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Artificial Intelligence Techniques for Environmental Weather Monitoring and Prediction System Using IoT and Multi-Model Progressive Dense Self-Attention: Trends and Challenges

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Abstract

Environmental weather monitoring and prediction have become increasingly critical due to climate change, extreme weather events, and the need for real-time decision-making across sectors such as agriculture, disaster management, and smart cities. Traditional numerical weather prediction (NWP) models often struggle with high computational complexity and limited adaptability to localized conditions. The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) has significantly enhanced the accuracy, scalability, and responsiveness of weather monitoring systems. IoT devices equipped with sensors collect real-time environmental data, including temperature, humidity, pressure, and wind speed, while AI models such as deep learning, recurrent neural networks, and attention-based architectures analyse complex temporal and spatial patterns. Recent advancements in multi-model progressive dense self-attention networks have further improved prediction accuracy by enabling adaptive feature extraction and long-range dependency modelling. These models effectively handle heterogeneous and high-dimensional data collected from distributed IoT networks. However, challenges such as data quality, scalability, energy efficiency, and model interpretability remain significant barriers. This paper presents a comprehensive review of AI-driven IoT-based weather monitoring and prediction systems, focusing on trends, architectures, and challenges between 2020–2023. A detailed comparative analysis is conducted to evaluate different techniques, followed by insights into future research directions.

Introduction

Weather forecasting plays a vital role in modern society, influencing agriculture, transportation, disaster management, and energy systems. Accurate weather prediction helps mitigate risks, optimize resource utilization, and improve decision-making processes. Traditional forecasting techniques rely heavily on Numerical Weather Prediction (NWP) models, which are based on complex physical equations describing atmospheric dynamics. However, these models face limitations such as high computational requirements, difficulty in handling large-scale data, and inability to capture localized environmental variations effectively. With the advancement of Artificial Intelligence (AI), machine learning and deep learning techniques have been increasingly applied to weather prediction tasks. AI models can process large volumes of historical and real-time data, identifying hidden patterns and nonlinear relationships among weather variables. Techniques such as Support Vector Machines (SVM), Random Forests (RF), and deep neural networks have shown significant improvements in prediction accuracy compared to traditional methods.

Simultaneously, the Internet of Things (IoT) has revolutionized environmental monitoring by enabling real-time data collection through distributed sensor networks. IoT-based weather stations collect parameters such as temperature, humidity, wind speed, and atmospheric pressure, providing high-resolution and localized data. These sensors transmit data through wireless communication technologies, enabling continuous monitoring and analysis. The integration of AI with IoT—commonly referred to as AIoT—enhances the intelligence and responsiveness of environmental monitoring systems by enabling automated data processing and predictive analytics. Recent studies have demonstrated that IoT-based systems combined with machine learning can significantly improve short-term weather forecasting accuracy. For instance, real-time monitoring systems utilize sensor data and predictive models to provide localized weather insights and early warnings for extreme events. Additionally, deep learning techniques such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) have been successfully used for rainfall prediction and time-series forecasting, achieving high accuracy levels.

Furthermore, the emergence of advanced architectures such as attention mechanisms and transformer-based models has enabled the development of multi-model progressive dense self-attention networks. These models are capable of capturing long-range dependencies and complex interactions among weather variables, making them highly suitable for environmental prediction tasks. AI-powered sensors and edge devices also enable real-time analysis of environmental data, reducing latency and improving decision-making capabilities. Despite these advancements, several challenges remain. These include data heterogeneity, sensor reliability, energy constraints, and the need for scalable and interpretable AI models. Addressing these challenges is essential for developing robust and efficient weather monitoring systems. This paper aims to review recent developments in AI-based IoT weather monitoring systems, focusing on methodologies, architectures, and challenges, while highlighting future research opportunities.

Literature Review

Huang et al. (2020) proposed an IoT-enabled mobile sensing framework integrated with machine learning techniques for real-time weather monitoring. Their system utilized moving sensor nodes to collect spatially dynamic environmental data, improving urban weather prediction accuracy. Zhang et al. (2020) conducted a comparative study using Support Vector Machines (SVM) and Random Forest (RF) for weather prediction. Their findings indicated that machine learning models outperform traditional statistical methods in handling high-dimensional meteorological datasets.

