RESEARCH ARTICLE OPEN ACCESS

LSTM and RBFN for Weather Forecasting: A Review

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ABSTRACT
Weather forecasting has experienced a major transformation with the emergence of deep learning techniques. Traditional Numerical Weather Prediction (NWP) systems, although powerful, often face challenges related to computational load and sensitivity to initial conditions. In contrast, machine learning approaches such as Long Short-Term Memory (LSTM) networks and Radial Basis Function (RBF) networks offer new opportunities for data-driven forecasting. This paper examines the performance, strengths, and limitations of LSTM and RBF models for weather prediction. LSTM models excel at capturing long-term temporal dependencies, whereas RBF networks are efficient in modeling nonlinear patterns with reduced computational requirements. Through a review of recent literature and comparative analysis, this study finds that LSTM generally provides higher forecasting accuracy for sequential weather data, while RBF networks remain advantageous for fast, short-term predictions. The findings highlight the potential of combining both models into hybrid architectures to improve real-world forecasting accuracy.
Kewords:- LSTM

INTRODUCTION

Weather forecasting remains a vital component of societal planning, influencing agriculture, transportation, disaster management, public safety, and industrial operations. With the increasing volatility of climate events, accurate forecasts have become more critical than ever. Traditional forecasting methods, including NWP models, rely on physical and mathematical representations of atmospheric processes. Although powerful, such models require extensive computational resources and may not adequately capture local micro-climatic variations [1].

The emergence of deep learning has changed the forecasting landscape. Models like LSTM networks can analyze sequential time-series data by learning long-term dependencies—making them well-suited for meteorological variables such as temperature, humidity, and wind speed [2]. Meanwhile, RBF networks provide rapid training and effective nonlinear mapping, making them suitable for short-term, localized forecasting tasks [3].

This paper provides an analytical comparison of LSTM and RBF networks in weather forecasting, examining their operational characteristics and evaluating their strengths and limitations in relation to modern meteorological challenges[2].

BACKGROUND ON WEATHER FORECASTING

Weather forecasting has evolved from empirical observations to satellite-based remote sensing and high-resolution modeling. The growth of meteorological data sources—IoT sensors, satellites, Doppler radars, and open-access data portals such as NOAA and IMD—has made data-driven modeling increasingly viable[4].

Deep learning approaches have demonstrated significant improvements in accuracy due to their ability to learn patterns without explicit physical equations. LSTM networks, in particular, have shown exceptional performance in handling weather-related time-series. Recent studies demonstrate their superiority in predicting variables like rainfall, temperature, and wind speed when compared to traditional machine learning methods [5].

RBF networks have also contributed to atmospheric modeling by providing efficient, nonlinear function approximation. They have been widely used for precipitation estimation, humidity prediction, and wind forecasting. Their major limitation, however, lies in their inability to capture deep temporal relationships in sequential data [1][6].

IMPORTANCE OF ACCURATE WEATHER PREDICTIONS

Accurate forecasting is essential for managing agricultural cycles, planning infrastructure, and reducing the consequences of extreme weather events. Farmers depend on reliable temperature and rainfall predictions to prevent crop damage, while disaster management agencies rely on accurate cyclone and flood forecasts to issue timely warnings [7]. With global climate change amplifying unpredictable weather patterns, forecasting errors can lead to significant socio-economic impacts.

In aviation and transportation, weather conditions determine route planning, fuel consumption, and safety measures. The energy sector—particularly renewable energy production—relies heavily on precise forecasts of sunlight, wind speed, and cloud cover[8]. As such, the integration of advanced deep learning techniques such as LSTM and RBF networks has enormous potential to enhance both the accuracy and granularity of weather forecasts[1].

LITERATURE REVIEW

Deep learning methods have gained prominence in meteorology due to their capacity to capture nonlinear and temporal patterns. Barzegar et al. [5] demonstrated that CNN-LSTM models outperformed conventional neural networks for precipitation forecasting. Li (2024) showed that combined CNN-LSTM models effectively predicted city-level temperatures using multivariate time-series data.

