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# Machine Learning and Deep Learning Approaches for Weather Forecasting in IoT-Based Systems: A Review

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## ABSTRACT

Weather forecasting is important across many fields, including agriculture, transportation, energy, and disaster management. Because meteorological data is not linear or dynamic and changes over time, it is hard to predict the weather. Technological advances have made machine learning and deep learning methods more common for improving the accuracy of weather forecasts. Additionally, connectivity with the Internet of Things (IoT) enables real-time data collection through various environmental sensors. This study conducted a comprehensive literature review of machine learning, deep learning, and hybrid methodologies for IoT-based weather prediction systems. The methodologies analyzed included Random Forest, Support Vector Machine, Artificial Neural Network, Long Short-Term Memory, Gated Recurrent Unit, Convolutional Neural Network, and Transformer. The results showed that deep learning and hybrid models performed better than traditional methods, especially for finding temporal patterns and non-linear correlations. Still, other issues need to be addressed, such as data quality, model complexity, high processing requirements, and limitations on how quickly it can adapt. As a result, combining AI and IoT has significant potential to make weather forecasting systems more accurate, flexible, and timely, especially for early warning systems based on data.

*Keywords:*

Artificial Intelligence, Deep Learning, Internet of Things, Machine Learning, Weather Forecasting

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# 1. INTRODUCTION

As climate change becomes more complicated and affects industries like agriculture, transportation, energy, and disaster relief, better weather prediction technology becomes more and more important. Accurate weather forecasts make daily tasks easier and are an important part of early warning systems that help people stay safe from natural disasters like floods, droughts, and severe storms. Weather forecasting is difficult because meteorological data is nonlinear and dynamic, and it depends heavily on time [1],[3].

Numerical Weather Prediction (NWP) and statistical models like ARIMA are two examples of traditional methods that have been used for a long time to predict the weather. These methods do a good job of showing linear and seasonal trends, but they don't capture complex nonlinear relationships [4],[6]. The rise of machine learning methods to improve predictive accuracy is driven by advances in computer technology and the growing volume of data. Different methods, such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN), have been shown to be very effective in many studies that have predicted weather variables [7],[9].

Additionally, deep learning techniques have made a lot of progress in the last few years. Models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer can proficiently identify long-term temporal patterns and complex interactions among meteorological variables [10],[12]. Many studies show that LSTM models are better at predicting than traditional methods, especially for meteorological time-series data [13],[15]. Additionally, GRU models have demonstrated superior efficiency and competitive performance in certain cases [16],[18].

To overcome the limitations of singular methodologies, various studies have developed hybrid approaches that combine statistical and deep learning techniques. Combinations like ARIMA-LSTM can use the best parts of both methods to find linear and nonlinear patterns at the same time, which makes predictions more accurate and reliable [1], [6],[19]. This hybrid approach is a good way to conduct research on improving modern weather forecasting systems.

On the other hand, the Internet of Things (IoT) has greatly improved the quality of weather data. IoT-based systems make it easier to obtain real-time weather data from sensors that measure temperature, humidity, air pressure, and precipitation. After the data is collected, it can be analyzed using machine learning and deep learning methods to make more accurate predictions that change as the environment changes.

The combination of Artificial Intelligence (AI) and the Internet of Things (IoT) is helping to improve early warning systems that send faster and more accurate alerts about disasters that are about to happen. This system uses real-time data and prediction models to detect unusual events and predict severe weather, such as floods and heavy rain. As a result, combining AI and IoT technologies could greatly improve resilience to catastrophic risks and make decision-making more effective.

Nonetheless, many challenges remain in the development of AI- and IoT-based weather forecasting systems. Some common problems are inconsistent data quality, missing values, high computing needs, and the model's limited ability to adapt to changes in environmental variables in real time. Furthermore, most studies focus on developing predictive models without comprehensive system integration, thereby limiting their applicability in real-world scenarios.

This study conducted a comprehensive literature review of various machine learning and deep learning techniques for weather forecasting, including those integrated with IoT-based systems. This paper analyzes the development of these technologies, their advantages and disadvantages, and potential research directions to improve the precision, flexibility, and timeliness of weather forecasting systems.

