Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 12 Issue 01, 2023

A Comprehensive Review of Environmental Weather Monitoring and Prediction System Using IoT and Multi-Model Progressive Dense Self-Attention

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Peer Review Information

Submission: 08 March 2023

Revision: 24 March 2023

Acceptance: 15 April 2023

Keywords

IoT, Weather Monitoring, Weather Prediction, Deep Learning, Self-Attention, Transformer, Environmental Monitoring, Smart Systems, Spatiotemporal Modeling, Climate Prediction

Abstract

Environmental weather monitoring and prediction systems are increasingly vital for applications such as agriculture, disaster management, smart cities, and climate analysis. Traditional approaches based on numerical and statistical models often struggle to capture complex spatiotemporal dependencies in environmental data. The integration of Internet of Things (IoT) and Artificial Intelligence (AI) has enabled real-time data collection and improved forecasting accuracy. This paper reviews IoT-based weather monitoring systems using advanced deep learning and self-attention mechanisms, focusing on the Multi-Model Progressive Dense Self-Attention Network. IoT sensors collect large-scale environmental data such as temperature, humidity, pressure, rainfall, and wind speed, requiring models capable of handling both spatial and temporal relationships. Deep learning techniques like CNNs, LSTMs, and hybrid models enhance prediction accuracy, while transformer-based architectures effectively capture long-range dependencies. Multimodal approaches integrating sensor, satellite, and meteorological data further improve performance. Despite these advancements, challenges such as computational complexity, data heterogeneity, scalability, and real-time implementation remain. This review highlights recent developments and identifies future research directions for efficient and intelligent weather prediction systems.

Introduction

Accurate environmental weather monitoring and prediction play a crucial role in various sectors, including agriculture, disaster management, aviation, and urban planning. Weather conditions such as temperature, humidity, rainfall, and wind patterns directly impact crop productivity, infrastructure safety, and human life. Traditional weather prediction systems rely heavily on numerical weather prediction (NWP) models, which are based on physical equations and require extensive computational resources. Although these models provide reliable forecasts, they often struggle with capturing fine-grained spatial and temporal variations.

The emergence of the Internet of Things (IoT) has transformed environmental monitoring by enabling real-time data collection through distributed sensor networks. IoT devices such as weather stations, environmental sensors, and remote monitoring systems continuously collect data on temperature, humidity, atmospheric pressure, and other environmental parameters. These systems provide high-resolution data, enabling more accurate and localized weather predictions.

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However, the massive volume of data generated by IoT systems requires advanced analytical techniques for processing and interpretation. Deep learning models have emerged as powerful tools for handling such complex datasets. Convolutional Neural Networks (CNNs) are widely used for spatial feature extraction, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are effective for temporal sequence modeling.

Despite their success, traditional deep learning models have limitations in capturing long-range dependencies in time-series data. This has led to the adoption of self-attention mechanisms and transformer-based architectures, which have revolutionized sequence modeling. The transformer architecture, based entirely on attention mechanisms, enables parallel processing and improved performance in capturing global dependencies.

Recent advancements in weather prediction models include the use of self-attention-based deep learning frameworks, which significantly improve prediction accuracy. For example, neural weather models such as MetNet utilize attention mechanisms to capture large-scale spatial dependencies and outperform traditional numerical methods in short-term forecasting. Similarly, hierarchical stacked self-attention architectures enhance multi-scale feature extraction and improve spatiotemporal forecasting performance.

Moreover, multimodal deep learning approaches combine IoT sensor data with satellite imagery and meteorological datasets, enabling comprehensive environmental analysis. These models improve prediction accuracy and reduce latency, making them suitable for real-time applications.

The proposed concept of a Multi-Model Progressive Dense Self-Attention Network integrates multiple deep learning models with dense connections and attention mechanisms. This architecture enhances feature fusion, captures complex spatiotemporal patterns, and improves prediction accuracy.

Despite these advancements, several challenges remain, including computational complexity, data heterogeneity, scalability, and energy constraints in IoT systems. Addressing these challenges is essential for developing efficient and scalable weather monitoring systems.

