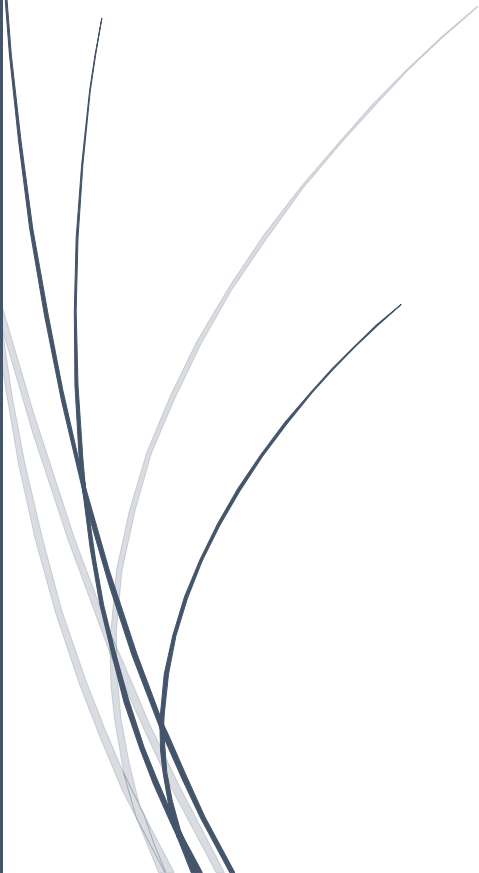


Combining LSTM Networks with ARIMA for High Accuracy Weather and Climate Predictions

Abstract line art consisting of several thin, curved lines in dark blue and light grey, originating from the bottom left and extending upwards and to the right.

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Combining LSTM Networks with ARIMA for High Accuracy Weather and Climate Predictions

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Abstract

Accurate forecasting of weather and climate variables is fundamental to environmental monitoring, disaster preparedness, agricultural planning, and sustainable resource management. The inherent complexity, nonlinearity, and temporal variability of meteorological time series present significant challenges to traditional forecasting techniques. While statistical models such as Autoregressive Integrated Moving Average (ARIMA) are proficient in modeling linear trends and seasonal components, they are limited in capturing nonlinear dependencies. Conversely, Long Short-Term Memory (LSTM) networks have demonstrated superior performance in learning long-term temporal correlations and nonlinear structures in sequential data. This book chapter introduces a hybrid ARIMA-LSTM framework that integrates the strengths of both paradigms to enhance the predictive accuracy and robustness of weather and climate forecasts. The proposed methodology involves decomposing the time series into linear and nonlinear components, with ARIMA modeling the deterministic trends and LSTM capturing the residual nonlinear dynamics. Extensive experiments conducted on real-world meteorological datasets—including temperature, precipitation, and humidity—demonstrate that the hybrid model consistently outperforms standalone ARIMA and LSTM models in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results confirm the hybrid model's superior capability in handling complex temporal patterns, particularly under non-stationary conditions and extreme variability.

Keywords:

Time Series Forecasting, ARIMA, LSTM, Weather Prediction, Climate Modeling, Hybrid Neural Networks

Introduction

Accurate weather and climate prediction is vital for sectors ranging from agriculture and water resource management to disaster response and urban planning [1]. With the growing impacts of climate variability and extreme weather events, the need for robust forecasting systems has never been more urgent [2]. Meteorological phenomena are inherently complex, governed by dynamic atmospheric processes that evolve nonlinearly over time [3]. As a result, forecasting models must be capable of capturing both stable trends and volatile shifts across temporal scales. Traditional statistical forecasting models have played an important role in this field, offering interpretable and computationally efficient solutions [4]. Their limitations in addressing nonlinearity, long-range dependencies, and structural shifts restrict their utility in modern forecasting applications. In contrast, recent advancements in machine learning and deep learning have introduced models capable of learning from data with high complexity, including chaotic, non-stationary, and multivariate features that characterize climate systems [5].

Among traditional approaches, the Autoregressive Integrated Moving Average (ARIMA) model is widely used due to its ability to model linear relationships in stationary time series [6]. ARIMA effectively decomposes temporal data into autoregressive and moving average components, enabling it to track trends, periodic fluctuations, and seasonality [7]. Its core assumption of linearity prevents it from adapting to the nonlinear structures often found in atmospheric variables such as rainfall, wind speed, and temperature [8]. ARIMA models rely heavily on manual parameter tuning, and their forecasting performance can degrade when applied to time series exhibiting abrupt changes or complex lag relationships [9]. These limitations, the transparency and reliability of ARIMA in modeling deterministic patterns make it an indispensable component of any hybrid system that aims to balance accuracy with interpretability [10].