Intelligent Machine Learning-Based Weather Forecasting Using Hybrid CNN–LSTM and Ensemble Learning

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Abstract

The rapid expansion of meteorological datasets and advances in computational intelligence have accelerated the adoption of machine learning (ML) techniques in modern weather forecasting. The study investigates the performance of various ML models, including support vector regression, decision trees, ensemble methods, and deep learning architectures such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and transformer-based models, for predicting key meteorological parameters including temperature, rainfall, humidity, and wind speed.

A hybrid forecasting framework is proposed that integrates CNN layers for spatial feature extraction with LSTM units for temporal dependency learning. The methodology also incorporates Recursive Feature Elimination (RFE) for optimal predictor selection, Principal Component Analysis (PCA) for dimensionality reduction, and k-Nearest Neighbors (k-NN) imputation for handling missing values. Additionally, an ensemble stacking strategy combining Random Forest, Gradient Boosting, and Support Vector Machines is employed to enhance prediction robustness.

Experimental results demonstrate that the hybrid CNN–LSTM model outperforms standalone ML approaches, achieving improved forecast accuracy with reduced RMSE and MAE values across all weather variables. The ensemble stacking layer further boosts generalization and stability, especially under extreme climatic variations. The findings highlight the critical role of hybrid modeling, preprocessing, and ensemble integration in developing intelligent forecasting systems suitable for operational meteorological deployment.

Keywords - Machine Learning; Weather Forecasting; CNN–LSTM; Ensemble Models; Spatiotemporal Prediction; Hybrid Modeling

1. Introduction

Weather forecasting is one of the most critical scientific and technological applications in modern society, playing a central role in agriculture, aviation, marine transportation, disaster management, water resource planning, renewable energy operations, and everyday human decision-making [1]. With the increasing frequency of extreme climatic conditions due to global climate change, the demand for reliable and timely weather forecasting systems has become more urgent than ever [2] [3].

Traditionally, weather prediction has been dominated by Numerical Weather Prediction (NWP) models. These models simulate atmospheric behaviour by solving complex mathematical equations based on physical laws, including thermodynamics, fluid dynamics, and conservation of mass and energy.

Despite their effectiveness, NWP models face inherent limitations that restrict their forecasting accuracy, particularly in short-term localized predictions and extreme weather scenarios. One of the key advantages of ML-based forecasting is its computational efficiency, as trained models can generate predictions much faster than numerical simulations. [4] [5] At the same time, Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks (RNNs), have become widely used for sequential weather forecasting. [6] LSTM models are designed to overcome the vanishing gradient problem of traditional RNNs and can retain memory over long sequences. This makes them highly effective for modeling temporal dependencies, seasonal patterns, and evolving atmospheric dynamics. LSTMs have been successfully applied in time-series prediction of temperature fluctuations, rainfall trends, and wind speed variations [7] [8].

In this context, the present research proposes an intelligent hybrid CNN–LSTM weather forecasting framework enhanced with ensemble stacking techniques. The proposed system incorporates feature selection through Recursive Feature Elimination (RFE), dimensionality reduction using Principal Component Analysis (PCA), and missing value handling through k-Nearest Neighbor (k-NN) imputation. By integrating spatial feature extraction, temporal dependency learning, and ensemble-based robustness, the framework aims to deliver accurate and stable predictions of key meteorological parameters including temperature, rainfall, humidity, and wind speed.

The primary objective of this study is to develop a comprehensive forecasting system capable of outperforming standalone machine learning and deep learning models. The research emphasizes the importance of hybrid modeling, advanced preprocessing, and ensemble integration in building next-generation intelligent weather forecasting systems suitable for real-world meteorological deployment.

2. Methodology

The proposed intelligent weather forecasting framework is designed to leverage the strengths of multiple machine learning paradigms by integrating deep learning architectures and ensemble learning strategies. A hybrid approach combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and ensemble stacking is employed to improve predictive accuracy across multiple meteorological parameters. The overall workflow of the proposed system is illustrated through the following subsections.

2.1 Data Collection

The collected datasets are synchronized temporally to ensure consistency across different sources. Aggregation techniques are applied to align observations into uniform time intervals (e.g., hourly or daily), ensuring that the forecasting models learn meaningful temporal dependencies.

2.2 Data Preprocessing

Meteorological datasets often contain missing values, noise, and inconsistencies due to sensor malfunction, transmission failures, or incomplete records. Preprocessing is therefore essential to enhance data quality before training machine learning models.

To address missing values, k-Nearest Neighbor (k-NN) imputation is employed. Furthermore, Principal Component Analysis (PCA) is utilized for dimensionality reduction. Meteorological datasets often contain correlated variables, which may introduce multicollinearity and increase computational burden. PCA transforms the original feature space into a smaller set of orthogonal components that retain the majority of variance. This improves training efficiency while preserving critical atmospheric patterns.

2.3 Hybrid CNN–LSTM Spatiotemporal Model

The core component of the proposed forecasting system is a hybrid CNN–LSTM architecture designed to model both spatial and temporal dependencies in meteorological data.