This paper provides a comprehensive review of recent methods and architectures for IoT-based environmental weather monitoring and prediction systems. It aims to analyze existing approaches, compare their performance, and identify future research directions.

Literature Review

Sønderby et al. (2020) introduced the MetNet model for precipitation forecasting using deep neural networks. The model incorporates self-attention mechanisms to capture large-scale spatial dependencies. It significantly outperforms traditional numerical weather prediction methods. However, it requires high computational resources .

Abdellaoui and Mehrkanoon (2020) proposed attention-based recurrent convolutional neural networks for multi-station weather forecasting. The model integrates attention mechanisms to improve feature representation. It enhances prediction accuracy across multiple locations. However, training complexity remains high .

Agarwal et al. (2023) developed an IoT-based hyperlocal weather prediction system. The model uses distributed sensor data for real-time forecasting. It improves spatial resolution and anomaly detection. However, scalability in large deployments remains a challenge.

Samo et al. (2023) applied attention-based deep learning for weather condition classification. The study shows that vision transformers outperform CNN models in weather prediction tasks. It improves accuracy in handling imbalanced datasets. However, data requirements are high.

Kumar et al. (2020) proposed an IoT-based environmental monitoring system using sensor networks. The system collects real-time weather data such as temperature and humidity. It improves environmental awareness and monitoring efficiency. However, data transmission reliability is a challenge.

Zhang et al. (2020) developed CNN-based weather prediction models for short-term forecasting. The model extracts spatial features from meteorological data. It improves prediction accuracy compared to statistical methods. However, it lacks long-term dependency modeling.

Liu et al. (2020) introduced LSTM-based models for time-series weather forecasting. The model captures temporal dependencies effectively. It improves accuracy in sequential data prediction. However, training time is high.

Wang et al. (2021) proposed hybrid CNN-LSTM models for weather prediction. The model integrates spatial and temporal learning. It enhances forecasting accuracy in complex environments. However, model complexity increases.

Sharma and Singh (2021) developed IoT-based smart weather monitoring systems. The system enables real-time environmental data collection. It improves decision-making in agriculture and

disaster management. However, system scalability remains an issue.
Patel et al. (2021) proposed machine learning models for weather prediction. The system improves prediction accuracy using regression techniques. It supports efficient climate analysis. However, it cannot handle complex patterns effectively.
Ahmed et al. (2021) introduced deep learning models for weather forecasting. The model improves prediction accuracy using neural networks. It handles large datasets effectively. However, computational cost is high.
Gupta et al. (2021) developed cloud-integrated IoT systems for environmental monitoring. The system enables centralized data processing. It improves system efficiency and scalability. However, latency is introduced due to cloud dependency.
Li et al. (2022) proposed transformer-based models for weather prediction. The model captures long-range dependencies in time-series data. It improves forecasting accuracy significantly. However, it requires large datasets.
Chen et al. (2022) introduced attention-based deep learning models for weather forecasting. The system improves feature selection and prediction accuracy. It enhances model interpretability. However, training complexity increases.
Zhao et al. (2022) proposed graph neural networks for weather prediction. The model captures spatial relationships among weather stations. It improves prediction performance. However, scalability remains an issue.
Huang et al. (2022) developed hybrid deep learning models combining CNN and transformer. The system improves feature extraction and prediction accuracy. It enhances multi-scale learning. However, computational cost is high.
Yang et al. (2022) introduced multi-model ensemble learning for weather prediction. The system combines multiple models to improve accuracy. It reduces prediction error. However, model complexity increases.
Sun et al. (2022) proposed IoT-based weather monitoring with edge computing. The system reduces latency and improves real-time performance. It enhances system efficiency. However, edge devices have limited resources.
Murugan et al. (2023) introduced deep learning-based environmental monitoring systems. The system improves prediction accuracy using neural networks. It enhances system reliability. However, it requires large datasets.
Das et al. (2023) reviewed deep learning approaches for weather forecasting. The study highlights CNN, LSTM, and transformer models. It identifies research gaps in scalability and deployment. However, it lacks experimental validation.
Li et al. (2023) proposed graph attention networks for weather prediction. The model captures complex spatial relationships. It improves prediction accuracy. However, training complexity is high.
Zhao et al. (2023) developed attention-based transformer models for forecasting. The system improves long-term dependency modeling. It enhances prediction performance. However, data requirements are high.
Chen et al. (2023) introduced attention-CNN hybrid models for environmental monitoring. The model improves feature extraction. It enhances system accuracy. However, model complexity increases.
Ahmed et al. (2023) proposed optimization-based weather prediction systems. The system improves efficiency using optimization techniques. It enhances prediction performance. However, parameter tuning is complex.
Wang and Liu (2023) developed cross-layer deep learning models for environmental prediction. The system integrates multiple data sources. It improves prediction stability. However, system design is complex.
Gupta et al. (2023) introduced hybrid AI-based environmental monitoring systems. The model combines ML and optimization. It improves system efficiency. However, implementation complexity remains high.
Singh et al. (2023) proposed attention-based deep learning models for weather forecasting. The system improves feature selection. It enhances prediction accuracy. However, computational cost is high.
Sharma et al. (2023) developed IoT-based hybrid AI systems for environmental monitoring. The system improves scalability and performance. It enhances real-time monitoring. However, system complexity is high.
Gao et al. (2023) introduced transformer-based intelligent weather systems. The model adapts to dynamic environmental conditions. It improves forecasting accuracy. However, resource requirements are high.

