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Recent Advances in Environmental Weather Monitoring and Prediction System Using IoT and Multi-Model Progressive Dense Self-Attention: A Systematic Review

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Abstract

Environmental weather monitoring and prediction systems are essential for applications such as agriculture, disaster management, and smart cities. Traditional numerical weather prediction models, while reliable, often struggle to capture fine-grained spatial and temporal dependencies and require high computational resources. The integration of Internet of Things (IoT) and Artificial Intelligence (AI) has enabled real-time data collection and advanced predictive analytics. This review focuses on IoT-based weather monitoring systems combined with deep learning and self-attention architectures, particularly the Multi-Model Progressive Dense Self-Attention Network. IoT sensors continuously gather environmental data such as temperature, humidity, rainfall, and wind speed, generating large-scale time-series datasets. While models like CNNs and LSTMs are widely used, they have limitations in capturing long-range dependencies. Transformer-based models and attention mechanisms address these issues by effectively modelling global spatial and temporal patterns. Hybrid architectures integrating CNNs, transformers, and graph-based methods have shown improved accuracy and robustness. Despite these advancements, challenges such as computational complexity, data heterogeneity, and scalability persist, highlighting the need for efficient and scalable prediction systems.

Introduction

Accurate weather monitoring and prediction play a vital role in multiple sectors, including agriculture, disaster management, transportation, and energy systems. Weather conditions directly influence crop productivity, infrastructure stability, and human safety. Traditional weather prediction methods rely heavily on Numerical Weather Prediction (NWP) models, which are based on physical equations describing atmospheric behaviour. Although these models are highly accurate at large scales, they require extensive computational resources and often fail to capture localized weather variations effectively. The emergence of the Internet of Things (IoT) has significantly improved environmental monitoring by enabling real-time data collection through distributed sensor networks. IoT devices such as weather stations and environmental sensors continuously measure parameters like temperature, humidity, wind speed, and atmospheric pressure. These systems provide high-resolution data that can be used to improve forecasting accuracy.

However, the massive volume of IoT-generated data presents challenges in processing and analysis. Traditional statistical models are insufficient for capturing the complex nonlinear relationships present in weather data. As a result, deep learning techniques have been increasingly adopted for weather prediction tasks. Convolutional Neural Networks (CNNs) are effective for extracting spatial features from environmental data, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are widely used for time-series forecasting. However, these models struggle with long-range dependencies and sequential processing limitations To overcome these issues, self-attention and transformer-based architectures have been introduced. Transformer models enable parallel processing and capture global dependencies efficiently. For example, MetNet utilizes self-attention to process large-scale spatial data and achieves superior performance compared to traditional forecasting models. Similarly, modern transformer-based models outperform recurrent networks in long-term forecasting tasks by capturing complex temporal patterns.

Recent advancements include hybrid architectures combining CNNs, transformers, and graph neural networks. These models integrate spatial, temporal, and relational features, improving prediction accuracy and robustness. Additionally, optimization techniques and ensemble learning methods have been used to enhance performance and reduce prediction errors. The proposed Multi-Model Progressive Dense Self-Attention Network builds upon these advancements by integrating multiple deep learning models with dense connections and attention mechanisms. This architecture enhances feature fusion and improves prediction accuracy. Despite these improvements, challenges such as computational complexity, scalability, and energy consumption remain. Addressing these challenges is essential for deploying real-time weather monitoring systems in IoT environments.

Literature Review

Sønderby et al. (2020) introduced MetNet, a deep neural network for precipitation forecasting. The model uses self-attention to capture global spatial dependencies. It significantly outperforms numerical weather prediction models. However, it requires high computational resources. Espeholt et al. (2022) developed MetNet-2, an improved deep learning weather model. The system provides high-resolution forecasts with superior accuracy. It outperforms ensemble-based NWP models. However, it requires large-scale training infrastructure. Abdellaoui and Mehrkanoon (2020) proposed attention-based CNN-RNN models for multi-station forecasting. The model improves spatial-temporal feature extraction. It enhances prediction accuracy across regions. However, training complexity remains high. Bilgin et al. (2021) introduced a transformer-based model (TENT) for temperature forecasting. The model captures spatiotemporal dependencies effectively. It outperforms CNN and LSTM models. However, it requires large datasets for training.

Zhang et al. (2025) reviewed machine learning methods for weather forecasting. The study highlights deep learning and transformer models as dominant approaches. It identifies challenges such as interpretability and scalability. However, practical deployment remains limited. Kumar et al. (2020) proposed an IoT-based environmental monitoring system using distributed sensors. The system collects temperature, humidity, and pressure data in real time. It improves monitoring accuracy and responsiveness. However, network reliability and data loss remain challenges.

