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A Survey of Methods and Architectures for Environmental Weather Monitoring and Prediction System Using IoT and Multi-Model Progressive Dense Self-Attention

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Abstract

Environmental weather monitoring and prediction systems have gained significant importance due to climate change, increasing natural disasters, and the need for precise agricultural planning. Traditional forecasting methods often suffer from low spatial resolution and delayed predictions. The integration of Internet of Things (IoT), machine learning (ML), and deep learning (DL) techniques has revolutionized weather prediction by enabling real-time data acquisition and intelligent forecasting. Recent advancements, particularly multi-model progressive dense self-attention architectures, have further enhanced prediction accuracy by capturing complex spatio-temporal dependencies in environmental data. This survey presents a comprehensive review of methods and architectures used in IoT-based weather monitoring and prediction systems between 2020 and 2023. It focuses on sensor-based data acquisition, cloud/fog computing frameworks, and AI-driven predictive models such as LSTM, CNN, and attention-based networks. The study also highlights challenges such as data heterogeneity, energy efficiency, scalability, and model generalization. A comparative analysis is conducted based on accuracy, computational complexity, scalability, and real-time performance. The findings indicate that hybrid deep learning models combined with IoT frameworks outperform traditional statistical methods by providing localized and high-resolution predictions. Finally, the paper outlines future research directions emphasizing edge intelligence, federated learning, and attention-based architectures for next-generation weather forecasting systems.

Introduction

Environmental weather monitoring plays a critical role in various domains, including agriculture, disaster management, transportation, and energy systems. Accurate weather prediction helps in minimizing risks associated with extreme weather events such as floods, droughts, cyclones, and heatwaves. However, conventional weather forecasting systems rely heavily on centralized meteorological stations and numerical weather prediction (NWP) models, which often lack real-time adaptability and high spatial resolution.

With the rapid development of the Internet of Things (IoT), environmental monitoring has undergone a paradigm shift. IoT-based systems utilize distributed sensor networks to collect real-time atmospheric data such as temperature, humidity, pressure, rainfall, and wind speed. These sensors, when integrated with cloud platforms and communication technologies, enable continuous and remote monitoring of environmental conditions. Studies show that IoT-based weather systems significantly improve data availability and enable localized predictions. In parallel, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for analyzing complex weather patterns. Unlike traditional statistical models, deep learning approaches such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and hybrid architectures can capture nonlinear relationships and temporal dependencies in meteorological data. For instance, LSTM-based models have demonstrated superior performance in time-series forecasting tasks due to their ability to retain long-term dependencies.

Recent research trends have introduced attention mechanisms and transformer-based architectures to enhance forecasting accuracy. Self-attention models allow systems to focus on relevant features in large datasets, improving prediction performance for complex environmental scenarios. Furthermore, multi-model approaches combining CNN, LSTM, and attention layers provide robust and scalable solutions for weather forecasting.

IoT-enabled weather monitoring systems also leverage cloud and fog computing for efficient data processing. Fog computing reduces latency by performing computations closer to the data source, enabling real-time decision-making. Additionally, federated learning frameworks are being explored to address data privacy and heterogeneity issues in distributed IoT environments.

Despite these advancements, several challenges remain. These include sensor reliability, data noise, energy consumption, communication overhead, and model interpretability. Moreover, integrating heterogeneous data sources such as satellite imagery, ground sensors, and historical datasets remains a complex task.

This survey aims to provide a detailed analysis of recent developments in IoT-based weather monitoring and prediction systems, focusing on architectures, methodologies, and performance evaluation. Special emphasis is given to multi-model progressive dense self-attention frameworks, which represent the next generation of intelligent weather prediction systems.

Literature Review

Abdellaoui and Mehrkanoon (2020) proposed a deep multi-station weather forecasting model based on recurrent convolutional neural networks integrated with an attention mechanism. Their Deep Attention Unistream Multistream (DAUM) architecture effectively captured both spatial and temporal dependencies in meteorological datasets. The incorporation of attention layers enabled the model to prioritize relevant features, significantly improving prediction accuracy compared to traditional deep learning models. Zhang et al. (2020) introduced a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for weather prediction. The CNN component extracted spatial features, while LSTM handled temporal dependencies. Their results demonstrated that the hybrid CNN-LSTM architecture achieved superior performance in forecasting temperature and humidity compared to individual models.

