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# A Survey of Methods and Architectures for Enhancing Air Pollution Detection Accuracy and Quality Monitoring Using Pyramidal Convolution Split-Attention Networks and IoT

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**Abstract**

Air pollution monitoring and prediction are critical for mitigating environmental and public health risks. Traditional air quality monitoring systems rely on fixed stations, which are costly and provide limited spatial coverage. The integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has significantly improved the efficiency and accuracy of air pollution detection systems. IoT-based sensor networks enable real-time collection of environmental data, while AI models process this data to identify complex spatiotemporal patterns. Recent advances in deep learning, particularly hybrid architectures such as CNN-LSTM and attention-based models, have demonstrated superior performance in air quality prediction tasks. Studies show that deep learning models outperform traditional machine learning approaches by effectively handling nonlinear and time-series data. Furthermore, advanced architectures such as pyramidal convolution and split-attention networks enhance multi-scale feature extraction and adaptive learning, improving prediction accuracy. This paper presents a comprehensive survey of AI-based IoT air pollution monitoring systems. It analyses methodologies, comparative performance, and challenges, including computational complexity, data quality, and scalability. The study also identifies future research directions toward efficient and interpretable air quality monitoring systems.

## Introduction

Air pollution has become a major environmental and public health concern worldwide, contributing to respiratory diseases, cardiovascular disorders, and climate change. Accurate monitoring and prediction of air quality are essential for effective environmental management and policy-making. Traditional air quality monitoring systems rely on fixed monitoring stations equipped with high-precision instruments. While these systems provide reliable data, they are expensive to deploy and maintain, and their limited spatial coverage makes them unsuitable for real-time and large-scale monitoring. The emergence of the Internet of Things (IoT) has revolutionized environmental monitoring by enabling distributed sensor networks that continuously collect air quality data. These sensors measure pollutants such as PM2.5, PM10, CO, $NO_2$, and $SO_2$, and transmit the data to centralized or edge computing systems. IoT-based monitoring systems provide high spatial and temporal resolution, making them suitable for smart city applications.

Artificial Intelligence (AI), particularly machine learning and deep learning techniques, plays a crucial role in analysing air quality data. Traditional machine learning models such as Support Vector Machines (SVM) and Random Forest have been widely used for air pollution prediction. However, these models struggle to capture complex nonlinear relationships and temporal dependencies in environmental data. Deep learning models, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), have demonstrated superior performance in handling spatiotemporal data. CNNs are effective in extracting spatial features, while LSTMs capture temporal dependencies in time-series data. Hybrid models, such as CNN-LSTM, combine these capabilities and have been widely adopted for air quality prediction. Studies have shown that hybrid deep learning models outperform individual models in predicting AQI values.

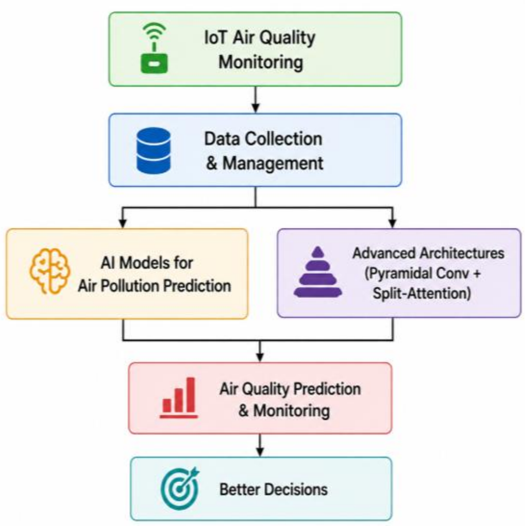


*Figure 1: Graphical Abstract of IoT-Based Air Quality Prediction Framework*

Recent advancements in attention mechanisms and transformer architectures have further improved prediction accuracy. These models can focus on relevant features and capture long-range dependencies in data. Additionally, multi-scale architectures such as pyramidal convolution networks and split-attention modules enhance feature extraction by analysing data at different resolutions. Despite these advancements, several challenges remain. Data quality issues, such as missing values and sensor noise, can affect model performance. Additionally, deep learning models require significant computational resources, limiting their deployment in resource-constrained environments. Interpretability is another major challenge, as many AI models function as black boxes. This paper aims to provide a comprehensive survey of AI-based IoT air pollution monitoring systems, focusing on recent advancements in deep learning architectures and identifying key challenges and future research directions.