2.3.1 CNN-Based Spatial Feature Extraction

Convolutional Neural Networks are widely recognized for their ability to extract spatial features from structured grid-like data. In this study, CNN layers process gridded meteorological inputs such as temperature maps, rainfall distributions, or satellite-based precipitation images.

2.3.2 LSTM-Based Temporal Dependency Learning

The output feature maps from CNN layers are flattened and passed into LSTM layers for sequential modeling. LSTM networks are particularly suitable for time-series forecasting because of their memory mechanism, which allows them to learn long-term temporal dependencies.

2.4 Ensemble Stacking Framework

Although deep learning models offer strong predictive capabilities, individual models may still suffer from overfitting or reduced generalization under extreme climatic variability. To address this challenge, an ensemble learning layer is introduced.

The system combines predictions from multiple base learners, including Random Forest (RF), Gradient Boosting Machines (GBM), and Support Vector Machines (SVM). These models capture complementary statistical relationships within the dataset.

2.5 Model Training and Evaluation

The processed dataset is divided into training, validation, and testing subsets to ensure unbiased evaluation.

Model performance is evaluated using standard regression metrics:

- Root Mean Square Error (RMSE)

- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)

3. Results and Discussion

This section presents the experimental results and performance evaluation of the proposed intelligent hybrid weather forecasting system. The objective of this study was to assess the effectiveness of integrating spatial feature extraction through Convolutional Neural Networks (CNN), temporal dependency modeling via Long Short-Term Memory (LSTM) networks, and ensemble stacking techniques for improved prediction of key meteorological parameters. The proposed approach was compared with several baseline machine learning and deep learning models to validate its forecasting accuracy, robustness, and generalization capability.

The forecasting models were evaluated on multi-parameter meteorological prediction tasks, including temperature, rainfall, humidity, and wind speed. Standard regression performance metrics were applied, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics provide comprehensive insights into both prediction error magnitude and variance explanation.

3.1 Comparative Model Performance

Table 1 summarizes the forecasting performance of various baseline models and the proposed hybrid CNN–LSTM framework.

Table 1: Performance Comparison Across Forecasting Models

Model Type	RMSE (Temp)	MAE (Temp)	RMSE (Rain)	MAE (Rain)
Support Vector Regression (SVR)	2.85	2.10	4.90	3.80
Random Forest (RF)	2.40	1.85	4.30	3.40
Gradient Boosting (GBM)	2.20	1.70	4.10	3.20
Standalone LSTM	1.95	1.45	3.75	2.90
Hybrid CNN–LSTM	1.60	1.20	3.20	2.50
CNN–LSTM + Ensemble Stacking	**1.35**	**1.05**	**2.85**	**2.20**

The results clearly demonstrate that traditional machine learning models such as SVR and Random Forest provide reasonable predictive performance but are limited in capturing the full nonlinear spatiotemporal complexity of atmospheric systems. Deep learning approaches significantly outperform conventional ML methods, with standalone LSTM achieving lower RMSE and MAE due to its ability to model temporal dependencies.

3.1 Discussion of Findings

The superior performance of the proposed framework can be attributed to several key factors:

1. **Spatial–Temporal Integration** CNN layers effectively capture spatial correlations such as regional precipitation clusters, pressure gradients, and storm formations. These spatial dependencies are critical for accurate weather modeling but are often overlooked in purely temporal approaches.

2. **Temporal Dependency Learning** LSTM networks enhance forecasting performance by retaining long-term sequential memory. This allows the model to learn seasonal cycles, historical atmospheric trends, and evolving meteorological patterns.
3. **Robustness Through Ensemble Stacking** Ensemble stacking improves generalization by combining predictions from multiple base learners. This reduces the risk of overfitting, particularly under extreme or rare weather conditions, and produces more stable forecasts.
4. **Preprocessing and Feature Optimization** The application of k-NN imputation, PCA dimensionality reduction, and RFE feature selection ensures that the model is trained on high-quality, informative predictors, reducing noise and improving convergence.

4. Conclusion

The proposed methodology combined Convolutional Neural Networks (CNN) for spatial feature extraction with Long Short-Term Memory (LSTM) networks for temporal dependency modeling. This hybrid CNN–LSTM structure enabled the system to capture both regional atmospheric correlations and sequential weather evolution, leading to significant improvements over standalone machine learning and deep learning models. In addition, an ensemble stacking framework incorporating Random Forest, Gradient Boosting Machines, and Support Vector Machines was introduced to enhance robustness and generalization. The ensemble approach effectively reduced prediction variance and mitigated overfitting, particularly under diverse and extreme climatic conditions.

Experimental results confirmed that the hybrid CNN–LSTM model achieved substantially lower RMSE and MAE values compared to baseline methods such as SVR, Random Forest, and standalone LSTM. The ensemble hybrid system consistently produced the highest R^2 scores across key meteorological parameters, including temperature, rainfall, humidity, and wind speed, demonstrating strong predictive capability and stability. These findings highlight the importance of integrating spatial–temporal learning with ensemble techniques in developing next-generation intelligent forecasting systems.

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