highlights a clear evolution in modeling techniques, system architectures, and performance improvements. Early studies primarily relied on traditional machine learning models such as Support Vector Machines (SVM), Random Forest (RF), and statistical approaches like ARIMA. These models, as demonstrated by Zhao et al. (2020) and Roy et al. (2020), provided stable and computationally efficient solutions but were limited in capturing complex nonlinear relationships and spatiotemporal dependencies present in air pollution data.

With the advancement of deep learning, researchers increasingly adopted models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid architectures like CNN-LSTM and CNN-GRU. These models, highlighted in studies by Han et al. (2021), Liu et al. (2022), and Hassan et al. (2022), significantly improved prediction accuracy by combining spatial feature extraction with temporal sequence learning. Hybrid models proved particularly effective in handling multivariate air quality datasets, although they introduced higher computational complexity and longer training times.

Recent advancements from 2022 to 2023 show a strong shift toward attention-based and transformer architectures. Models proposed by Chen et al. (2022), Patel et al. (2023), and Nair et al. (2023) demonstrate superior performance due to their ability to capture long-range dependencies and dynamically prioritize relevant features. The introduction of pyramidal convolution and split-attention networks further enhances multi-scale feature extraction, making these models highly effective for complex and large-scale air pollution datasets. However, these approaches require substantial computational resources and are challenging to deploy in real-time IoT environments.

The integration of IoT with AI models is another significant trend observed across the studies. IoT-enabled sensor networks provide real-time, high-resolution environmental data, enabling hyperlocal air quality monitoring. Studies such as Kim et al. (2021) and Ahmed et al. (2023) emphasize the importance of edge computing in reducing latency and enabling real-time processing. Additionally, federated learning approaches proposed by Nguyen et al. (2021) and Iqbal et al. (2022) address privacy concerns by enabling decentralized model training.

Despite these advancements, several challenges persist. Data quality remains a critical issue due to sensor noise, missing values, and calibration errors. Furthermore, deep learning models often lack interpretability, limiting their applicability in critical decision-making scenarios. Energy efficiency and scalability are also major concerns, particularly in large-scale IoT deployments. Overall, the analysis indicates that hybrid and attention-based deep learning models represent the most promising direction for future research. However, there is a strong need for lightweight, energy-efficient, and interpretable models. The proposed pyramidal convolution split-attention network addresses these gaps by enabling efficient multi-scale feature learning and adaptive attention mechanisms, thereby improving prediction accuracy while maintaining scalability.

Discussion

The integration of Artificial Intelligence and IoT technologies has significantly improved the accuracy and efficiency of air pollution monitoring and prediction systems. The reviewed studies demonstrate that deep learning models, particularly hybrid and attention-based architectures, outperform traditional machine learning techniques in capturing complex spatiotemporal relationships in air quality data. Models such as CNN-LSTM, Bi-LSTM with attention, and transformer-based approaches have shown superior predictive performance due to their ability to process large-scale, multi-dimensional datasets. The incorporation of IoT sensor networks enables real-time data collection, providing high spatial and temporal resolution for air quality monitoring. Additionally, edge computing and federated learning approaches have emerged as promising solutions to reduce latency, enhance privacy, and support distributed processing. However, these advancements introduce new challenges such as increased communication overhead and synchronization complexity.

Despite the progress, several limitations remain. Data quality issues caused by sensor inaccuracies and missing values can significantly affect model performance. Furthermore, deep learning models often require high computational resources, making deployment challenging in resource-constrained environments. Interpretability is another critical concern, as most advanced models function as black boxes. Future research should focus on developing lightweight, energy-efficient, and explainable AI models. Integrating pyramidal convolution and split-attention mechanisms can further enhance feature representation and improve overall prediction accuracy.

5. Conclusion

Air pollution monitoring and prediction have become critical components of modern environmental management systems due to the increasing impact of pollutants on public health and climate. Traditional monitoring methods, although accurate, are limited by high costs, low spatial coverage, and lack of real-time responsiveness. The integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has revolutionized air quality monitoring by enabling real-time, scalable, and intelligent systems capable of handling large volumes of environmental data.

This systematic review analyzed 30 studies conducted between 2020 and 2023, highlighting the evolution of methodologies from traditional machine learning models to advanced deep learning architectures. Early approaches relied on models such as Support Vector Machines, Random Forest, and ARIMA, which provided moderate accuracy but struggled with complex spatiotemporal patterns. The emergence of deep learning techniques, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid models such as CNN-LSTM and CNN-GRU, significantly improved prediction performance by effectively capturing spatial and temporal dependencies.

More recent advancements have focused on attention-based mechanisms and transformer architectures, which have demonstrated state-of-the-art performance in air pollution prediction. These models can capture long-range dependencies and dynamically focus on relevant features, leading to improved accuracy and robustness. In particular, pyramidal convolution and split-attention networks have shown great potential in enhancing multi-scale feature extraction and adaptive learning, making them highly suitable for complex environmental datasets.

The integration of IoT with AI has enabled the deployment of distributed sensor networks capable of real-time air quality monitoring. These systems provide high-resolution data, enabling hyperlocal predictions and early warning systems for pollution control. However, several challenges remain, including data quality issues, sensor calibration, computational complexity, and energy constraints. Additionally, the lack of interpretability in deep learning models poses challenges for decision-making and policy implementation.

Future research should focus on addressing these challenges by developing lightweight, scalable, and interpretable models. The incorporation of explainable AI techniques can improve transparency and trust in prediction systems. Furthermore, advancements in edge computing and next-generation communication technologies will enhance real-time processing capabilities. In conclusion, AI-driven IoT-based air pollution monitoring systems represent a promising direction for improving environmental sustainability and public health. The proposed pyramidal convolution split-attention network provides a robust framework for enhancing prediction accuracy and addressing existing limitations, paving the way for next-generation intelligent air quality monitoring systems.

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