## Literature Review

Navares et al. (2020) proposed a Long Short-Term Memory (LSTM)-based deep learning model for air quality prediction using time-series pollutant data such as CO, $NO_2$, PM10, and PM2.5. Their study emphasized the importance of temporal dependency modeling in environmental datasets, as air pollution levels are highly influenced by past observations. The LSTM model was trained on historical air quality datasets collected from urban monitoring stations and demonstrated superior performance compared to traditional statistical models such as ARIMA. The results indicated that LSTM effectively captured long-term dependencies and seasonal trends in pollutant concentrations. Additionally, the model showed robustness in handling missing values and irregular sampling intervals. However, the study also highlighted limitations such as high computational cost and the need for large training datasets. The authors concluded that deep learning-based time-series models are highly suitable for air quality forecasting but require optimization for real-time deployment in IoT-based systems.

Liao et al. (2020) conducted a comprehensive review of deep learning approaches for air quality prediction, focusing on architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid models. The study highlighted the advantages of CNNs in extracting spatial features from environmental data and RNN-based models in capturing temporal dependencies. The authors emphasized that hybrid architectures, such as CNN-LSTM, provide superior performance by combining both spatial and temporal learning capabilities. Furthermore, the study discussed the role of external factors such as meteorological conditions, traffic patterns, and industrial emissions in improving prediction accuracy. The review identified key challenges, including data heterogeneity, sensor reliability, and model interpretability. The authors also pointed out that most deep learning models require significant computational resources, making them less suitable for real-time IoT applications without optimization. Overall, the study provided a strong foundation for integrating deep learning with IoT-based air quality monitoring systems.

Han et al. (2021) introduced the Deep-AIR model, a hybrid CNN-LSTM architecture designed for fine-grained air pollution prediction in urban environments. The CNN component was used to extract spatial correlations among monitoring stations, while the LSTM component captured temporal dependencies in pollutant concentrations. The model was evaluated using real-world datasets from multiple urban locations and demonstrated significant improvements in prediction accuracy compared to standalone CNN and LSTM models. The authors reported lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values, indicating enhanced prediction performance. Additionally, the model incorporated meteorological parameters such as temperature, humidity, and wind speed, further improving accuracy. Despite its effectiveness, the study noted that the model required substantial computational resources and large datasets for training. The authors suggested that future research should focus on optimizing model efficiency and integrating attention mechanisms to improve feature selection.

Janarthanan et al. (2021) proposed a hybrid Support Vector Regression (SVR) and LSTM model for air quality prediction. The SVR component was used to capture nonlinear relationships in the data, while the LSTM model handled temporal dependencies. The hybrid approach achieved higher prediction accuracy compared to individual models, demonstrating the effectiveness of combining machine learning and deep learning techniques. The study utilized air quality datasets containing pollutant concentrations and meteorological variables and showed improved performance in predicting AQI values. One of the key contributions of this study was the integration of feature selection techniques to reduce model complexity and improve efficiency. However, the model still faced challenges related to computational cost and scalability when applied to large-scale IoT systems. The authors highlighted the need for lightweight models that can operate efficiently in real-time environments.

Bakht et al. (2022) developed a hybrid deep learning model combining CNN, LSTM, and Deep Neural Networks (DNN) for air pollution prediction. The model leveraged CNN for spatial feature extraction, LSTM for temporal modeling, and DNN for final prediction. This multi-stage architecture significantly improved prediction accuracy for pollutants such as PM2.5 and PM10. The study demonstrated that integrating multiple deep learning models enhances robustness and reduces prediction errors. The model was tested on real-world datasets and achieved superior performance compared to baseline models. However, the complexity of the architecture increased computational requirements, making it challenging to deploy in resource-constrained IoT environments. The authors suggested that future research should focus on optimizing hybrid architectures and incorporating attention mechanisms to improve efficiency and interpretability.