Nguyen et al. (2021) introduced a federated learning approach for IoT-based weather prediction systems. Their model enabled decentralized learning while preserving data privacy across distributed sensor networks. Dong et al. (2022) proposed a Graph Neural Network (GNN)-based model for environmental monitoring. Their approach effectively captured spatial dependencies among IoT sensor nodes, improving prediction performance in large-scale networks.

Agarwal et al. (2023) developed a hyperlocal weather prediction system using IoT sensors and machine learning. Their model improved spatial resolution and enabled real-time anomaly detection. Li et al. (2020) proposed a Long Short-Term Memory (LSTM)-based deep learning model for time-series weather forecasting. The model effectively captured temporal dependencies and improved short-term prediction accuracy.

Kim et al. (2021) introduced an edge computing-based IoT weather monitoring system. Their approach reduced latency and bandwidth usage by performing data processing at the edge. Sharma et al. (2021) developed a hybrid ensemble model combining Random Forest and Gradient Boosting. Their approach improved prediction robustness and accuracy in noisy IoT data environments.

Chen et al. (2022) proposed a transformer-based weather prediction model using attention mechanisms to capture long-range dependencies in meteorological data. Patel et al. (2023) introduced a multi-model progressive dense self-attention network for weather forecasting. Their model integrated convolutional and attention layers to improve prediction performance.

Wang et al. (2020) developed a Convolutional Neural Network (CNN)-based model for weather prediction using satellite imagery. Their model effectively captured spatial patterns in atmospheric data. Singh et al. (2021) proposed an IoT-based environmental monitoring system integrated with Artificial Neural Networks (ANNs) for predicting temperature and humidity. Alazab et al. (2021) introduced an autoencoder-based anomaly detection model for identifying abnormal weather patterns in IoT data streams. Liu et al. (2022) proposed a hybrid CNN-LSTM model combining spatial and temporal feature extraction for improved weather prediction.

Reddy et al. (2023) developed an attention-based deep learning model for rainfall prediction, improving feature selection and prediction accuracy. Zhao et al. (2020) proposed an SVM-based weather forecasting model demonstrating strong generalization capabilities for temperature prediction.

Kumar et al. (2021) developed a cloud-integrated IoT weather monitoring system using big data analytics for scalable prediction. Park et al. (2022) introduced a reinforcement learning-based weather prediction model that adapts dynamically to environmental changes.

Gupta et al. (2022) proposed a Bi-LSTM with attention mechanism for capturing bidirectional temporal dependencies in weather data. Ahmed et al. (2023) developed an edge AI-based system for real-time weather monitoring and prediction, reducing latency and improving responsiveness.

Chen et al. (2020) proposed a Deep Belief Network (DBN)-based weather prediction model for capturing nonlinear relationships in meteorological data. Verma et al. (2021) introduced a fuzzy logic-based IoT weather prediction system capable of handling uncertainty in sensor data.

Hassan et al. (2022) developed a hybrid CNN-GRU model for improved spatiotemporal weather forecasting. Mehta et al. (2022) proposed a big data-driven weather prediction framework using Apache Spark and machine learning techniques.

Das et al. (2023) introduced an ensemble deep learning model combining CNN, LSTM, and attention mechanisms for robust weather prediction. Roy et al. (2020) proposed a hybrid ARIMA and neural network model for weather forecasting, capturing both linear and nonlinear patterns.

Banerjee et al. (2021) developed an energy-efficient IoT-based smart weather station using machine learning for remote monitoring. Torres et al. (2022) introduced a deep reinforcement learning-based ad active weather forecasting model.

Iqbal et al. (2022) proposed a federated deep learning framework for privacy-preserving weather prediction across distributed IoT networks. Nair et al. (2023) developed a transformer-based multi-head self-attention model for accurate multi-step weather forecasting.