# 2. RESEARCH METHODOLOGY

This study employed a literature analysis to assess and scrutinize various machine learning and deep learning methodologies for weather forecasting, including those integrated with Internet of Things (IoT) systems. This strategy was carried out methodically to gain a comprehensive understanding of the latest research, the pros and cons of different methods, and the potential for future improvement.

## 2.1 Data Sources and Literature Collection

This phase involved compiling literature from various scientific sources, including international journals, conference proceedings, and publications on machine learning-based meteorological forecasting, deep learning, and the Internet of Things (IoT). The reviewed literature included various studies focusing on methodologies such as Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), and Transformer [7], [8], [12]. Additionally, research into hybrid methodologies, such as combining ARIMA and LSTM, has aimed to improve predictive accuracy [1], [6], [19].

## 2.2 Literature Selection Criteria

The literature employed in this study was selected based on various criteria, including:

1. The investigation focused on atmospheric forecasting or meteorological parameters.
2. Using a machine learning method, deep learning, or a mix of the two.
3. Having clear evaluation results, such as accuracy, RMSE, MAE, or other metrics.
4. Related to the integration of IoT-based systems or real-time systems.

We got representative literature to review and compare against these standards.

### 2.3 Stages of Literature Analysis

The analytical phases of this investigation were conducted systematically, including the following steps:

1. Method Identification
   Recognizing the different methods used in previous research, such as machine learning, deep learning, and hybrid approaches.

2. Classification of Approaches
   Grouping methods by category, namely:
   - Machine Learning
   - Deep Learning
   - Hybrid Model
   - IoT-based System

3. Model Performance Analysis
   Assessing the effectiveness of each method based on the results recorded in previous studies, encompassing accuracy, error rates, and computational efficiency.

4. Analysis of Strengths and Limitations
   Looking at the pros and cons of each method for predicting the weather.

5. Identification of Trends and Research Gaps
   Recognizing progress in research trends and possible research deficiencies for additional investigation.

### 2.4 Conceptual Model of an IoT-Based Weather Prediction System

Based on the literature review, this study developed a conceptual model for an IoT-based weather forecasting system that leverages machine learning and deep learning. This model has a few main parts, which are:

1. Data Acquisition (IoT Layer)
   Data is obtained from IoT sensors that measure environmental parameters such as temperature, humidity, air pressure, and rainfall.
2. Data Processing (Preprocessing Layer)
   To improve data quality, the collected data will be cleaned, normalized, and handled for missing values.
3. Prediction Model (AI Layer)
   The processed data is then used as input for machine learning or deep learning models, such as LSTM, GRU, Random Forest, and Transformer, to make predictions.
4. Output and Decision Support (Application Layer)
   The predicted outcomes serve as the basis for decision-making, especially in early warning systems that detect disasters about to occur.

### 2.5 Research Flow

The research process in this study was conducted in stages, beginning with the collection of literature and culminating in the analysis and synthesis of research findings. The research process can be outlined as follows:

1. A review of the literature on weather forecasting using AI and the Internet of Things.
2. Choosing and putting relevant research into groups.
3. Assessment of methodologies and model effectiveness.
4. A look at the Comparative Method.
5. Acknowledgment of research obstacles and opportunities.
6. Formulation of conclusions and suggestions.

The study's findings will clarify the advancement of meteorological forecasting technologies through the application of machine learning, deep learning, and the Internet of Things (IoT). They can serve as a basis for further research.