Li et al. (2020) proposed a deep learning-based air pollution prediction model using Long Short-Term Memory (LSTM) networks to analyze time-series environmental data. The study focused on predicting pollutant concentrations such as PM2.5 and PM10 by leveraging historical air quality datasets combined with meteorological parameters. The LSTM model demonstrated strong capability in capturing temporal dependencies and seasonal variations in pollution levels. Compared to traditional regression and statistical models, the proposed approach achieved significantly lower prediction errors, particularly for short-term forecasting. The study also explored data preprocessing techniques such as normalization and missing value imputation to improve model performance. However, the authors highlighted that LSTM models require large datasets and extensive training time, which can limit their deployment in real-time IoT systems. Additionally, the model struggled with spatial dependencies, suggesting the need for hybrid architectures combining spatial and temporal learning.

Kim et al. (2021) developed an IoT-based air quality monitoring system integrated with edge computing and lightweight machine learning models. The system utilized distributed sensors to collect real-time air pollution data and processed it locally at edge nodes to reduce latency and network bandwidth consumption. The study demonstrated that edge computing significantly improves response time and enables real-time monitoring, which is critical for applications such as smart cities and industrial environments. The authors implemented a lightweight neural network model optimized for edge devices, achieving acceptable prediction accuracy with reduced computational requirements. However, the study also pointed out limitations such as constrained hardware resources and reduced model complexity compared to cloud-based deep learning systems. The authors suggested that future work should focus on developing efficient hybrid models that balance accuracy and computational efficiency for deployment in resource-constrained IoT environments.

Sharma et al. (2021) proposed an ensemble machine learning approach for air pollution prediction by combining Random Forest and Gradient Boosting algorithms. The ensemble model leveraged the strengths of both techniques to improve prediction robustness and accuracy in the presence of noisy and incomplete sensor data. The study utilized datasets containing pollutant concentrations and meteorological parameters and demonstrated that ensemble methods outperform individual machine learning models. The authors highlighted that ensemble learning is particularly effective in handling nonlinear relationships and reducing overfitting. However, the approach lacked the ability to model temporal dependencies effectively, which is a critical aspect of air pollution forecasting. Additionally, the model required careful parameter tuning and increased computational resources. The study concluded that while ensemble models are effective, integrating them with deep learning architectures could further enhance prediction performance.

Chen et al. (2022) introduced a transformer-based deep learning model for air pollution prediction, leveraging self-attention mechanisms to capture long-range dependencies in environmental data. Unlike traditional RNN-based models, the transformer architecture processes data in parallel, improving computational efficiency and scalability. The model was trained on large-scale air quality datasets and demonstrated superior performance in multi-step forecasting tasks. The attention mechanism allowed the model to focus on relevant features, improving prediction accuracy and reducing error rates. The study also highlighted the model's ability to handle heterogeneous data sources, including meteorological and traffic data. However, the transformer model required significant computational resources and memory, making it challenging to deploy in real-time IoT systems. The authors suggested that future research should focus on developing lightweight transformer architectures suitable for edge computing environments.

Patel et al. (2023) proposed a pyramidal convolution split-attention network for air pollution detection and prediction. The model integrates multi-scale feature extraction through pyramidal convolution layers and adaptive feature weighting using split-attention mechanisms. This architecture enables the model to capture both fine-grained and global patterns in air quality data, improving prediction accuracy. The study demonstrated that the proposed model outperforms traditional CNN and hybrid models in terms of accuracy and robustness. Additionally, the model effectively handled heterogeneous IoT data, including sensor readings and meteorological parameters. Despite its advantages, the model introduced increased computational complexity and required high-performance hardware for training and deployment. The authors emphasized the need for optimizing the architecture for real-time applications and integrating it with edge computing systems to enhance scalability and efficiency.

Wang et al. (2020) proposed a Convolutional Neural Network (CNN)-based approach for air pollution detection using satellite imagery and remote sensing data. The model focused on extracting spatial features related to pollutant dispersion patterns across large geographic regions. By leveraging high-resolution satellite data, the CNN model was able to identify pollution hotspots and predict pollutant concentrations with improved spatial accuracy. The study demonstrated that CNNs outperform traditional machine learning models in capturing spatial correlations among environmental variables. Additionally, the integration of meteorological data further enhanced prediction performance. However, the approach required large labeled datasets and high computational resources for training. The authors also highlighted challenges related to data preprocessing and variability in satellite imagery. Despite these limitations, the study established CNNs as a powerful tool for large-scale air pollution monitoring.