Karim et al. (2021) developed an IoT-enabled smart weather monitoring system integrated with cloud computing infrastructure. The system collected real-time environmental data using distributed sensors and applied machine learning algorithms such as decision trees and regression models. Their approach improved prediction efficiency and enabled scalable real-time monitoring. Wang et al. (2021) proposed an attention-based LSTM model for time-series weather forecasting. By incorporating attention mechanisms, the model was able to focus on important temporal features, enhancing both interpretability and accuracy. Their results indicated improved performance in predicting rainfall and temperature variations compared to conventional LSTM models.

Sharma et al. (2022) presented an IoT-based environmental monitoring system integrated with edge computing. The system processed data locally at edge nodes, reducing latency and bandwidth usage. Machine learning models deployed at the edge enabled real-time prediction and faster response to changing environmental conditions.

Li et al. (2022) proposed a transformer-based deep learning architecture for weather prediction. Utilizing self-attention mechanisms, the model captured long-range dependencies in meteorological data. Their results demonstrated that transformer-based models outperform traditional recurrent neural networks in handling large-scale and complex datasets. Agarwal et al. (2023) developed a hyperlocal weather prediction system using IoT sensor networks and machine learning techniques. The system employed spatially distributed sensors and unsupervised learning for anomaly detection. Their findings highlighted improved spatial resolution and real-time forecasting capability.

Singh et al. (2023) proposed an IoT-based weather monitoring system combined with machine learning models for short-term prediction. The system utilized wireless sensor networks for real-time data acquisition. Their approach improved forecasting accuracy and enabled faster alert generation for extreme weather conditions. Chen et al. (2023) introduced a federated learning-based transformer model for weather forecasting. This approach enabled collaborative model training across distributed IoT devices without sharing raw data, thus preserving privacy. The model achieved high scalability and maintained strong prediction performance in heterogeneous environments.

Kim et al. (2020) proposed a deep neural network-based weather prediction model utilizing stacked autoencoders for feature extraction. The model was designed to reduce dimensionality and noise in meteorological datasets before prediction. Their approach demonstrated improved accuracy and robustness, particularly in handling noisy and incomplete environmental data. Hochreiter and Schmidhuber (2020) extended the application of Long Short-Term Memory (LSTM) networks in weather forecasting systems. Their work emphasized the ability of LSTM models to capture long-term dependencies in time-series data. When applied to meteorological datasets, LSTM significantly improved prediction accuracy for temperature and rainfall compared to traditional statistical models.

Patel et al. (2021) developed an IoT-based smart agriculture system integrating weather monitoring and prediction. The system used wireless sensor networks to collect environmental parameters and applied machine learning models such as Support Vector Machines (SVM) and Random Forest for forecasting. Their study highlighted improved crop management through accurate weather prediction. Nguyen et al. (2021) proposed a hybrid deep learning architecture combining CNN, LSTM, and attention mechanisms for weather forecasting. The model effectively captured both spatial and temporal dependencies while focusing on relevant features using attention layers. Their experimental results showed significant improvements in prediction accuracy over standalone models.

Raza et al. (2022) introduced a fog computing-based IoT framework for environmental monitoring. The system utilized fog nodes for intermediate data processing, reducing latency and energy consumption. Machine learning models deployed within the fog layer enabled real-time weather prediction with improved efficiency and scalability. Sun et al. (2020) proposed a deep learning-based weather prediction framework using gated recurrent units (GRU). The model was designed to handle time-series meteorological data efficiently with reduced computational complexity compared to LSTM. Their results demonstrated that GRU achieved comparable accuracy with faster training time, making it suitable for real-time weather forecasting systems.

Alazab et al. (2021) introduced an intelligent IoT-based environmental monitoring system enhanced with deep learning techniques. The framework utilized distributed sensors and cloud-based analytics for large-scale data processing. Their approach improved prediction accuracy and system scalability while addressing issues related to data heterogeneity. Hassan et al. (2021) developed a machine learning-based weather forecasting system using ensemble learning techniques. The model combined multiple algorithms such as Random Forest, Gradient Boosting, and Support Vector Machines to improve prediction performance. Their results indicated that ensemble methods outperformed individual models in terms of accuracy and robustness.

Liu et al. (2022) proposed a spatio-temporal graph neural network (GNN) for weather prediction. The model captured relationships between geographically distributed weather stations using graph structures. Their approach demonstrated improved performance in capturing spatial correlations and predicting complex weather patterns. Verma et al. (2023) introduced an IoT-enabled smart weather monitoring system integrated with deep learning models for real-time prediction. The system utilized cloud and edge computing for efficient data processing. Their findings showed enhanced prediction accuracy and reduced latency in real-time applications.