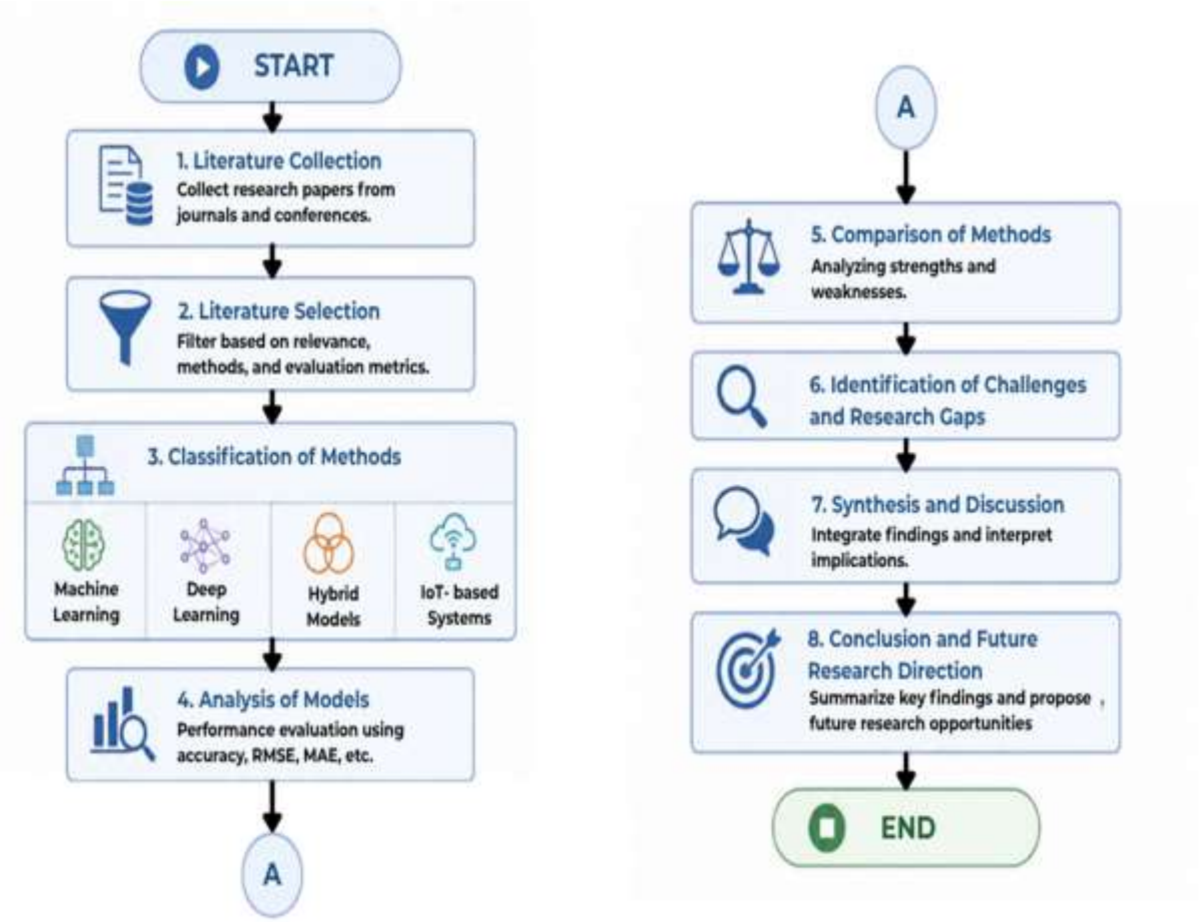

**Figure 1.** Flowchart Research Method

## 3. RESULT AND DISCUSSION

This section outlines the results of a literature review focused on various machine learning, deep learning, and hybrid model methodologies for Internet of Things (IoT)-based weather forecasting. The analytical results are well-organized so that they give a full picture of how well the methods work, their advantages and disadvantages, and what new research trends are on the way.

### 3.1 Analysis of Machine Learning Approaches

The literature review indicates that machine learning techniques are among the most widely utilized methodologies in weather forecasting. Methods such as Linear Regression, Support Vector Machine (SVM), Random Forest, and Artificial Neural Network (ANN) have shown strong effectiveness in modeling the connections between different weather variables. Random Forest is known for being good at handling complicated data and making accurate predictions about things like temperature and humidity. The SVM approach may effectively characterize nonlinear interactions; however, it often demonstrates limited generalization across various datasets. Nonetheless, most machine learning methods have a hard time understanding long-term temporal correlations, which makes them less than ideal for time-series data, such as weather data.

