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Application of Machine Learning in Weather Forecasting

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Abstract. Weather prediction is of great significance for public safety, disease prevention, agriculture, transportation, and natural disasters. Despite being well-established and extensively studied, current Numerical Weather Prediction (NWP) models continue to encounter certain limitations. For example, they rely on high-performance computing environments, consume a large amount of energy, and involve high computational costs. Therefore, using Machine Learning (ML) algorithms for weather prediction, integrating data with numerically driven models, and improving prediction accuracy by learning historical data are of crucial importance. However, most existing research tends to concentrate on particular use cases and technical implementations of ML in weather forecasting, without offering a thorough and in-depth overview of its broader application methods. This paper begins by outlining various ML techniques and the distinct features of meteorological data. It then explores the role of ML in weather forecasting from three key perspectives: short-term weather prediction, extreme weather prediction, and spatial regional modeling, and summarizes the common application methods of ML. Finally, this paper points out the deficiencies of future research and suggests the directions for future research.

Keywords: Machine learning, weather forecasting, meteorological data, numerical weather prediction.

1. Introduction

Weather forecasting, a branch of applied meteorology, predicts future atmospheric conditions using various methods and techniques. It plays a crucial role in sectors like energy, maritime transportation, aviation, agriculture, and forestry. For example, weather forecasts help farmers plan their activities and minimize crop loss. Precise regional weather predictions are crucial for organizations that rely on weather-related information to guide their decision-making.

Conventional weather forecasting mainly depends on Numerical Weather Prediction (NWP) models, which estimate atmospheric conditions by simulating the flow of energy and matter on Earth. Since the inception of Joint Numerical Weather Prediction Unit in 1955, the NWP centers have been formed all over the world [1]. These models take help of data from automated weather stations and they compute thermodynamic, dynamic and moist processes with the help of complex physical models. But the traditional methods suffer a lot from various disadvantages such as high computational cost, high energy consumption, unstable predictions of disturbances of weather systems and low resolution, etc.

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Similarly, Weather prediction has also improved a lot in recent years by utilizing Machine Learning (ML). It can handle various types of data and extract trends from past weather archives to make a more accurate weather prediction. For example, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are used a lot in the field of weather predictions. MiMa model, which combines the near-surface observational data from meteorological stations in Kentucky with atmospheric data, improves the accuracy of regional weather forecasting. Pangu-Weather and Graph Cast have also achieved better performance than traditional NWP models in computational speed.

This research work has studied how ML is used in the area of short-term forecasting, extreme weather event prediction and regional climate modeling. The aim is to discover and identify the effective ML techniques for respective scenarios to provide some insights to guide future research and improve forecasting practices.

2. Fundamentals of ML and characteristics of meteorological data

This chapter provides an overview of common ML techniques and some basic types and characteristics of meteorological data. By examining the core features of both ML techniques and meteorological data, this study offers an initial understanding of how ML can be applied to weather forecasting. It also emphasizes the significance, advantages, and limitations of applying ML in this field.

2.1. ML methods

ML approaches mainly include supervised learning, unsupervised learning, and association rule learning models.

Supervised learning methods commonly employed are linear and logistic regressions, decision trees, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and neural networks. Linear regressions are commonly used in building the relationship between multiple variables and one variable, fitting a line or a hyperplane to predict value or to classify data. Logistic regression, however, is suited best for classifying problems, binary or multi-class, and estimates the likelihood of an event taking place based on predictors such as age or income. The decision trees are a model-based structure that has each node as a decision rule for a particular feature and leads to an outcome at the leaf nodes. They are intuitive and can handle numerical and categorical inputs. KNN, a very simple and effective technique for classification, classifies new points by examining the k closest examples from the learning set and taking the majority class or average from those neighbors. SVM are binary classification models whose goal is to find a separation principle that maximizes the margin, ultimately transforming it into a convex quadratic programming problem for solution. They can be used for either regression or classification problems. In forecasting weather, for example, they operate through meteorological data to derive predictions by finding the best hyperplanes in the high-dimensional space—either for discriminating among different weather classes or for estimating continuous values. Artificial neural networks, heavily utilized for supervised learning, also predominate for applications such as marketing. RNNs, Long Short-Term Memory networks (LSTMs), and some other networks are very effective at learning temporal relationships in data. LSTMs are also especially appropriate in time series analysis because LSTM networks can retain or forget long-term information within long sequences—a very desirable characteristic for accurately forecasting weather patterns that develop long-term trends.