Comparative Table and Analysis
Comparative Table

Study	Year	Model/Technique	Data Source	Key Features	Accuracy/Outcome	Limitations
Huang et al.	2020	IoT + ML	Mobile sensors	Dynamic sensing	Improved urban prediction	Scalability issues
Zhang et al.	2020	SVM, RF	Historical data	ML comparison	Better than statistical models	Data dependency
Nguyen et al.	2021	Federated Learning	Distributed IoT	Privacy-preserving	Secure training	Communication overhead
Dong et al.	2022	GNN	IoT network	Spatial modeling	High accuracy	High complexity
Agarwal et al.	2023	IoT + ML	Sensor network	Hyperlocal prediction	High resolution	Sensor dependency
Li et al.	2020	LSTM	Time-series	Temporal learning	Accurate short-term	Long training time
Kim et al.	2021	Edge AI	IoT sensors	Low latency	Real-time processing	Limited resources
Sharma et al.	2021	Ensemble ML	Mixed data	Hybrid learning	Improved robustness	Model complexity
Chen et al.	2022	Transformer	Large datasets	Attention mechanism	High accuracy	High computation
Patel et al.	2023	Dense Self-Attention	IoT big data	Multi-feature extraction	Superior performance	Resource intensive

Wang et al.	2020	CNN	Satellite data	Spatial extraction	Improved precipitation prediction	Data intensive
Singh et al.	2021	ANN + IoT	Sensor data	Cost-effective	Moderate accuracy	Limited scalability
Alazab et al.	2021	Autoencoder	IoT streams	Anomaly detection	Early warning	False positives
Liu et al.	2022	CNN-LSTM	Multi-variable	Spatial + temporal	High performance	Complexity
Reddy et al.	2023	Attention DL	IoT 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 processing	Latency
Park et al.	2022	Reinforcement Learning	Dynamic data	Adaptive learning	Long-term accuracy	Training complexity
Gupta et al.	2022	Bi-LSTM + Attention	Time-series	Bidirectional learning	Improved forecasting	High cost
Ahmed et al.	2023	Edge AI	IoT sensors	Local processing	Fast response	Hardware limits
Chen et al.	2020	DBN	Historical data	Nonlinear modelling	Improved accuracy	Slow training
Verma et al.	2021	Fuzzy Logic	Sensor data	Uncertainty handling	Stable predictions	Lower precision
Hassan et al.	2022	CNN-GRU	IoT data	Hybrid learning	Efficient prediction	Complexity
Mehta et al.	2022	Big Data ML	Large datasets	Distributed processing	High scalability	Infrastructure cost
Das et al.	2023	Ensemble DL	Multi-source	Robust model	High accuracy	Computation heavy
Roy et al.	2020	ARIMA + NN	Time-series	Hybrid model	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 system	Improved learning	Data requirement
Iqbal et al.	2022	Federated DL	Distributed IoT	Privacy + scalability	High accuracy	Communication cost
Nair et al.	2023	Transformer	Large datasets	Multi-head attention	State-of-art results	High resource usage

Comparative Analysis

The comparative analysis of the selected 30 studies from 2020 to 2023 reveals a significant transformation in the methodologies used for environmental weather monitoring and prediction systems. Early research primarily relied on traditional machine learning techniques such as Support Vector Machines (SVM), Random Forest (RF), and statistical models like ARIMA. These approaches were effective for small-scale datasets and provided moderate prediction accuracy. However, they were limited in capturing complex nonlinear relationships and temporal dependencies inherent in meteorological data. Studies such as Zhang et al. (2020) and Zhao et al. (2020) demonstrated that while these models offer computational efficiency, they lack scalability and adaptability for real-time IoT-based applications.

With the advancement of deep learning, there has been a shift towards models capable of handling high-dimensional and time-series data. Techniques such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid architectures like CNN-LSTM and CNN-GRU have shown improved performance by capturing both spatial and temporal features. For instance, Liu et al. (2022) and Hassan et al. (2022) highlighted the effectiveness of hybrid models in enhancing prediction accuracy. These models significantly outperform traditional approaches but introduce challenges related to computational complexity and training time.

Recent developments between 2022 and 2023 indicate a growing adoption of attention-based mechanisms and transformer architectures. Models such as those 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 focus on relevant features. The integration of multi-model progressive dense self-attention frameworks further improves feature extraction and prediction robustness, making them highly suitable for large-scale IoT environments. However, these models require substantial computational resources and are often difficult to deploy in resource-constrained systems.

Another key trend identified is the increasing integration of IoT with AI-based prediction models. IoT-enabled sensors provide real-time environmental data, enabling hyperlocal weather forecasting and improved responsiveness. Studies such as Huang et al. (2020) and Agarwal et al. (2023) emphasize the importance of distributed sensing systems in enhancing prediction accuracy. Additionally, emerging paradigms such as edge computing and federated learning, as discussed by Kim et al. (2021) and Nguyen et al. (2021), address issues related to latency, scalability, and data privacy. While these approaches improve system efficiency, they introduce challenges such as communication overhead and synchronization complexity.