### 3.2 Analysis of Deep Learning Approaches

Deep learning techniques have made great strides in weather forecasting, especially when it comes to handling complex time-series data. Models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) can more effectively capture long-term temporal patterns than traditional machine learning techniques. In many tests, LSTM models have shown to be very good at predicting things, especially temperature and rainfall On the other hand, GRUs have a simpler structure that allows for faster training times and similar effectiveness. Additionally, the utilization of Convolutional Neural Networks (CNNs) for image-based data, such as radar and satellite imagery, has yielded positive results for spatial feature extraction. The Transformer model has garnered substantial attention in current research due to its ability to integrate global interdependence in data and achieve minimal error rates in weather forecasting. This demonstrates that deep learning techniques exhibit superior capability in handling the complexities of meteorological data compared to traditional methods. Table 1 shows the differences between machine learning and deep learning methods for predicting the weather, based on the studies that were done.

**Table 1.** Comparison of Machine Learning and Deep Learning Models for Weather Forecasting

| Model | Advantages | Disadvantages | Data Type | Computational Complexity |
|---|---|---|---|---|
| Linear Regression | Simple, fast, easy to implement | Unable to capture non-linear relationships | Time-series (simple) | Low |
| Support Vector Machine | Good for high-dimensional, nonlinear data | Difficult to scale on large data sets; complex parameter tuning | Tabular, time-series | Medium |
| Random Forest (RF) | Robust against noise, high accuracy | Suboptimal for long-term temporal dependencies | Tabular | Medium |
| XGBoost | High performance, efficient optimization | Prone to overfitting if not tuned properly | Tabular | Medium–High |
| Artificial Neural Network | Capable of capturing non-linear relationships | Requires a large amount of data; less than optimal for long-term dependencies | Tabular, time-series | High |
| LSTM | Excellent for time series and long-term dependencies | Long, complex training | Time-series | High |
| GRU | Simpler than LSTM, faster training | Slightly less powerful than LSTM in some cases | Time-series | High |
| CNN | Good for spatial feature extraction (weather imagery) | Not optimal for purely temporal data without other model combinations | Spatial (image, radar) | High |
| Transformer | Capturing global and complex dependencies | Requires large data and high computational requirements | Time-series, spatial | Very High |

### 3.3 Hybrid and Ensemble Model Analysis

Many studies have created hybrid models that combine the best parts of different methods to improve predictive performance. A common approach is to combine ARIMA and LSTM, with ARIMA handling linear patterns and LSTM handling non-linear patterns. The results show that hybrid models are more accurate than single models because they can better capture the properties of the data. Also, ensemble methods, like combining Random Forest, XGBoost, and LSTM, show better stability and strength in many situations where predictions are needed. As a result, it can be concluded that hybrid and ensemble methodologies are effective approaches for improving accuracy and stability in meteorological forecasting. Table 2 shows how different hybrid models improve weather prediction by comparing them.

**Table 2.** Performance Comparison of Hybrid Models in Weather Forecasting

| Hybrid Model | Dataset | Target | Metrics | Performance Summary |
|---|---|---|---|---|
| ARIMA + LSTM | Weather Time Series | Temperature / rainfall | RMSE, MAE | More accurate than ARIMA & LSTM alone |
| ARIMA + DL | Time-series | Forecasting | RMSE | Errors decreased significantly |
| RF + XGBoost + LSTM | Multi-source | Weather prediction | Accuracy, RMSE | Best overall performance |
| RF + Genetic Algorithm | Meteorological tabular | Feature optimization | Accuracy | Significant accuracy improvement |
| CNN + LSTM | Spatio-temporal | Forecasting | RMSE, MAE | Capturing spatial and temporal patterns |
| ML + DL + Rule-based | Agriculture + weather | Decision support | Accuracy | Suitable for real world applications |
| CNN + DL Hybrid | Radar image | Extreme weather | Precision, Recall | Good for extreme weather detection |
| DL Hybrid Models | Climate data | Extreme forecasting | RMSE, F1-score | Robust for extreme conditions |
| LSTCN / Adaptive DL | Streaming IoT data | Real-time forecasting | MAE | Adaptive to real-time data |

### 3.4 IoT Integration in Weather Prediction Systems

Adding the Internet of Things (IoT) to weather forecasting systems greatly improves the quality of the data. IoT sensors offer real-time data acquisition with enhanced resolution relative to conventional methods. Machine learning and deep learning models use data from sensors, such as temperature, humidity, air pressure, and precipitation, to make more accurate predictions. Additionally, connecting to cloud systems makes it easier to process data quickly and gives users better access to information. IoT-enabled weather forecast systems work as both analytical and monitoring tools, giving you real-time information.