Unsupervised learning is a kind of ML approach which do not have targeted label, designed to classify data through data analysis and find potential model or structure behind data. For example,

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K-means clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Principal Component Analysis (PCA), and t-distributed Stochastic Neighbor Embedding (t-SNE) are included in Unsupervised learning. K-means is a popular algorithm for clustering that works by the iteration of moving cluster center locations and assigning the data points the nearest center and dividing the data set into k clusters based on average values. Clustering by density, such as DBSCAN, is efficient for unveiling clusters of variable shape and is also less affected by noise in the data. Hierarchical methods, on the other hand, construct a nested hierarchy by recursively forming or splitting data points into clusters and therefore provide a tree-like structure. PCA is a popular dimensionality reduction technique that reduces datasets by selecting only those most important variables, facilitating easier analysis while preserving essential pieces of information. t-SNE is also a dimensionality reduction technique, which includes reducing data's dimension and changing high-dimensional data into low-dimensional one.

Association rule learning is a data mining technique for discovering the association relationships among different variables in a dataset. Its goal is to identify strong rules existing in the data and is commonly used in market basket analysis, but also applied in areas such as intrusion detection, network usage mining, and bioinformatics. Common association rule learning algorithms include Apriori and FP-Growth.

2.2. Meteorological data types and their characteristics

Meteorological data is diverse, covering various categories such as surface meteorological observations, upper-air meteorological sounding, and remote sensing meteorology. Each type of data has its own characteristics due to differences in observation methods and coverage. In meteorological forecasting, high-resolution temporal data from surface observations is the foundation for accurately predicting short-term and near-term weather. Upper-air meteorological sounding data helps analyze the vertical structure of the atmosphere, allowing forecasters to grasp the development trend of weather systems. Remote sensing meteorological data, with its wide coverage advantage, can monitor the evolution of large-scale weather systems in advance. In the field of climate research, long-term accumulated meteorological data is the core basis for exploring climate change trends and conducting attribution analysis.

The effective analysis and application of meteorological data is the key link that connects the precise improvement of meteorological forecasting, disaster prevention and people's livelihood security. Only by deeply mining the value of data can meteorological services better meet the diverse needs of society.

2.2.1. Meteorological data types

Meteorological data can mainly be categorized into three main types: surface observations, upper-air observations, and remote sensing data.

Surface meteorological observation data are collected by the meteorological station on the ground. The surface meteorological observation data usually include the following basic variables: air temperature, atmospheric pressure, humidity, wind speed and direction, precipitation and visibility. Surface meteorological observation data have high temporal resolution and relatively high observation accuracy, and they are the basic data used for weather forecasting and climate data analysis. For example, as shown in table 1, the temperature and precipitation data at a meteorological station in a certain area can be collected every hour.

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Collected using instruments like radiosondes and aircraft, upper-atmosphere meteorological data include essential variables like temperature and wind speed. These data can provide information in the vertical direction of the atmosphere and are very important for studying atmospheric structure and the changes in weather.

Table 1. An example of surface meteorological observation data in Beijing

Date	Time	Temperature℃	Humidity%	Pressure(hPa)	Precipitation (mm/h)	Wind(m/s)
2022/1/1	0:00:00	-6.65311	68.19329	1025.307	0.000159	-0.50279
2022/1/1	1:00:00	-6.20319	65.15887	1024.633	0.000159	-0.70681
2022/1/1	2:00:00	-5.78492	63.43261	1024.445	0.000159	-0.34345
2022/1/1	3:00:00	-6.57273	66.77775	1023.32	0.000159	0.1483
2022/1/1	4:00:00	-6.37861	65.34243	1022.68	0.000159	-0.25656
2022/1/1	5:00:00	-7.30936	71.3228	1022.876	0.000159	-0.12976
2022/1/1	6:00:00	-8.02326	75.63919	1022.603	0.000159	0.406661
2022/1/1	7:00:00	-8.53736	78.77886	1022.841	0.000159	0.625625
2022/1/1	8:00:00	-6.7652	75.32402	1023.115	0.000159	0.605752

Remote sensing meteorological data mainly refer to the observations of meteorological elements in the atmosphere using remote sensing devices such as satellites and radars. For example, in the figure 1, the cloud layer in the atmosphere can be observed and located by using satellite cloud image. Remote sensing meteorological data have the advantages of large coverage area and high spatial resolution, and can observe weather systems in a large range. Meteorological radar can also be used to observe the intensity and range of precipitation echoes.