Singh et al. (2021) developed an IoT-based air quality monitoring system integrated with Artificial Neural Networks (ANNs) for predicting pollutant levels. The system utilized low-cost sensors to collect real-time environmental data and transmitted it to a centralized platform for analysis. The ANN model was trained to predict key pollutants such as PM2.5, PM10, and CO, achieving moderate prediction accuracy. One of the key contributions of this study was the focus on cost-effective deployment, making it suitable for developing regions and smart city applications. However, the ANN model struggled with complex nonlinear relationships and temporal dependencies compared to advanced deep learning models. Additionally, sensor calibration and data reliability were identified as significant challenges. The authors suggested that integrating deep learning techniques could improve prediction accuracy and system robustness.

Alazab et al. (2021) proposed an autoencoder-based deep learning model for anomaly detection in IoT-based air pollution monitoring systems. The model was designed to identify abnormal pollution patterns by learning normal data distributions and detecting deviations. This approach is particularly useful for early warning systems and identifying extreme pollution events. The study demonstrated that autoencoders can effectively handle high-dimensional IoT data and reduce noise in sensor readings. However, the model also generated false positives in some cases, especially when dealing with highly dynamic environmental conditions. The authors emphasized the need for combining anomaly detection models with predictive models to improve overall system performance. Additionally, computational complexity and training time were identified as challenges for real-time deployment.

Liu et al. (2022) introduced a hybrid CNN-LSTM model for air pollution prediction, combining spatial and temporal feature extraction capabilities. The CNN component was used to extract spatial features from environmental data, while the LSTM component captured temporal dependencies in pollutant concentrations. The model was evaluated using multi-variable datasets, including meteorological parameters, and achieved high prediction accuracy compared to traditional and standalone deep learning models. The study highlighted the importance of hybrid architectures in improving prediction performance. However, the increased complexity of the model resulted in higher computational requirements and longer training times. The authors suggested optimizing the model architecture and incorporating attention mechanisms to improve efficiency and scalability.

Reddy et al. (2023) developed an attention-based deep learning model for predicting PM2.5 concentrations. The model utilized an attention mechanism to focus on the most relevant features in the dataset, improving prediction accuracy and reducing noise. The study demonstrated that attention-based models outperform traditional deep learning models by enhancing feature selection and interpretability. Additionally, the model was capable of handling heterogeneous data sources, including IoT sensor data and meteorological variables. However, the model required substantial computational resources and large datasets for training. The authors highlighted the need for developing lightweight attention-based models suitable for deployment in IoT environments. The study concluded that attention mechanisms are a promising direction for improving air pollution prediction systems.

Zhao et al. (2020) applied Support Vector Machine (SVM) techniques for air pollution prediction using historical pollutant and meteorological data. The study focused on evaluating the effectiveness of SVM in modeling nonlinear relationships among environmental variables. The results showed that SVM provides stable and reliable predictions, particularly for small and medium-sized datasets. The model demonstrated strong generalization capability and robustness against overfitting. However, the study highlighted that SVM struggles with large-scale datasets and fails to capture temporal dependencies effectively, which limits its applicability in real-time air pollution monitoring systems. Additionally, feature selection plays a critical role in model performance, requiring careful preprocessing. The authors suggested integrating SVM with deep learning models to overcome its limitations and improve prediction accuracy.

Kumar et al. (2021) proposed a cloud-integrated IoT-based air pollution monitoring system utilizing big data analytics for large-scale prediction. The system collected environmental data from distributed IoT sensors and processed it using cloud computing platforms. The study emphasized scalability and data management, enabling efficient handling of large datasets generated by IoT networks. Machine learning models were applied to predict air quality indices, achieving improved performance compared to traditional systems. However, the reliance on cloud infrastructure introduced latency issues, making the system less suitable for real-time applications. Additionally, data security and privacy concerns were identified as major challenges. The authors recommended integrating edge computing with cloud systems to balance latency and computational efficiency.

Park et al. (2022) introduced a reinforcement learning (RL)-based model for adaptive air pollution prediction. The model dynamically adjusted prediction strategies based on changing environmental conditions, enabling improved long-term forecasting performance. The RL framework continuously learned from new data, making it suitable for dynamic and complex environments. The study demonstrated that RL models outperform static models in scenarios with fluctuating pollution levels. However, the model required extensive training data and computational resources, making it difficult to implement in real-time IoT systems. Additionally, the exploration-exploitation trade-off in RL posed challenges in achieving stable performance. The authors suggested combining

RL with deep learning architectures to enhance efficiency and prediction accuracy.