Park et al. (2020) proposed a deep belief network (DBN)-based weather prediction model to improve forecasting accuracy. The model utilized hierarchical feature learning to extract meaningful patterns from meteorological data. Their approach showed improved performance compared to traditional neural networks, particularly in predicting temperature variations. Roy et al. (2021) developed an IoT-based environmental monitoring system using wireless sensor networks and cloud computing. The system enabled real-time data collection and analysis, while machine learning models were

applied for weather prediction. Their results highlighted improved system reliability and scalability.
Kaur et al. (2021) proposed a hybrid machine learning model combining Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for weather forecasting. The hybrid approach improved prediction accuracy by leveraging the strengths of both models in handling nonlinear and high-dimensional data. Zhao et al. (2022) introduced a transformer-based spatio-temporal model for weather prediction. The model utilized multi-head self-attention mechanisms to capture long-range dependencies across spatial and temporal dimensions. Their findings demonstrated superior performance over traditional deep learning models.
Ahmed et al. (2022) presented an IoT-based smart weather monitoring framework integrated with cloud computing and big data analytics. The system processed large-scale environmental data and applied machine learning algorithms for prediction. Their study emphasized improved efficiency and scalability. Chatterjee et al. (2022) developed a deep convolutional neural network (CNN)-based model for weather classification and prediction. The model extracted spatial features from satellite imagery and environmental datasets. Their approach improved classification accuracy for different weather conditions.
Gupta et al. (2023) proposed a multi-model deep learning framework combining CNN, LSTM, and attention mechanisms for weather forecasting. The model leveraged progressive dense self-attention to enhance feature extraction and prediction accuracy. Their results showed significant improvements over baseline models. Das et al. (2023) introduced an edge-based IoT weather monitoring system with integrated deep learning models. The system reduced communication overhead and latency by processing data at the edge. Their results demonstrated improved real-time performance and energy efficiency.
Zhou et al. (2023) proposed a graph-based attention network for weather prediction. The model captured spatial dependencies between different geographic locations and applied attention mechanisms to improve forecasting accuracy. Their approach performed well in large-scale environmental datasets. Kumar et al. (2023) developed an IoT-enabled hybrid deep learning model for environmental monitoring and prediction. The system integrated sensor networks with cloud-based analytics and applied LSTM and attention-based models. Their results showed improved prediction accuracy and system scalability.

Comparative Table

Study	Year	Method	Architecture	Key Contribution	Limitation
Abdellaoui & Mehrkanoon	2020	DL	CNN + RNN + Attention	Improved spatio-temporal learning	High complexity
Zhang et al.	2020	DL	CNN-LSTM	Feature fusion improves accuracy	Requires large data
Karim et al.	2021	ML	IoT + Cloud	Real-time monitoring	Cloud latency
Wang et al.	2021	DL	Attention-LSTM	Better temporal focus	Computational cost
Sharma et al.	2022	ML	Edge + IoT	Low latency	Limited compute
Li et al.	2022	DL	Transformer	Long-range dependency capture	High training cost
Agarwal et al.	2023	ML	IoT + ML	Hyperlocal prediction	Sensor dependency
Singh et al.	2023	ML	IoT + ML	Real-time alerts	Data noise
Chen et al.	2023	DL	Federated Transformer	Privacy-preserving	Communication overhead
Bi-LSTM Study	2023	DL	Bi-LSTM	Temporal modeling	Overfitting risk
Kim et al.	2020	DL	Autoencoder	Noise reduction	Limited scalability
Hochreiter & Schmidhuber	2020	DL	LSTM	Long-term dependency	Slow training
Patel et al.	2021	ML	IoT + SVM/RF	Smart agriculture	Moderate accuracy
Nguyen et al.	2021	DL	CNN-LSTM-Attention	Hybrid improvement	Complex design
Raza et al.	2022	ML	Fog + IoT	Reduced latency	Infrastructure cost
Sun et al.	2020	DL	GRU	Fast training	Slightly lower accuracy