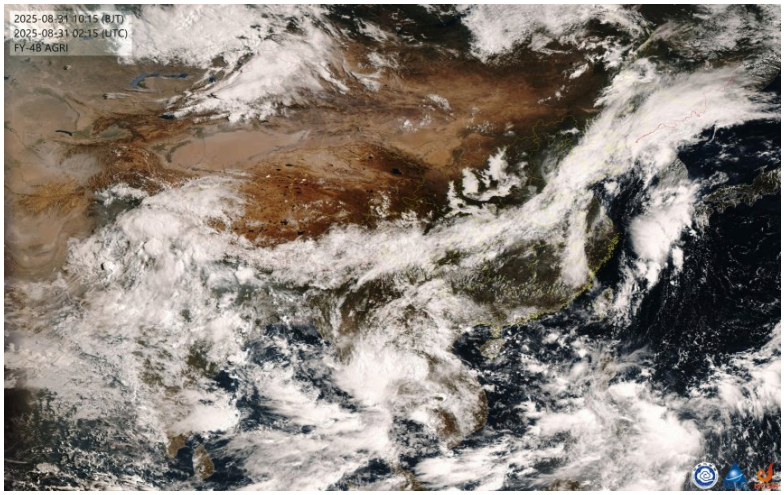

Figure 1. Satellite cloud image (partial)

2.2.2. Meteorological data characteristics

Meteorological data mainly include characteristics such as high nonlinearity, high-frequency sampling, incompleteness and noise, seasonality and periodicity, and so on.

The high nonlinearity of meteorological data mainly refers to the complex nonlinear relationships in atmospheric movement, which also lead to nonlinear relationships among meteorological elements. Traditional linear models are difficult to accurately describe them.

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The high-frequency sampling of meteorological data mainly refers to the fact that meteorological data are usually sampled hourly or even by the minute, supporting high temporal resolution analysis. High-frequency sampling can capture the instantaneous characteristics of weather changes and provide a data basis for refined forecasting.

The incompleteness and noise of meteorological data refer to the fact that meteorological data are subject to sensor limitations and environmental interference, which may result in data missing and noise. For example, sensor failures, data transmission errors, etc., may lead to incomplete data or abnormal values. Environmental interference may also cause data missing. Therefore, data quality control is an important part of meteorological data analysis.

Meteorological data also have seasonality and periodicity, mainly referring to the fact that the changes in meteorological elements have obvious seasonal and periodic patterns. For example, the seasonal cycle changes in temperature and the interannual changes in precipitation. These patterns provide important basis for long-term climate prediction.

3. Application of ML in weather forecasting

3.1. Short-term weather prediction

The use of ML in weather forecasting in short term can be categorized into conventional techniques and more integrated, model-based approaches. Traditional methods involve algorithms such as Extreme Gradient Boosting (XGBoost), Gradient Boosting, and Random Forest (RF) for predicting short-term weather conditions. Among these, XGBoost demonstrated the highest accuracy, achieving a prediction rate of 82.25%, outperforming both RF and Gradient Boosting models. All models performed well in normal weather conditions but had the poorest predictive ability in predicting less common phenomena. This shows that ML faces challenges when using imbalanced datasets for weather forecasting [2]. For instance, based on historical meteorological records from the Indian subcontinent, the short-term weather phenomena prediction was performed by using LSTM, and the rate of correctness was quite high at 80.11% for urban flood and rain prediction. Compared to other models of supervised learning such as regression and ensemble models, LSTM was the model that has the highest prediction rate and it is effective for tackling the issue of scalability and limited computation [3]. Another example was about active testing of neural networks, Naive Bayes, and so on for their precision in weather prediction. The result was that Naive Bayes which is an algorithm outperformed other models of ML in weather prediction .it also showed higher precision and recall and higher rate of correctness, thus consolidated the significant role of machine learning in weather forecasting and provided the possibility of improving the accuracy of weather prediction [4].

3.2. Predictions of extreme weather conditions

ML models also have extensive applications in the prediction of extreme weather. For instance, they can be used to identify and predict extreme weather conditions such as typhoons and heavy rain. By developing ML models and integrating them with traditional weather forecasting models, it is possible to issue early warnings for extreme weather events like storms and floods, thereby reducing casualties and property losses. For example, precipitation in the Jinsha River Basin can be simulated using the WRF model, with subsequent error correction performed through Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and ML techniques. Different models can be compared to find the one that best improves the accuracy of precipitation forecasts. It