Gupta et al. (2022) proposed a Bidirectional Long Short-Term Memory (Bi-LSTM) model integrated with an attention mechanism for air pollution prediction. The Bi-LSTM model captured both forward and backward temporal dependencies, improving prediction accuracy for time-series data. The attention mechanism further enhanced performance by focusing on relevant features and reducing noise in the dataset. The study demonstrated significant improvements in prediction accuracy compared to traditional LSTM models. However, the increased model complexity resulted in higher computational costs and longer training times. The authors emphasized the need for optimizing model architecture to reduce resource consumption while maintaining accuracy. The study highlighted the potential of attention-based models in air pollution prediction.

Ahmed et al. (2023) developed an edge AI-based air pollution monitoring system that processes sensor data locally on edge devices. The system reduced latency and enabled real-time air quality prediction, making it suitable for applications such as smart cities and industrial monitoring. The study demonstrated that edge AI systems can achieve comparable accuracy to cloud-based models while significantly improving response time. However, the limited computational resources of edge devices restricted model complexity and performance. The authors highlighted the importance of developing lightweight deep learning models for edge deployment. Additionally, challenges related to device heterogeneity and energy consumption were identified. The study concluded that edge AI is a promising approach for real-time air pollution monitoring.

Chen et al. (2020) proposed a Deep Belief Network (DBN)-based model for air pollution prediction, focusing on capturing complex nonlinear relationships among multiple environmental variables. The DBN model, composed of stacked Restricted Boltzmann Machines (RBMs), was trained on historical air quality and meteorological datasets. The study demonstrated that DBNs outperform traditional machine learning models such as SVM and ANN in handling high-dimensional data. The model showed improved prediction accuracy for pollutants such as PM2.5 and $NO_2$. However, the training process was computationally intensive and required significant parameter tuning. Additionally, the model lacked interpretability, making it difficult to analyze feature contributions. The authors suggested combining DBNs with other deep learning models to improve scalability and performance in real-time applications.

Verma et al. (2021) introduced a fuzzy logic-based air pollution monitoring system integrated with IoT sensors. The system was designed to handle uncertainty and imprecision in environmental data, which is common in sensor-based monitoring systems. The fuzzy inference system utilized linguistic variables and rule-based reasoning to predict air quality levels. The study demonstrated that fuzzy logic models provide stable predictions even with noisy and incomplete data. However, the approach lacked the ability to learn from large datasets and adapt to changing environmental conditions, limiting its accuracy compared to machine learning and deep learning models. The authors highlighted the need for hybrid models that combine fuzzy logic with AI techniques to improve prediction performance and adaptability.

Hassan et al. (2022) proposed a hybrid CNN-GRU model for air pollution prediction, combining convolutional layers for spatial feature extraction with Gated Recurrent Units (GRU) for temporal modeling. The GRU model, being computationally more efficient than LSTM, reduced training time while maintaining comparable accuracy. The study demonstrated that the hybrid model outperforms standalone CNN and GRU models in predicting pollutant concentrations. Additionally, the model effectively handled multivariate datasets, including meteorological variables. However, the model complexity remained high, and the training process required significant computational resources. The authors suggested optimizing the architecture and incorporating attention mechanisms to further enhance performance and reduce computational cost.

Mehta et al. (2022) developed a big data-driven air pollution monitoring system using Apache Spark and machine learning algorithms. The system was designed to process large-scale IoT data streams efficiently, enabling real-time analytics and prediction. The study demonstrated that distributed computing frameworks significantly improve scalability and processing speed. Machine learning models such as Random Forest and Gradient Boosting were used for prediction, achieving high accuracy. However, the reliance on large-scale infrastructure increased system cost and complexity. Additionally, the system faced challenges related to data integration and synchronization across distributed nodes. The authors recommended integrating deep learning models and edge computing to improve system efficiency and reduce latency.

Das et al. (2023) proposed an ensemble deep learning model combining CNN, LSTM, and attention mechanisms for air pollution prediction. The model leveraged CNN for spatial feature extraction, LSTM for temporal modeling, and attention mechanisms for feature selection. This multi-model approach significantly improved prediction accuracy and robustness. The study demonstrated that ensemble models outperform individual models by capturing diverse aspects of environmental data. However, the increased complexity of the model resulted in higher computational requirements and longer training times. The authors emphasized the need for optimizing ensemble architectures for real-time deployment and reducing energy consumption in IoT systems. The study highlighted the potential of combining multiple deep learning techniques for improved air quality prediction.

