Archives available at journals.mriindia.com

Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 12 Issue 01, 2025

A Comprehensive Review of Enhancing Air Pollution Detection Accuracy and Quality Monitoring Using Pyramidal Convolution Split-Attention Networks and IoT

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Peer Review Information

Submission: 08 March 2025

Revision: 24 March 2025

Acceptance: 07 April 2025

Keywords

Air Pollution Detection, IoT, Deep Learning, CNN, Split-Attention, Pyramidal Convolution, AQI Prediction.

Abstract

Air pollution has become a major environmental challenge affecting human health, climate stability, and ecological sustainability. Accurate monitoring of pollutants such as PM2.5, CO_2, NO_2, and SO_2 is essential for environmental protection and effective decision-making. Traditional air quality monitoring systems are often expensive, limited in coverage, and unable to provide real-time analysis. The integration of Internet of Things (IoT) technologies with deep learning models has significantly improved air pollution detection by enabling continuous, distributed, and cost-effective environmental monitoring. IoT sensor networks collect real-time atmospheric data, while deep learning architectures such as CNNs, LSTMs, and attention-based models analyze complex pollutant patterns and improve prediction accuracy. Advanced architectures including pyramidal convolution networks, split-attention mechanisms, and hybrid CNN-BiLSTM frameworks have demonstrated strong performance in Air Quality Index prediction and pollution classification tasks. In addition, optimization techniques such as feature engineering, dimensionality reduction, and hyperparameter tuning enhance computational efficiency and model reliability. Attention-based and multi-scale deep learning models further improve feature extraction from heterogeneous IoT data streams. Despite these advancements, challenges including sensor calibration, scalability, data heterogeneity, and energy efficiency remain significant concerns. Emerging approaches such as federated learning, edge computing, and graph-based deep learning offer promising directions for future intelligent air quality monitoring systems.

Introduction

Air pollution is a major global concern, contributing to millions of premature deaths annually and posing severe risks to environmental sustainability. Rapid industrialization, urbanization, and increased vehicular emissions have significantly elevated pollution levels in both developed and developing countries. Pollutants such as particulate matter (PM2.5 and PM10), nitrogen oxides (NOx), carbon monoxide (CO), and sulphur dioxide (SO_2) are among the primary contributors to deteriorating air quality. Monitoring and predicting these pollutants accurately are essential for mitigating their adverse effects. Traditional air quality monitoring systems rely on centralized stations equipped with high-precision instruments. While these systems provide accurate measurements, they are expensive, sparsely distributed, and lack real-time adaptability. The emergence of Internet of Things (IoT) technologies has enabled the deployment of low-cost, distributed sensor networks capable of continuous environmental monitoring. IoT-based systems collect real-time data from multiple locations, significantly improving spatial and temporal coverage of air quality measurements.

IoT devices integrate various sensors such as MQ-series gas sensors, temperature and humidity sensors, and particulate matter detectors to capture environmental parameters. These sensors transmit data to cloud platforms for processing and analysis, enabling real-time visualization and decision-making. However, IoT-generated data is often noisy, incomplete, and heterogeneous, requiring advanced analytical techniques for effective interpretation. Deep learning has emerged as a powerful tool for analysing complex environmental data. Models such as Convolutional Neural Networks (CNNs) are effective in extracting spatial features, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies. Hybrid models combining CNN and LSTM have demonstrated improved performance in air quality prediction by leveraging both spatial and temporal characteristics of pollution data.

Recent advancements have introduced attention mechanisms and split-attention architectures, which enable models to focus on the most relevant features in large datasets. For example, attention-based deep learning models can dynamically assign importance to different pollutants and time steps, improving prediction accuracy and interpretability. Advanced frameworks such as stacked attention networks and vector map convolution models have shown significant improvements in air pollution prediction accuracy. Additionally, pyramidal convolution architectures enhance feature extraction by capturing multi-scale spatial patterns, making them suitable for analysing complex environmental datasets. These models, when integrated with IoT systems, enable scalable and efficient air quality monitoring solutions.

Another important aspect is the use of optimization techniques to improve model performance. Methods such as metaheuristic optimization, feature selection, and hyperparameter tuning help reduce computational complexity and enhance prediction accuracy. For instance, hybrid models combining factor analysis, ANN, and ARMA have demonstrated improved AQI prediction performance, achieving accuracy improvements of up to 94.8%. Despite significant progress, several challenges remain, including sensor calibration issues, data inconsistency, and high computational requirements. Advanced techniques such as graph neural networks (GNNs) and federated learning are being explored to address these challenges by improving spatial modelling and data privacy. This review aims to provide a comprehensive overview of deep learning and optimization approaches for IoT-based air pollution monitoring systems, focusing on research contributions in recent years, with special emphasis on pyramidal convolution and split-attention architectures.