Comparative Table

No.	Author(s) & Year	Technique / Model	Application	Key Contribution	Limitation
1	Sønderby et al. (2020)	Deep Neural Network (MetNet)	Weather forecasting	High accuracy precipitation prediction	High computation
2	Abdellaoui & Mehrkanoon (2020)	Attention CNN-RNN	Multi-station forecasting	Improved spatial-temporal learning	Complexity
3	Kumar et al. (2020)	IoT + Sensors	Monitoring	Real-time data collection	Reliability issues
4	Zhang et al. (2020)	CNN	Weather prediction	Spatial feature extraction	No long-term modeling
5	Liu et al. (2020)	LSTM	Forecasting	Temporal dependency modeling	Training time
6	Wang et al. (2021)	CNN-LSTM	Prediction	Hybrid learning	Complexity
7	Sharma & Singh (2021)	IoT System	Monitoring	Real-time system	Scalability
8	Patel et al. (2021)	ML Model	Prediction	Efficient forecasting	Limited accuracy
9	Ahmed et al. (2021)	Deep Learning	Forecasting	High accuracy	Computational cost
10	Gupta et al. (2021)	IoT + Cloud	Monitoring	Centralized processing	Latency
11	Li et al. (2022)	Transformer	Forecasting	Long dependency modeling	Data requirement
12	Chen et al. (2022)	Attention DL	Prediction	Improved feature selection	Complexity
13	Zhao et al. (2022)	GNN	Forecasting	Spatial relationship modeling	Scalability
14	Huang et al. (2022)	CNN + Transformer	Prediction	Hybrid model	High computation
15	Yang et al. (2022)	Ensemble Learning	Forecasting	Reduced error	Complexity
16	Sun et al. (2022)	IoT + Edge	Monitoring	Low latency	Limited resources
17	Murugan et al. (2023)	Deep Learning	Monitoring	Improved accuracy	Data dependency
18	Das et al. (2023)	DL Review	Forecasting	Identified gaps	No implementation
19	Li et al. (2023)	Graph Attention Network	Prediction	Improved accuracy	Complexity
20	Zhao et al. (2023)	Transformer + Attention	Forecasting	Long-term prediction	Data requirement
21	Chen et al. (2023)	Attention CNN	Monitoring	Better feature extraction	Complexity
22	Ahmed et al. (2023)	Optimization DL	Forecasting	Improved efficiency	Tuning required
23	Wang & Liu (2023)	Cross-layer DL	Prediction	Stability	Complex design
24	Gupta et al. (2023)	Hybrid AI	Monitoring	Efficiency	Complexity
25	Singh et al. (2023)	Attention DL	Prediction	Accuracy improvement	High computation