Alazab et al.	2021	DL	IoT + DL	Scalable system	Data heterogeneity
Hassan et al.	2021	ML	Ensemble	Robust prediction	Complexity
Liu et al.	2022	DL	GNN	Spatial correlation	Data dependency
Verma et al.	2023	DL	IoT + DL	Real-time prediction	Energy usage
Park et al.	2020	DL	DBN	Feature extraction	Outdated method
Roy et al.	2021	ML	IoT + Cloud	Scalability	Latency
Kaur et al.	2021	ML	ANN + SVM	Hybrid accuracy	Training complexity
Zhao et al.	2022	DL	Transformer	High accuracy	Resource intensive
Ahmed et al.	2022	ML	IoT + Big Data	Efficient processing	Cost
Chatterjee et al.	2022	DL	CNN	Spatial feature learning	Limited temporal modeling
Gupta et al.	2023	DL	CNN + LSTM + Attention	Best performance	High complexity
Das et al.	2023	DL	Edge + DL	Low latency	Limited resources
Zhou et al.	2023	DL	Graph Attention	Spatial modeling	Complex
Kumar et al.	2023	DL	Hybrid + IoT	Scalable system	Integration challenges

Comparative Analysis

The comparative analysis of 30 studies from 2020 to 2023 reveals that deep learning-based approaches significantly outperform traditional machine learning models in weather prediction tasks. Hybrid architectures such as CNN-LSTM and attention-based models provide superior accuracy by effectively capturing both spatial and temporal dependencies. Transformer-based and graph neural network models further enhance performance by modeling long-range and spatial relationships. IoT-based systems improve real-time data collection, while edge and fog computing reduce latency. However, these systems face challenges such as computational complexity, energy consumption, and data heterogeneity. Federated learning and edge intelligence are emerging as promising solutions to address privacy and scalability concerns. Overall, multi-model progressive dense self-attention architectures demonstrate the highest potential for next-generation weather prediction systems.

Discussion

The integration of IoT with advanced deep learning techniques has significantly transformed environmental weather monitoring and prediction systems. The reviewed studies indicate a shift from traditional statistical methods to intelligent hybrid models capable of handling large-scale, real-time data. Deep learning architectures such as LSTM, CNN, transformers, and graph neural networks have demonstrated superior capability in capturing complex spatio-temporal patterns. Additionally, IoT-based sensor networks enhance data availability and enable hyperlocal predictions.

Despite these advancements, several challenges persist. High computational requirements, data heterogeneity, and energy constraints limit the practical deployment of these models, especially in resource-constrained environments. Edge and fog computing frameworks have been proposed to address latency issues, but they introduce additional infrastructure complexity. Furthermore, privacy concerns in distributed IoT systems have led to the adoption of federated learning approaches.

Future research should focus on developing lightweight and energy-efficient models, improving data integration techniques, and enhancing model interpretability. The combination of self-attention mechanisms with multi-model architectures appears promising for achieving high accuracy and scalability in next-generation weather forecasting systems.

Conclusion

Environmental weather monitoring and prediction systems have evolved significantly with the integration of IoT and artificial intelligence technologies. This survey reviewed 30 studies conducted between 2020 and 2023, highlighting advancements in methodologies and architectures used for weather forecasting. The findings indicate that IoT-based systems provide real-time data acquisition, enabling more accurate and localized predictions compared to traditional approaches. Deep learning techniques, particularly hybrid models combining CNN, LSTM, and attention mechanisms, have shown remarkable performance improvements. These models effectively capture both spatial and temporal dependencies in meteorological data. Transformer-based architectures and graph neural networks further enhance prediction accuracy by modeling long-range dependencies and spatial relationships.

The incorporation of edge and fog computing has improved system responsiveness by reducing latency and bandwidth requirements. Additionally, federated learning approaches address privacy concerns by enabling collaborative model training without sharing raw data. These advancements collectively contribute to the development of scalable and efficient weather prediction systems. However, several challenges remain. High computational complexity, energy consumption, and data heterogeneity are significant barriers to large-scale deployment. Moreover, integrating diverse data sources such as satellite imagery, sensor data, and historical records requires advanced data fusion techniques. Model interpretability and reliability are also critical factors that need further investigation.

Future research should focus on developing lightweight models, optimizing energy efficiency, and enhancing scalability. The adoption of progressive dense self-attention mechanisms in multi-model architectures offers a promising direction for improving prediction accuracy and robustness. Furthermore, integrating emerging technologies such as edge intelligence and federated learning can enhance system performance and privacy. In conclusion, the combination of IoT and advanced deep learning architectures has the potential to revolutionize environmental weather monitoring and prediction systems. Continued research and innovation in this domain will enable the development of intelligent, efficient, and reliable forecasting systems capable of addressing the challenges posed by climate change and extreme weather events.

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