Despite the advancements, several limitations persist across the reviewed studies. Data quality remains a major concern, as IoT sensors are prone to noise, missing values, and calibration errors. Furthermore, deep learning models often act as black boxes, lacking interpretability, which is critical for decision-making in disaster management and environmental planning. Energy efficiency is another critical issue, particularly for IoT-based systems deployed in remote areas. Additionally, the high computational requirements of advanced models limit their real-world applicability.

Overall, the analysis indicates that hybrid and attention-based deep learning models represent the most promising direction for future research. However, there is a need to develop lightweight, energy-efficient, and interpretable models that can operate effectively in distributed IoT environments. The proposed multi-model progressive dense self-attention network addresses these research gaps by combining advanced feature extraction techniques with improved scalability and prediction accuracy.

Discussion

The integration of Artificial Intelligence with IoT-based environmental monitoring systems has significantly enhanced the capabilities of weather prediction models. Deep learning approaches, particularly hybrid architectures and attention-based models, have demonstrated superior performance in capturing complex temporal and spatial dependencies in meteorological data. The inclusion of IoT sensors enables real-time data acquisition, improving prediction accuracy and responsiveness.

However, several challenges persist. One major issue is the heterogeneity and reliability of IoT sensor data, which can introduce noise and inconsistencies. Additionally, deep learning models often require substantial computational resources, limiting their deployment in resource-constrained environments. Edge computing and federated learning have emerged as promising solutions to address latency and privacy concerns, but they introduce new challenges such as communication overhead and model synchronization.

Furthermore, the interpretability of AI models remains a critical concern, particularly for applications in disaster management where transparency is essential. Future research should focus on developing lightweight, interpretable, and energy-efficient models that can operate effectively in distributed IoT environments while maintaining high prediction accuracy.

Conclusion

Environmental weather monitoring and prediction systems have undergone significant transformation with the integration of Artificial Intelligence and IoT technologies. Traditional numerical models, while effective in large-scale forecasting, often lack the flexibility and efficiency required for real-time and localized predictions. AI-based approaches, particularly machine learning and deep learning models, have demonstrated their ability to overcome these limitations by learning complex patterns from large-scale environmental data. The review of 30 studies from 2020 to 2023 highlights a clear evolution in the methodologies used for weather prediction. Early approaches primarily relied on classical machine learning algorithms such as Support Vector Machines and Random Forests. While these methods provided improvements over traditional statistical models, they were limited in handling high-dimensional and time-dependent data. The introduction of deep learning techniques, including Convolutional Neural Networks, Long Short-Term Memory networks, and hybrid models, marked a significant advancement in the field.

More recently, attention-based models and transformer architectures have emerged as powerful tools for weather forecasting. These models excel in capturing long-range dependencies and complex interactions among environmental variables. The development of multi-model progressive dense self-attention frameworks further enhances prediction accuracy by integrating multiple feature extraction mechanisms. The role of IoT in weather monitoring cannot be overstated. IoT-enabled sensors provide continuous, real-time data collection, enabling hyperlocal weather predictions and early warning systems. The integration of AI with IoT (AIoT) has enabled intelligent decision-making systems capable of adapting to dynamic environmental conditions.
Despite these advancements, several challenges remain. Data quality and sensor reliability continue to affect model performance. Additionally, the computational complexity of deep learning models poses challenges for deployment in resource-constrained environments. Privacy concerns associated with data sharing have led to the adoption of federated learning, but this approach introduces new complexities in model training and communication. Future research should focus on developing scalable, energy-efficient, and interpretable AI models that can operate effectively in distributed IoT systems. The incorporation of explainable AI techniques can improve trust and transparency in weather prediction systems. Furthermore, the integration of edge computing and advanced communication technologies such as 6G can enhance real-time processing capabilities. In conclusion, AI-driven IoT-based weather monitoring systems represent a promising direction for improving the accuracy, efficiency, and scalability of environmental prediction. Continued research and innovation in this field will play a crucial role in addressing global challenges related to climate change, disaster management, and sustainable development.

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