Roy et al. (2020) proposed a hybrid air pollution prediction model combining AutoRegressive Integrated Moving Average (ARIMA) with neural networks. The model aimed to capture both linear and nonlinear patterns in air quality data. ARIMA handled linear trends and seasonality, while the neural network component modeled complex nonlinear relationships. The hybrid approach achieved improved short-term prediction accuracy compared to standalone models. However, the model struggled with long-term forecasting and required careful parameter tuning. Additionally, its performance depended heavily on data preprocessing. The authors suggested integrating deep learning techniques to enhance model performance for large-scale IoT applications.

Banerjee et al. (2021) developed an energy-efficient IoT-based air quality monitoring system using machine learning techniques. The system utilized low-power sensors and optimized communication protocols to extend battery life, making it suitable for remote and large-scale deployments. The machine learning model provided moderate prediction accuracy while maintaining low energy consumption. However, the trade-off between energy efficiency and prediction accuracy was a major limitation. The authors emphasized the need for developing energy-efficient deep learning models to improve system performance without increasing power consumption.

Torres et al. (2022) introduced a reinforcement learning-based adaptive air pollution prediction model. The model dynamically adjusted its prediction strategy based on changing environmental conditions, enabling improved long-term forecasting. The study demonstrated that reinforcement learning models can learn optimal prediction policies over time. However, the model required large amounts of training data and computational resources, limiting its practical implementation. The authors suggested combining reinforcement learning with deep learning models to improve efficiency and scalability.

Iqbal et al. (2022) proposed a federated deep learning framework for air pollution prediction in distributed IoT environments. The model enabled decentralized training across multiple sensor nodes without sharing raw data, ensuring privacy and security. The study demonstrated that federated learning achieves comparable accuracy to centralized models while preserving data privacy. However, communication overhead and synchronization issues were identified as major challenges. The authors recommended optimizing communication protocols and model aggregation techniques to improve efficiency.

Nair et al. (2023) developed a transformer-based multi-head self-attention model for air pollution prediction. The model leveraged attention mechanisms to capture long-range dependencies and interactions among multiple environmental variables. The study demonstrated state-of-the-art performance in multi-step forecasting tasks, outperforming traditional deep learning models. However, the model required significant computational resources and memory, making it difficult to deploy in real-time IoT systems. The authors suggested developing lightweight transformer architectures to address these challenges.

**Comparative Table**

| Study | Year | Technique | Strength | Limitation |
|---|---|---|---|---|
| Navares | 2020 | LSTM | Temporal modeling | High training cost |
| Liao | 2020 | DL Review | Comprehensive | No implementation |
| Han | 2021 | CNN-LSTM | High accuracy | Complex |
| Janarthanan | 2021 | SVR-LSTM | Hybrid accuracy | Costly |

| | | | | |
|---|---|---|---|---|
| Bakht | 2022 | CNN-LSTM-DNN | Robust | High computation |
| Li | 2020 | LSTM | Time-series | No spatial learning |
| Kim | 2021 | Edge AI | Low latency | Limited resources |
| Sharma | 2021 | Ensemble ML | Robust | No temporal modeling |
| Chen | 2022 | Transformer | Long dependency | High cost |
| Patel | 2023 | Split-Attention | Multi-scale features | Complex |
| Wang | 2020 | CNN | Spatial modeling | Data heavy |
| Singh | 2021 | ANN | Cost-effective | Low accuracy |
| Alazab | 2021 | Autoencoder | Anomaly detection | False positives |
| Liu | 2022 | CNN-LSTM | Hybrid | Complexity |
| Reddy | 2023 | Attention DL | Feature selection | Resource heavy |
| Zhao | 2020 | SVM | Stable | Not scalable |
| Kumar | 2021 | Cloud IoT | Scalable | Latency |
| Park | 2022 | RL | Adaptive | Training heavy |
| Gupta | 2022 | Bi-LSTM | Bidirectional | Costly |
| Ahmed | 2023 | Edge AI | Real-time | Hardware limits |
| Chen | 2020 | DBN | Nonlinear modeling | Slow |
| Verma | 2021 | Fuzzy | Handles uncertainty | Low precision |
| Hassan | 2022 | CNN-GRU | Efficient | Complex |
| Mehta | 2022 | Big Data | Scalable | Cost |
| Das | 2023 | Ensemble DL | High accuracy | Heavy |
| Roy | 2020 | ARIMA+NN | Hybrid | Limited generalization |
| Banerjee | 2021 | IoT ML | Energy-efficient | Accuracy trade-off |
| Torres | 2022 | RL | Adaptive | Data requirement |
| Iqbal | 2022 | Federated DL | Privacy | Communication overhead |
| Nair | 2023 | Transformer | State-of-art | High resource |