Literature Review

Zhao et al. (2020) developed an IoT-based air quality monitoring platform integrating sensor networks and cloud-based analytics. The system enabled real-time pollution tracking and decision-making. The study emphasized the importance of IoT architectures in improving environmental monitoring efficiency and scalability Kumar et al. (2020) proposed a machine learning-based IoT air pollution detection system using multiple gas sensors. The system applied feature extraction and preprocessing techniques to improve detection accuracy. It demonstrated effective real-time pollution monitoring but faced challenges related to sensor noise and calibration.

Campanile et al. (2021) introduced a machine learning framework for analysing pollution and weather data using IoT systems. The study highlighted the integration of environmental data analytics with IoT platforms for improved urban air quality management. Nemade & Shah

(2022) proposed an IoT-based deep learning modified neural network (DLMNN) for air pollution prediction. The model incorporated feature selection, data balancing, and optimization techniques, significantly improving prediction accuracy and system performance.

Prajul et al. (2023) developed an IoT cloud-based deep learning model with stacked attention mechanisms for air pollution prediction. The proposed split-attention-based vector map convolution network achieved superior performance with low error rates, demonstrating the effectiveness of attention-based architectures. Li et al. (2020) proposed a Convolutional Neural Network (CNN)-based air quality prediction model that utilizes historical pollution data and meteorological variables. The model demonstrated improved performance in predicting PM2.5 concentrations by effectively extracting spatial features from multi-dimensional datasets. However, it lacked temporal modelling capability, limiting long-term prediction accuracy.

Zhang et al. (2021) developed a hybrid CNN-LSTM model for air pollution forecasting. The CNN component extracted spatial features from pollutant data, while the LSTM captured temporal dependencies. The model achieved higher accuracy compared to standalone models, particularly in predicting short-term AQI variations. Jiang et al. (2021) introduced an attention-based BiLSTM model for air quality prediction. The attention mechanism enabled the model to assign different weights to input features, improving prediction accuracy and interpretability. The model was particularly effective in handling multivariate environmental data.

Wang et al. (2022) proposed a deep autoencoder-based feature extraction model combined with machine learning algorithms for AQI prediction. The model reduced data dimensionality and improved prediction efficiency while maintaining high accuracy. However, some information loss was observed during compression. Chen et al. (2023) introduced a Transformer-based air pollution prediction model that leverages multi-head self-attention mechanisms. The model demonstrated superior performance in capturing long-range dependencies in air quality data and outperformed traditional RNN-based models in large-scale datasets.

Alam et al. (2020) proposed an IoT-enabled air pollution monitoring system integrated with cloud computing. The system collected real-time data using distributed sensors and applied machine learning algorithms for AQI prediction. The study highlighted improved scalability and real-time responsiveness but noted challenges in sensor calibration and data reliability. Guo et al. (2021) introduced a deep residual learning (ResNet) model for air quality prediction. The use of residual connections enabled deeper network architectures and improved feature extraction. The model showed enhanced performance in predicting PM2.5 levels, especially in urban environments with complex pollution patterns.

Liu et al. (2021) developed a Gated Recurrent Unit (GRU)-based air quality prediction model. Compared to LSTM, the GRU model reduced computational complexity while maintaining similar prediction accuracy. The study emphasized efficiency in real-time applications. Qin et al. (2022) proposed a dual-stage attention-based recurrent neural network (DA-RNN) for air pollution forecasting. The model used both input attention and temporal attention mechanisms to enhance feature selection and improve prediction accuracy for multiple pollutants.

Sun et al. (2023) introduced a Graph Neural Network (GNN)-based air quality prediction model that captures spatial dependencies between monitoring stations. The model significantly improved regional prediction accuracy by modelling relationships among geographically distributed sensors. Singh et al. (2020) proposed a Deep Neural Network (DNN)-based air quality prediction system using historical pollutant and meteorological data. The model demonstrated strong capability in capturing nonlinear relationships among pollutants but required large datasets for optimal performance.

Zhao et al. (2021) introduced a stacked autoencoder (SAE)-based deep learning model for feature extraction and AQI prediction. The model effectively reduced dimensionality and improved prediction accuracy, especially for large-scale urban datasets. Zhou et al. (2022) developed a Temporal Convolutional Network (TCN) for air pollution prediction. The model leveraged dilated causal convolutions to capture long-term dependencies while enabling parallel processing. It achieved faster training and competitive accuracy compared to LSTM models.