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was found that the CEEMDAN-CSA-BILSTM method, which combines WRF with ML algorithms, can improve the level of accuracy in WRF numerical precipitation model, enabling timely warnings for precipitation and flood disasters and minimizing losses of personnel and goods [5]. Another example is thunderstorms [6]. Thunderstorm prediction is of unparalleled importance for airspace management in Europe. Convective weather can cause severe delays in the airspace system. Current convective weather forecasts lack spatial and temporal resolution, leading to passive and uncoordinated adjustments by Air Navigation Service Providers (ANSPs). Through the application of CNNs for extracting features from spatial patterns in weather observations and developing models from CNN-based structures, the accuracy of point predictions can be increased remarkably and longer lead times for the prediction of thunderstorms—thereby allowing for more efficient detection and control of rare weather events. Similarly, for hurricanes, a wide selection of ML models, such as decision trees, classification and regression trees, RF, extremely randomized trees, gradient boosting, adaptive boosting, deep learning models and so on, can be utilized for the prediction of power outages and estimation of potential damage from electrical infrastructure [7]. The most suitable ML method can be applied to predict power outages in the distribution system during hurricanes.

3.3. Spatial modeling and regional prediction

ML is becoming increasingly vital in spatial modeling and regional forecasting, as it excels at processing complex spatial datasets and discovering potential patterns in predicting weather, improving the accuracy and efficiency of predictive outcomes. Spatial modeling refers to the process of using mathematical and computational methods to simulate geographical spatial phenomena, while regional prediction is mainly about forecasting future events or trends in a specific geographical area. ML Algorithms like SVM, RF can be used as robust tools for analyzing spatial data.

In spatial modeling, machine learning can be used for precise mapping [8]. For instance, convolutional neural networks can effectively extract image features by analyzing remote sensing images and other spatial data, thereby predicting different land use types and detecting changes in land use. Ultimately, by using data collected multiple times by unmanned aerial vehicles, precise and detailed land cover mapping can be produced.ML can also be used in environmental monitoring and pollution prediction. For instance, ML can be applied to map the concentration of fine particulate matter (PM2.5) in a given region [9]. LSTM networks, XGBoost, and various ensemble models are the most frequently used techniques in PM2.5's prediction.

When we use machine learning, we can also apply it in to the risk assessment of natual disaster like landslides, floods and earthquakes [10]. For instance, some scientists have developed a dynamic model integrating dynamic algorithms by using machine learning algorithms. This dynamic strategy has been applied to the temporal landslide prediction in the Kvaum area in southeastern Norway already. Through evaluation metrics, it was found that the results of the machine learning model can accurately predict spatio-temporal landslide phenomena, matching the historical control records of temporal landslides. ML models can support disaster early warning and prevention by identifying high-risk areas and predicting the probability of disaster occurrence.

4. Discussion

ML is widely used in meteorological prediction, extreme weather, spatial modeling, and regional forecasting, and has significant advantages over traditional numerical weather prediction methods,

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including the ability to quickly adapt to climate variability, the effective utilization of large datasets, and the capacity to generate real-time forecasts. However, it also faces several challenges.

the volume and quality of the training data can greatly influence the exactness of ML models. In regions with limited observational coverage, such as remote areas, data scarcity can significantly hinder the accuracy of weather forecasts [11]. Additionally, issues like missing, inaccurate, or inconsistent data further compromise the reliability and performance of these models.

When facing unfamiliar and unseen datasets, ML models usually cannot maintain its high accuracy rate, even though they act really well in training datasets, that is exactly the limitations of the generalization ability of machine learning [12]. Moreover, ML models usually cannot directly simulate physical processes in the atmosphere, such as radiation transfer, phase change, and dynamic processes. Therefore, data-driven ML models alone may fail to capture certain important weather phenomena [13]. Additionally, weather systems are highly nonlinear and chaotic, and there may be a great many possible outcomes when predicting the weather. Therefore, machine learning may not be accurate in predicting the weather [14].

Currently, there is no complete system for evaluating ML. Current evaluation approaches primarily depend on metrics like Root Mean Square Error (RMSE), Accuracy (ACC), and Continuous Ranked Probability Score (CRPS), which may not comprehensively capture the overall performance or effectiveness of the models. Usually, these data-driven models are evaluated by data scientists who lack expertise in meteorology and climate assessment, leading to incomplete or flawed evaluations [15].

5. Conclusion

This article provides an in-depth discussion of the applications of ML in weather forecasting and identifies three areas of utmost relevance, that is, short-term forecasting, forecasting of extreme weather conditions, and spatial and regional modeling. Three classes of applications have originated from the literature, that is, traditional ML methods, hybrids, and applications of ML and traditional forecasting models. Overall, applications of ML approaches result in improved forecasting accuracy, improved detection of weather patterns, and improved weather-based decisions in day-today operations.