Bukhari et al. (2022) proposed a hybrid deep learning architecture for temperature and rainfall forecasting, highlighting the strength of LSTM in temporal modeling. Similarly, Sharma (2023) reviewed LSTM-based forecasting applications and concluded that LSTM consistently achieves superior accuracy compared to traditional machine learning models.

On the other hand, RBF networks have also been studied extensively. Veeramsetty (2023) demonstrated that RBF neural networks provide fast and reliable short-term predictions for temperature and humidity in semi-arid regions. Studies such as Abumohsen (2024) further confirmed that RBF-based hybrid systems can enhance forecasting performance when combined with deep learning architectures.

Recent advancements in hybrid and ensemble models, such as decomposition-based deep learning frameworks (Zouaidia et al., 2023) and optimized models for wind forecasting (Yang, 2024), indicate that no single model is universally optimal. Instead, the research trend is shifting toward integrated systems that combine physics-based NWP with machine learning techniques.

METHODOLOGY

The methodology for evaluating LSTM and RBF models in weather prediction typically includes using publicly available time-series datasets from agencies such as NOAA (USA) and IMD (India). The data often consists of variables including daily temperature, humidity, wind speed, pressure, and rainfall.

Preprocessing steps usually involve missing-value treatment, normalization, and conversion of continuous weather data into supervised time-series formats. The LSTM model is typically implemented with stacked layers, a time window input, dropout regularization, the Adam optimizer, and Mean Squared Error (MSE) as the loss function [9].

The RBF network is commonly implemented with three components: a radial basis hidden layer, center selection via K-means clustering, and linear output weights determined by least-squares optimization [6]. Performance is evaluated using MAE, RMSE, and R^2 metrics[2].

RESULTS AND DISCUSSION

The reviewed studies consistently indicate that LSTM models outperform RBFN models, particularly in time-series–based weather prediction. LSTM networks demonstrate superior accuracy due to their inherent ability to capture long-term temporal dependencies and nonlinear patterns in meteorological data. Performance metrics such as RMSE, MAE are generally lower for LSTM-based models, especially in medium- to long-term forecasting scenarios[5].

In contrast, RBFN models show competitive performance in short-term forecasting, where relationships between inputs and outputs are relatively stable. RBFNs perform well when the data distribution is smooth and less volatile, but their accuracy tends to degrade when the time series exhibits strong seasonality or abrupt climatic variations[4].

A significant advantage of LSTM lies in its memory cells and gating mechanisms, which enable it to retain and selectively update historical information. This makes LSTM particularly effective for weather datasets that exhibit seasonal cycles, trends, and delayed effects, such as monsoon rainfall or temperature persistence[10].

RBFNs, being feedforward networks, lack an internal memory mechanism. As a result, they rely heavily on feature engineering and lagged input selection to model temporal relationships. This limitation reduces their effectiveness in capturing complex long-term dependencies inherent in atmospheric processes[1].

From a computational perspective, RBFNs are simpler and faster to train compared to LSTMs. They require fewer hyperparameters and converge quickly, making them suitable for applications with limited computational resources or real-time short-horizon forecasting[2].

LSTM models, while more accurate, involve higher computational cost, longer training times, and careful hyperparameter tuning. However, with the availability of modern GPUs and optimized deep learning frameworks, this limitation is becoming less restrictive in practical applications[9].

LSTM-based models exhibit better generalization capability when trained on large and diverse datasets, including multivariate inputs from multiple meteorological parameters. They are also more robust to noisy and incomplete data[9].

RBFNs are sensitive to the selection of centers and spread parameters. Improper tuning can lead to overfitting or poor generalization, especially when applied to highly dynamic weather systems[6].

CONCLUSION

This study concludes that LSTM networks provide superior accuracy for time-series weather forecasting due to their ability to model long-term dependencies. In contrast, RBF networks remain valuable for rapid, short-term forecasting tasks. Given the strengths and limitations of each model, hybrid architectures—integrating LSTM with CNN or RBF components—represent a promising direction for future research.

As climate variability continues to increase, the combination of deep learning and traditional NWP models will become essential for achieving high-precision weather forecasting across diverse geographical regions. Continued research is needed to incorporate real-time data streams, address data quality issues, and develop adaptive models capable of learning from evolving weather patterns.

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