Huang et al. (2022) proposed a hybrid CNN-BiLSTM with attention mechanism for air quality prediction. The model combined spatial feature extraction with temporal learning and attention-based weighting, resulting in improved AQI prediction accuracy. Li et al. (2023) introduced a multi-head self-attention Transformer model for air pollution prediction. The model effectively captured long-range temporal dependencies and showed superior performance on large datasets compared to traditional RNN-based approaches.

Kim et al. (2020) proposed a deep reinforcement learning (DRL)-based optimization framework for air pollution prediction. The model dynamically adjusted learning parameters to improve forecasting accuracy under varying environmental conditions. It demonstrated adaptability but suffered from training instability. Zhang & Wang (2021) developed a hybrid GRU-CNN model for AQI prediction. The GRU reduced computational complexity compared to LSTM, while CNN extracted spatial features. The model achieved efficient performance in real-time prediction scenarios.

Patel et al. (2022) proposed an IoT-based air quality monitoring system integrated with edge computing and deep learning models. The system enabled local data processing, reducing latency and improving real-time responsiveness in smart city applications. Chen et al. (2022) introduced a multi-task deep learning model for simultaneous prediction of multiple air pollutants. The shared feature learning framework improved generalization and reduced redundancy, though task interference affected performance in some cases.

Xu et al. (2023) developed an ensemble deep learning framework combining CNN, LSTM, and Transformer models for air pollution prediction. The ensemble approach improved robustness and accuracy by leveraging complementary strengths of different architectures. Alazab et al. (2020) proposed a deep learning-based anomaly detection system for air pollution monitoring using IoT sensor data. The model effectively identified abnormal pollution spikes, improving early warning capabilities. However, it suffered from false positives in highly dynamic environments.

Zhou & Feng (2021) introduced a deep forest (gcForest) model for air quality prediction. The cascade structure enabled hierarchical feature learning with lower computational cost compared to deep neural networks. It performed well on small datasets but lacked scalability for large-scale applications. Rahman et al. (2022) proposed a federated learning-based air quality monitoring framework using distributed IoT devices. The approach preserved data privacy and reduced communication overhead while enabling collaborative model training across multiple nodes.

Tang et al. (2022) developed a spatiotemporal graph attention network (ST-GAT) for air pollution prediction. The model captured both spatial relationships among monitoring stations and temporal dependencies, significantly improving regional AQI prediction accuracy. Huang et al. (2023) proposed a pyramidal convolution split-attention network for air pollution detection and prediction. The model utilized multi-scale feature extraction and split-attention mechanisms to enhance feature representation and improve prediction accuracy. It demonstrated superior performance in handling heterogeneous IoT data and complex pollution patterns.

Comparative Table

No.	Author (Year)	Model	Technique	Strengths	Limitations
1	Zhao (2020)	IoT System	Sensor + Cloud	Real-time monitoring	Sensor noise
2	Kumar (2020)	ML + IoT	Feature extraction	Low cost	Calibration issues
3	Campanile (2021)	ML Framework	Data analytics	Urban monitoring	Data dependency
4	Nemade (2022)	DLMNN	Optimized DL	High accuracy	Complex training
5	Prajul (2023)	Attention CNN	Split-attention	High precision	Computational cost
6	Li (2020)	CNN	Spatial features	Good accuracy	No temporal learning
7	Zhang (2021)	CNN-LSTM	Hybrid	Balanced performance	Complexity
8	Jiang (2021)	BiLSTM + Attention	Feature weighting	High accuracy	Training overhead
9	Wang (2022)	Autoencoder	Dimensionality reduction	Efficient	Info loss
10	Chen (2023)	Transformer	Self-attention	Long dependency	High cost
11	Alam (2020)	IoT + Cloud	Distributed system	Scalable	Data reliability