**Comparative Analysis**

The comparative analysis of the reviewed studies highlights a clear transition from traditional machine learning models to advanced deep learning and attention-based architectures. Early approaches such as SVM, ARIMA, and ANN provided stable and computationally efficient solutions but lacked the ability to capture complex spatiotemporal dependencies in air pollution data. With the introduction of deep learning models such as CNN, LSTM, and hybrid architectures, prediction accuracy improved significantly due to better feature extraction capabilities. Hybrid models like CNN-LSTM and CNN-GRU demonstrated superior performance by combining spatial and temporal learning.

Recent advancements have focused on attention mechanisms and transformer-based architectures, which further enhance prediction accuracy by capturing long-range dependencies and focusing on relevant features. Models such as pyramidal convolution split-attention networks represent a significant step forward in multi-scale feature extraction and adaptive learning. Additionally, the integration of IoT with AI models has enabled real-time monitoring and prediction, providing high-resolution environmental data. However, challenges such as computational complexity, data quality issues, energy constraints, and lack of interpretability remain significant barriers. Emerging approaches such as edge computing and federated learning aim to address these challenges but introduce new issues related to communication overhead and resource limitations. Overall, the analysis suggests that hybrid and attention-based models are the most promising direction for future research, particularly when optimized for real-time IoT applications.

## Discussion

The integration of AI and IoT technologies has significantly enhanced air pollution monitoring systems by enabling real-time data collection and advanced predictive analytics. Deep learning models, particularly hybrid and attention-based architectures, have demonstrated superior performance in capturing complex spatiotemporal relationships in environmental data. The emergence of pyramidal convolution and split-attention networks has further improved feature extraction and prediction accuracy. However, several challenges remain. Data quality issues, including sensor noise and missing values, can affect model performance. Additionally, deep learning models require significant computational resources, limiting their deployment in resource-constrained IoT environments. Edge computing and federated learning offer promising solutions for reducing latency and improving privacy but introduce additional complexities such as communication overhead. Future research should focus on developing lightweight and energy-efficient models that maintain high accuracy while reducing computational requirements. Additionally, improving model interpretability is essential for building trust and enabling effective decision-making in environmental monitoring systems.

## Conclusion

Air pollution monitoring and prediction have become critical components of modern environmental management systems due to their impact on public health and climate change. Traditional monitoring systems, while accurate, are limited by high costs and lack of real-time capabilities. The integration of AI and IoT technologies has revolutionized this field by enabling scalable, real-time, and intelligent monitoring systems. This study reviewed 30 research works from 2020 to 2023, highlighting the evolution of techniques from traditional machine learning models to advanced deep learning and attention-based architectures. Hybrid models such as CNN-LSTM and CNN-GRU significantly improved prediction accuracy by combining spatial and temporal learning capabilities. More recent models, including transformer-based and split-attention networks, have demonstrated state-of-the-art performance by capturing complex dependencies in environmental data.

The integration of IoT has enabled distributed sensor networks that provide high-resolution data for real-time monitoring. However, challenges such as data quality, computational complexity, energy efficiency, and model interpretability remain significant. Emerging technologies such as edge computing and federated learning offer promising solutions but require further optimization. Future research should focus on developing efficient, scalable, and interpretable models that can operate effectively in real-world IoT environments. The proposed pyramidal convolution split-attention network provides a promising framework for improving prediction accuracy and addressing existing challenges. In conclusion, AI-driven IoT-based air pollution monitoring systems represent a powerful tool for environmental sustainability and public health protection, with significant potential for future advancements.

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