Zhang et al. (2020) developed CNN-based models for short-term weather forecasting. The model extracts spatial features from meteorological data. It improves prediction accuracy compared to statistical methods. However, it lacks long-term temporal modelling. Liu et al. (2020) introduced LSTM-based models for time-series forecasting. The model captures temporal dependencies effectively. It improves sequential prediction accuracy. However, training time and resource consumption are high.

Wang et al. (2021) proposed hybrid CNN-LSTM models for weather prediction. The system integrates spatial and temporal feature extraction. It enhances forecasting performance in complex environments. However, model complexity increases significantly. Sharma and Singh (2021) developed IoT-based smart weather monitoring systems. The system enables real-time environmental data collection. It supports decision-making in agriculture and disaster management. However, scalability issues remain.

Patel et al. (2021) applied machine learning models for weather prediction. The system improves forecasting accuracy using regression techniques. It enhances climate analysis efficiency. However, it struggles with nonlinear patterns. Ahmed et al. (2021) introduced deep learning-based weather forecasting models. The system improves prediction accuracy using neural networks. It handles large-scale datasets effectively. However, computational cost is high.

Gupta et al. (2021) proposed cloud-integrated IoT systems for environmental monitoring. The system enables centralized processing and storage. It improves system scalability. However, latency is introduced due to cloud dependency. Li et al. (2022) introduced transformer-based models for weather forecasting. The model captures long-range dependencies efficiently. It improves prediction accuracy significantly. However, it requires large datasets.

Chen et al. (2022) proposed attention-based deep learning models for forecasting. The system improves feature selection and interpretability. It enhances prediction performance. However, training complexity increases. Zhao et al. (2022) introduced graph neural networks for weather prediction. The model captures spatial relationships among weather stations. It improves prediction accuracy. However, scalability is a limitation.

Huang et al. (2022) developed hybrid CNN-transformer models. The system improves multi-scale feature extraction. It enhances forecasting accuracy. However, computational overhead is high. Yang et al. (2022) proposed ensemble learning models for weather prediction. The system combines multiple models to reduce error. It improves prediction reliability. However, model complexity increases.

Sun et al. (2022) introduced IoT-based monitoring systems with edge computing. The system reduces latency and improves real-time performance. It enhances system efficiency. However, edge devices have limited capacity. Murugan et al. (2023) developed deep learning-based 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 techniques for weather forecasting. The study highlights CNN, LSTM, and transformer models. It identifies research gaps in scalability. However, it lacks experimental validation.Li et al. (2023) proposed graph attention networks for weather prediction. The model captures complex spatial relationships. It improves forecasting accuracy. However,

Zhao et al. (2023) developed transformer-based attention models. The system improves long-term forecasting. It enhances prediction accuracy. However, it requires large training datasets.Chen et al. extraction and classification accuracy. It enhances system performance. However, model complexity increases.

Ahmed et al. (2023) introduced optimization-based forecasting models. The system improves prediction efficiency using optimization techniques. It enhances system performance. However, parameter tuning is complex. Wang and Liu (2023) developed cross-layer deep learning models. The system integrates multiple data sources. It improves prediction stability. However, system design is complex.

Gupta et al. (2023) proposed hybrid AI-based monitoring systems. The system combines machine learning and optimization. It improves efficiency and accuracy. However, implementation complexity remains high. Singh et al. (2023) introduced attention-based deep learning models. The system improves feature selection and prediction accuracy. It enhances forecasting performance. However, computational cost is high.

Sharma et al. (2023) developed IoT-based hybrid AI systems. The system improves scalability and real-time monitoring. It enhances system performance. However, system complexity is high. Gao et al. (2023) proposed transformer-based intelligent weather systems. The model adapts to dynamic environmental conditions. It improves prediction accuracy. However, resource requirements are high.

Comparative Table

No.	Author(s) & Year	Technique / Model	Application	Key Contribution	Limitation
1	Sønderby et al. (2020)	MetNet (DL + Attention)	Precipitation forecasting	High accuracy	High computation
2	Abdellaoui & Mehrkanoon (2020)	Attention CNN-RNN	Multi-station forecasting	Spatiotemporal learning	Complexity
3	Kumar et al. (2020)	IoT Sensors	Monitoring	Real-time data collection	Reliability issues
4	Zhang et al. (2020)	CNN	Forecasting	Spatial feature extraction	No long-term learning
5	Liu et al. (2020)	LSTM	Forecasting	Temporal modeling	Training time
6	Wang et al. (2021)	CNN-LSTM	Prediction	Hybrid learning	Complexity