Through adopting a broader and more holistic perspective, the book offers a deeper and systematic understanding of the role that ML contributes to weather forecasting. It corrects for the piecemeal approach of previous research—by which research focused on a single aspect—and more extensively addresses numerous facets from multiple outlooks. This article not only synthesizes knowledge available, but it also establishes a macroscopic landscape for the integration of ML into meteorological forecasting and serves as a general reference for further research in this regard.

However, the article only briefly summarizes and generalizes the application of ML in weather prediction. It doesn't focus on the mechanism of ML in weather prediction, how ML can further improve the accuracy of weather prediction, and new applications of ML in weather prediction. In the future, maybe scientists should pay more attention in the combination of machine learning and traditional weather forecasts model in order to develop more advanced system to handle more complex weather problems.

References

[1] Zhang, Y., Turney, B., Sigdel, P., Yuan, X., Rappin, E., Lago, A., Kimball, S., Chen, L., Darby, P., Peng, L., Aygun, S., Tu, Y., Najafi, M. H., & Tzeng, N.-F. (2024). Regional Weather Variable Predictions by Machine Learning with Near-Surface Observational and Atmospheric Numerical Data (Version 2).

DOI: 10.54254/2755-2721/2025.LD28521

[2] Tanuj jadon, Prince Pachauri, Aamir warsi (2025). Predict Weather with Machine Learning. International Journal on Science and Technology, 16(1).
[3] Sunil Khatri. (2024). Advanced Weather Forecasting with Machine Learning: Leveraging Meteorological Data for Improved Predictions. Communications on Applied Nonlinear Analysis, 32(5s), 01–16.
[4] S. Bhatia, B. B. Naib, N. Goel, B. Agarwal, B. Mallikarjun and M. Arvindhan, "A New Era in Weather Forecasting: Harnessing the Potential of Machine Learning, "(2024) IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 2024, 1355-1361
[5] Chen, L., Han, B., Wang, X., Zhao, J., Yang, W., & Yang, Z. (2023). Machine Learning Methods in Weather and Climate Applications: A Survey. Applied Sciences, 13(21), 12019.
[6] Meng, C., Hu, Z., Wang, Y., Zhang, Y., & Dong, Z. (2024). A forecasting method for corrected numerical weather prediction precipitation based on modal decomposition and coupling of multiple intelligent algorithms. Meteorology and Atmospheric Physics, 136(5).
[7] Jardines, A., Eivazi, H., Zea, E., García-Heras, J., Simarro, J., Otero, E., Soler, M., & Vinuesa, R. (2024). Thunderstorm prediction during pre-tactical air-traffic-flow management using convolutional neural networks. Expert Systems with Applications, 241, 122466.
[8] Fatima, K., Shareef, H., Costa, F. B., Bajwa, A. A., & Wong, L. A. (2024). Machine learning for power outage prediction during hurricanes: An extensive review. Engineering Applications of Artificial Intelligence, 133, 108056.
[9] Hu, Q., Woldt, W., Neale, C., Zhou, Y., Drahota, J., Varner, D., Bishop, A., LaGrange, T., Zhang, L., & Tang, Z. (2021). Utilizing unsupervised learning, multi-view imaging, and CNN-based attention facilitates cost-effective wetland mapping. Remote Sensing of Environment, 267, 112757.
[10] Nocentini, N., Rosi, A., Piciullo, L., Liu, Z., Segoni, S., & Fanti, R. (2024). Regional-scale spatiotemporal landslide probability assessment through machine learning and potential applications for operational warning systems: a case study in Kvam (Norway). Landslides, 21(10), 2369–2387.
[11] Yadav, K., Malviya, S., & Tiwari, A. K. (2025). Improving Weather Forecasting in Remote Regions Through Machine Learning. Atmosphere, 16(5), 587.
[12] Bonavita, M. (2024). On Some Limitations of Current Machine Learning Weather Prediction Models. Geophysical Research Letters, 51(12).
[13] Jaseena, K. U., & Kovoor, B. C. (2022). Deterministic weather forecasting models based on intelligent predictors: A survey. Journal of King Saud University - Computer and Information Sciences, 34(6), 3393–3412.
[14] Vonich, P. T., & Hakim, G. J. (2025). Testing the Limit of Atmospheric Predictability with a Machine Learning Weather Model (Version 1). arXiv.
[15] Dayeh, M. A., Starkey, M. J., Chatterjee, S., Elliott, H., Hart, S., & Moreland, K. (2025). A Machine Learning-Ready Data Processing Tool for Near Real-Time Forecasting. arXiv.