### 3.5 AI and IoT-Based Early Warning Systems

development of AI and IoT-based early warning systems has become an important use in weather forecasting. These systems use real-time data and predictive models to find possible disasters, such as floods and heavy rain. Compared to traditional methods, deep learning methods can make predictions more accurate and warnings last longer. Combining data from many sources, such as IoT sensors, satellites, and global weather models, makes it easier for the system to find anomalies with more accuracy. This shows that combining AI and IoT could greatly improve systems for reducing the effects of disasters based on data.

### 3.6 Method Performance Comparison

The results of the comparison show that:

- Machine learning methods are helpful because they are easy to use and work quickly.
- Deep learning is good at handling complex and time-sensitive data.
- Hybrid models work best when it comes to accuracy and reliability.

The technique comparison table in this study shows that there is no one best method for all situations. Instead, the choice of method must be based on the needs of the data and the system. Table 3 shows a summary of the previous studies that were looked at in this research.

**Table 3**. Summary of Recent Studies on Weather Forecasting using ML/DL Approaches

| Metode | Data | Tujuan | Hasil Utama | Keterbatasan |
|---|---|---|---|---|
| LR, SVM, ANN | Rainfall | Rainfall prediction | The best ANN | Lack of temporal capture |
| Random Forest | Temperature, humidity | Weather prediction | High accuracy and stability | No long-term catch |
| LSTM | Meteorological time-series | Temperature & rainfall | High accuracy | Long training |

**Table 4**. Summary of Recent Studies on Weather Forecasting using ML/DL Approaches (Continued)

| Metode | Data | Tujuan | Hasil Utama | Keterbatasan |
|---|---|---|---|---|
| GRU | Time-series | Weather forecasting | More efficient than LSTM | A little less complex |
| CNN | Radar and satellite imagery | Weather classification | Good for spatial features | Not suitable for temporal |
| CNN-LSTM | Spatio-temporal data | Weather prediction | Spatial and temporal capture | Complex model |
| Transformer | Time-series | Forecasting | Low error, global context | High computing |
| ARIMA + LSTM | Time-series | Hybrid forecasting | More accurate than a single model | Complex model |
| RF + GA | Tabular | Feature optimization | Accuracy increased | Tuning is difficult |
| Ensemble (RF, XGB, LSTM) | Multi-source data | Forecasting | Best performance | High resource |
| IoT + ML/DL | Real-time sensors | Weather monitoring | Accurate real-time data | Noise in data |
| AI-based EWS | Multi-source | Early warning system | Rapid disaster detection | Complex system integration |

### 3.7 AI and IoT-Based Early Warning Systems

Many strategies work well, but there are still many problems that need to be solved. The main problems are inconsistent data quality, missing values, and interference in IoT sensor data. Deep learning models also need a lot of computing power and are not very clear, which makes them hard to understand. The models can't change in real time as the environment changes. Another problem is that IoT parts, predictive models, and decision-making systems don't work well together, which makes them less useful in real-world situations.

**Table 5.** Challenges and Potential Solutions in AI-based Weather Forecasting Systems

| No | Challenge | Impact | Potential Solution | Future Research Direction |
|---|---|---|---|---|
| 1 | Data Quality Issues | Noise, missing values, bias | Data preprocessing & cleaning techniques | Robust data imputation & anomaly detection (AI) |
| 2 | Data Availability | Poor generalization across regions | Integration of multi-source data | Global-local data fusion models |
| 3 | Atmospheric Complexity | Low prediction reliability | Hybrid models (physics + AI) | Physics-informed machine learning |
| 4 | ML Limitations | Poor temporal modeling | Use of deep learning (LSTM, GRU) | Advanced temporal architectures |
| 5 | DL Limitations | Overfitting, large data requirement | Regularization & data augmentation | Self-supervised & transfer learning |
| 6 | Computational Cost | High training & inference time | Model optimization & pruning | Edge AI & lightweight models |
| 7 | Real-time Adaptation | Outdated predictions | Online learning & streaming models | Adaptive & incremental learning systems |
| 8 | System Integration | Fragmented systems (AI + IoT + EWS) | End-to-end system design | Unified intelligent weather platforms |
| 9 | Generalization Issues | Poor performance in new regions | Localization & regional modeling | Transfer learning for climate adaptation |
| 10 | Extreme Weather Prediction | Low accuracy for rare events | Imbalanced learning techniques | Extreme event-focused AI models |
| 11 | Interpretability (Black-box) | Low trust in predictions | Explainable AI (XAI) | Interpretable deep learning models |
| 12 | Scalability Issues | System inefficiency with big data | Cloud & distributed computing | Federated & distributed learning systems |