7	Sharma & Singh (2021)	IoT System	Monitoring	Real-time monitoring	Scalability
8	Patel et al. (2021)	ML Model	Forecasting	Efficient prediction	Limited accuracy
9	Ahmed et al. (2021)	Deep Learning	Prediction	High accuracy	Computational cost
10	Gupta et al. (2021)	IoT + Cloud	Monitoring	Centralized processing	Latency
11	Li et al. (2022)	Transformer	Forecasting	Long dependency modelling	Data requirement
12	Chen et al. (2022)	Attention DL	Prediction	Improved feature selection	Complexity
13	Zhao et al. (2022)	GNN	Forecasting	Spatial modelling	Scalability
14	Huang et al. (2022)	CNN + Transformer	Prediction	Hybrid modelling	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)	GAT	Forecasting	Better accuracy	Complexity
20	Zhao et al. (2023)	Transformer + Attention	Prediction	Long-term modelling	Data requirement
21	Chen et al. (2023)	Attention-CNN	Monitoring	Feature enhancement	Complexity
22	Ahmed et al. (2023)	Optimization DL	Forecasting	Efficiency improvement	Tuning needed
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	Forecasting	Accuracy improvement	High computation
26	Sharma et al. (2023)	IoT + AI	Monitoring	Scalability	Complexity
27	Gao et al. (2023)	Transformer	Prediction	Adaptive forecasting	Resource heavy
28	Agarwal et al. (2023)	IoT + ML	Forecasting	Hyperlocal prediction	Scalability
29	Samo et al. (2023)	Vision Transformer	Classification	Improved accuracy	Data dependency
30	Parada & Sanz (2025)	LSTM-based DL	Forecasting	Short-term accuracy	Long-term limitation

Comparative Analysis

The comparative analysis highlights a clear evolution in environmental weather monitoring and prediction systems, transitioning from traditional machine learning approaches to advanced deep learning and transformer-based architectures. Early approaches primarily relied on IoT-based sensor systems and basic ML models, which provided real-time data but lacked the ability to capture complex spatial-temporal dependencies. Deep learning models such as CNNs and LSTMs significantly improved prediction capabilities by enabling spatial and temporal feature extraction. However, these models struggled with long-range dependencies and required sequential processing, limiting their scalability.

Hybrid models such as CNN-LSTM addressed these limitations by integrating spatial and temporal learning. These models improved accuracy but introduced higher computational complexity. Recent advancements focus on transformer-based and attention-driven models, which provide superior performance by capturing global dependencies efficiently. Graph-based models further enhance prediction by modelling spatial relationships among sensors. Additionally, optimization techniques improve efficiency and decision-making processes. Overall, hybrid architectures combining IoT, deep learning, attention mechanisms, and optimization techniques deliver the best performance. However, challenges such as computational complexity, scalability, and energy consumption remain.

Discussion

The reviewed studies demonstrate that IoT-based weather monitoring systems have significantly improved environmental data collection and forecasting accuracy. The integration of deep learning techniques, particularly CNNs and LSTMs, has enhanced the ability to analyse complex environmental patterns. However, these models are limited in capturing long-range dependencies and handling large-scale datasets efficiently. The emergence of attention mechanisms and transformer architectures represents a major advancement in weather prediction systems. These models enable efficient modelling of global dependencies and improve prediction accuracy. Hybrid architectures combining CNNs, transformers, and graph-based models further enhance performance by integrating multiple learning paradigms.

Despite these advancements, several challenges persist. High computational requirements, data heterogeneity, and scalability issues limit real-world deployment. Additionally, IoT systems face energy constraints, which require the development of lightweight and efficient models. Future research should focus on optimizing model architectures for real-time deployment, improving data integration techniques, and reducing computational overhead. The integration of edge computing and federated learning can further enhance system performance while ensuring data privacy and efficiency.

Conclusion

Environmental weather monitoring and prediction systems play a critical role in addressing global challenges such as climate change, disaster management, and agricultural sustainability. This systematic review examined recent advancements in IoT-based environmental monitoring systems integrated with deep learning and attention-based architectures. Traditional weather prediction methods rely on numerical models and statistical techniques, which are often computationally intensive and limited in capturing localized weather variations. The integration of IoT technology has enabled real-time data collection through distributed sensor networks, significantly improving monitoring capabilities.

Deep learning models, particularly CNNs and LSTMs, have enhanced weather prediction by extracting spatial and temporal features from environmental data. Hybrid models combining CNN and LSTM further improve performance by integrating both types of learning. However, these models face limitations in capturing long-range dependencies and require significant computational resources. The introduction of attention mechanisms and transformer-based architectures has addressed these limitations by enabling efficient modelling 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 integrates multiple deep learning models with dense connections and attention mechanisms. This architecture enhances feature extraction and improves prediction accuracy while handling large-scale environmental data. Despite these advancements, challenges such as computational complexity, scalability, and energy consumption remain. Future research should focus on developing lightweight, scalable, and energy-efficient models for real-time deployment in IoT environments. The integration of edge computing and federated learning can further enhance system performance and reduce latency.

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

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