26	Sharma et al. (2023)	Hybrid IoT-AI	Monitoring	Scalability	Complexity
27	Gao et al. (2023)	Transformer	Forecasting	Adaptive prediction	Resource heavy
28	Agarwal et al. (2023)	IoT + ML	Prediction	Hyperlocal forecasting	Scalability
29	Samo et al. (2023)	Vision Transformer	Classification	Improved accuracy	Data dependency

Comparative Analysis

The comparative analysis of the selected studies demonstrates a significant evolution in environmental weather monitoring and prediction systems, transitioning from traditional machine learning approaches to advanced deep learning and hybrid AI-based architectures. Early approaches primarily relied on IoT-based sensor networks and basic machine learning models, which enabled real-time data collection but lacked the capability to model complex spatiotemporal relationships.

The introduction of deep learning models such as CNNs and LSTMs marked a major advancement, enabling efficient spatial and temporal feature extraction. CNN models improved the processing of spatial weather patterns, while LSTM networks enhanced time-series forecasting by capturing temporal dependencies. However, these models were limited in handling long-range dependencies and global context.

Hybrid models such as CNN-LSTM emerged to address these limitations by combining spatial and temporal learning. These models significantly improved forecasting accuracy but introduced higher computational complexity and training overhead. As a result, scalability and real-time deployment became challenging.

Recent research has shifted towards attention-based and transformer architectures, which provide superior performance by modeling global dependencies using self-attention mechanisms. Transformer-based models and attention-enhanced CNNs have demonstrated improved accuracy in weather prediction tasks, particularly for long-term forecasting. However, these models require large datasets and high computational resources, limiting their practical implementation in resource-constrained IoT environments.

Additionally, graph-based models such as Graph Neural Networks (GNNs) have been introduced to capture spatial relationships among weather stations, further improving prediction performance. Optimization techniques and hybrid AI models have also been employed to enhance system efficiency and decision-making.

Overall, hybrid architectures integrating deep learning, attention mechanisms, and optimization techniques provide the best performance, offering a balance between accuracy, adaptability, and efficiency. However, challenges such as computational complexity, scalability, and energy consumption remain critical concerns.

Conclusion

Environmental weather monitoring and prediction systems have become increasingly important in addressing global challenges such as climate change, disaster management, and agricultural sustainability. This study presented a comprehensive review of IoT-based environmental monitoring systems integrated with deep learning and advanced attention-based architectures.

Traditional weather prediction systems rely on numerical models and statistical methods, which are often computationally intensive and limited in capturing complex environmental patterns. The integration of IoT technology has enabled real-time data collection through distributed sensor networks, significantly improving monitoring capabilities. However, the large volume of data generated by IoT devices requires advanced analytical methods for effective processing.

Deep learning models, particularly CNNs and LSTMs, have demonstrated strong performance in weather prediction tasks by extracting spatial and temporal features from environmental data. Hybrid models combining CNN and LSTM further enhance prediction accuracy by integrating both types of learning. However, these models face limitations in capturing long-range dependencies.

The introduction of attention mechanisms and transformer-based architectures has addressed these limitations by enabling efficient modeling of global dependencies. These models significantly improve prediction accuracy and adaptability, making them suitable for complex environmental forecasting tasks.

The proposed Multi-Model Progressive Dense Self-Attention Network represents a promising approach that combines multiple deep learning models with dense connections and attention mechanisms. This architecture enhances feature extraction, improves prediction accuracy, and enables efficient handling of large-scale environmental data.

Despite these advancements, several challenges remain. High computational complexity, data heterogeneity, and scalability issues limit the deployment of these models in real-world environments. Additionally, energy constraints in IoT systems necessitate the development of lightweight and efficient models.

Future research should focus on developing scalable, energy-efficient, and real-time AI-based weather monitoring systems. The integration of edge computing and federated learning can further enhance system performance by reducing latency and improving data privacy. Furthermore, the development of lightweight transformer models and efficient attention mechanisms will be crucial for enabling real-time deployment in resource-constrained environments.

In conclusion, the integration of IoT, deep learning, and attention-based architectures provides a powerful framework for next-generation environmental monitoring systems. Continued research in this domain will play a vital role in improving weather prediction accuracy and supporting sustainable development.

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