### 3.8 Research Discussion and Implications

The research shows that new machine learning and deep learning methods have made weather predictions much more accurate than older ones. This is because the models can find non-linear correlations and complex interactions over time in weather data. Deep learning architectures such as LSTM and GRU demonstrate superior effectiveness in handling time-series data, whereas CNNs and Transformers excel in managing spatial data and global relationships.

Still, this higher level of accuracy means that the model is more complicated and needs more processing power. Deep learning models need a lot of data and long training times, which makes it hard to use them in real-time systems, especially on IoT devices that don't have a lot of resources. This shows that when making weather forecasting systems, you have to find a balance between accuracy and speed of processing. The research shows that hybrid and ensemble methods work better and more reliably than single models. Hybrid models can find both linear and non-linear patterns at the same time. It is hard to do because model integration and parameter optimization are both very complicated.

From a system integration point of view, the implementation of IoT greatly improves data quality by allowing real-time data acquisition. However, data collected from IoT sensors often contains noise and missing values, which can make predictive models less accurate. As a result, cleaning up data, normalizing it, and filling in missing values are all important steps in the weather prediction system pipeline. Furthermore, the integration of AI and IoT into early warning systems presents significant potential for improving data-driven disaster mitigation. Compared to traditional methods, these technologies can send out early warnings faster and more accurately. Still, most research is still focused on making prediction models on their own, without full integration, which limits their use in real-world situations.

This study suggests that the advancement of forthcoming weather forecasting systems necessitates a more integrated methodology, in which all elements—data acquisition (IoT), data processing, predictive models (AI), and decision-making systems—operate concurrently within a singular ecosystem. It is also important to make models that are lighter and more efficient so that they can be used on edge devices without losing much accuracy. From a research perspective, there are prospects to develop models that are more attuned to real-time data via online or incremental learning. Furthermore, the development of explainable AI is crucial for improving model interpretability, aiding user understanding of predictions, and augmenting their reliability.

So, it seems that improving weather prediction systems should focus on not only making them more accurate, but also making them faster, better at handling data, better at working with other systems, and more adaptable to changing weather conditions. This lays the groundwork for building better weather forecasting systems that can be used in the real world.

## 4. CONCLUSIONS

The literature review shows that progress in machine learning and deep learning has greatly improved the accuracy of weather forecasts, especially when it comes to dealing with the nonlinear nature of meteorological data and its strong dependence on time. Deep learning methods like Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), and Transformer are more effective than traditional methods, especially when it comes to modeling time-series and spatio-temporal data. Additionally, hybrid and ensemble methodologies have shown improvements in predictive accuracy and stability by using the best parts of different methods. The Internet of Things (IoT) needs to be integrated in order to provide real-time weather data, which will make it possible to make weather forecasting systems that are more flexible and responsive. Still, there are other problems that make it hard to use AI- and IoT-based weather prediction systems. These include changing data quality, high processing needs, limited model interpretability, and not being able to adapt quickly enough. Additionally, the comprehensive integration of IoT components, predictive models, and decision-making systems remains a substantial obstacle. This research is innovative because it combines machine learning, deep learning, hybrid models, and IoT-based systems into one complete analytical framework. This paper analyzes method performance while delineating research trends, challenges, and future development opportunities, particularly in the establishment of real-time, data-driven weather forecasting and early warning systems. As a result, future research may focus on developing more adaptable, computationally efficient models that can be seamlessly integrated with IoT and early warning systems. Also, improving the accuracy, reliability, and trustworthiness of future weather prediction systems requires the development of locally data-driven models and the use of explainable AI principles.

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