12	Guo (2021)	ResNet	Deep residual	Deep learning efficiency	Heavy model
13	Liu (2021)	GRU	Efficient RNN	Fast training	Less memory
14	Qin (2022)	DA-RNN	Dual attention	Accurate	Complex
15	Sun (2023)	GNN	Spatial modeling	High regional accuracy	Graph complexity
16	Singh (2020)	DNN	Nonlinear learning	Good prediction	Data requirement
17	Zhao (2021)	SAE	Feature extraction	Reduced dimension	Info loss
18	Zhou (2022)	TCN	Dilated conv	Fast training	Limited adaptability
19	Huang (2022)	CNN-BiLSTM	Hybrid attention	High accuracy	Complex
20	Li (2023)	Transformer	Multi-head attention	Scalable	Expensive
21	Kim (2020)	DRL	Optimization	Adaptive	Instability
22	Zhang (2021)	GRU-CNN	Hybrid	Efficient	Moderate accuracy
23	Patel (2022)	IoT + Edge	Edge computing	Low latency	Resource limits
24	Chen (2022)	Multi-task DL	Shared learning	Generalization	Task interference
25	Xu (2023)	Ensemble DL	Hybrid fusion	Robust	High complexity
26	Alazab (2020)	DNN	Anomaly detection	Early warning	False positives
27	Zhou (2021)	Deep Forest	Cascade learning	Low computation	Scalability
28	Rahman (2022)	Federated Learning	Distributed	Privacy	Communication overhead
29	Tang (2022)	ST-GAT	Graph attention	High accuracy	Complex
30	Huang (2023)	Pyramidal Split-Attention CNN	Multi-scale attention	Best performance	Very complex

Comparative Analysis

The comparative analysis of the 30 studies demonstrates a significant evolution in air pollution monitoring methodologies from 2020 to 2023. Early studies primarily focused on IoT-based monitoring systems and traditional machine learning models, emphasizing real-time data acquisition and cost-effective deployment. However, these systems often faced limitations such as sensor noise, calibration issues, and limited prediction accuracy. As research progressed, deep learning models such as CNN, LSTM, and GRU gained prominence due to their ability to capture nonlinear relationships in environmental data. Hybrid architectures, including CNN-LSTM and CNN-BiLSTM, further improved performance by integrating spatial and temporal learning capabilities. The introduction of attention mechanisms marked a major advancement, allowing models to focus on relevant features and significantly enhancing prediction accuracy.

Recent studies highlight the dominance of Transformer-based models, Graph Neural Networks, and ensemble approaches, which effectively capture long-range dependencies and spatial relationships. Additionally, IoT integration with edge computing and federated learning has improved scalability, privacy, and real-time processing capabilities. Among all approaches, the pyramidal convolution split-attention network stands out as the most advanced, offering multi-scale feature extraction and improved accuracy. However, increasing model complexity and computational requirements remain major challenges. Future research should focus on developing lightweight, energy-efficient, and explainable models for practical deployment.

Discussion

The integration of IoT and deep learning has significantly enhanced air pollution detection and monitoring systems. IoT devices provide real-time environmental data, while deep learning models enable accurate prediction and analysis. Hybrid models and attention-based architectures have demonstrated superior performance by effectively capturing spatial and temporal dependencies. Despite these advancements, challenges such as data heterogeneity, sensor calibration, and computational complexity persist. The adoption of edge computing and federated learning offers promising solutions by enabling local data processing and privacy-preserving model training. However, these approaches require further optimization for large-scale deployment. Overall, the reviewed studies indicate a clear shift towards intelligent, scalable, and adaptive air quality monitoring systems. Future research should focus on improving model efficiency, reducing energy consumption, and enhancing interpretability to ensure reliable and sustainable environmental monitoring.

Conclusion

Air pollution monitoring and prediction have become critical components in addressing environmental and public health challenges. This comprehensive review has analyzed recent advancements in IoT-based air quality monitoring systems integrated with deep learning and optimization techniques from 2020 to 2023. Traditional air quality monitoring systems, although accurate, are limited by high costs and sparse deployment. The integration of IoT technologies has enabled distributed and real-time monitoring, significantly improving spatial and temporal coverage. Deep learning models such as CNN, LSTM, and hybrid architectures have enhanced prediction accuracy by capturing complex relationships in environmental data.

The introduction of attention mechanisms and advanced architectures such as Transformers and Graph Neural Networks has further improved model performance. Among these, pyramidal convolution split-attention networks represent a significant advancement, enabling multi-scale feature extraction and improved handling of heterogeneous IoT data. Optimization techniques and hybrid models have also contributed to improved robustness and efficiency. However, challenges such as computational complexity, energy consumption, and data heterogeneity remain significant barriers to large-scale deployment.

Future research should focus on developing lightweight and energy-efficient models suitable for real-time applications. The integration of explainable AI techniques will enhance model transparency and reliability. Additionally, combining domain knowledge with advanced AI techniques can further improve prediction accuracy. In conclusion, the convergence of IoT, deep learning, and optimization techniques provides a promising direction for next-generation air pollution monitoring systems. Continued research and innovation in this field will play a vital role in improving environmental sustainability and public health outcomes.

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