Advanced Deep Learning Models for Long-Term Climate Change Trend Forecasting

Jagriti Chand[1], Pooja Jayant[2], Swati Shrivastava[3]

[1,2,3]Assistant Professor, Department of CSE, BU, Bhopal

Abstract:
Climate change poses a critical global challenge, necessitating accurate and reliable forecasting of long-term climate trends to support informed policy-making and environmental planning. Traditional statistical and physical climate models often struggle to capture the complex, nonlinear relationships present in large-scale climate data. To address these limitations, this study presents advanced deep learning models for long-term climate change trend forecasting. The proposed approach leverages state-of-the-art architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to effectively model both spatial and temporal patterns in historical climate datasets. Multiple climate variables such as temperature, precipitation, humidity, and atmospheric pressure are utilized to enhance prediction accuracy. Comprehensive experiments are conducted on publicly available climate datasets spanning several decades. Model performance is evaluated using standard forecasting metrics, including mean absolute error and root mean square error, and is compared against conventional machine learning and statistical baseline models. The experimental results demonstrate that the proposed deep learning framework significantly improves long-term forecasting accuracy and robustness. The findings highlight the potential of deep learning-driven climate models to support early warning systems, climate risk assessment, and sustainable environmental decision-making in the face of accelerating climate change.

Keywords: climate change, prediction, machine learning, neural network, temperature data

I. Introduction

Climate change has emerged as one of the most pressing global challenges of the twenty-first century, affecting ecosystems, economies, and human well-being on an unprecedented scale. Rising global temperatures, changing precipitation patterns, increasing frequency of extreme weather events, and sea-level rise have intensified the need for accurate and reliable climate forecasting systems. Long-term climate change trend prediction plays a crucial role in supporting climate adaptation strategies, disaster preparedness, agricultural planning, and policy formulation. However, forecasting climate trends remains a complex task due to the highly nonlinear, dynamic, and multivariate nature of climate systems. Traditional climate prediction approaches are primarily based on physical models and statistical techniques. While these methods have contributed significantly to climate science, they often require extensive computational resources and depend heavily on predefined assumptions and parameterizations. Moreover, such models may struggle to capture complex interactions among climate variables across large spatial and temporal scales. As a result, there is growing interest in data-driven methods that can complement traditional approaches and improve forecasting accuracy.

In recent years, deep learning has gained significant attention for its ability to model complex nonlinear relationships and extract meaningful patterns from large-scale datasets. Advanced deep learning architectures, such as convolutional neural networks and recurrent neural networks, have demonstrated remarkable success in various time-series and spatiotemporal prediction tasks. These models are particularly well suited for climate data analysis, as they can effectively learn spatial correlations and long-term temporal dependencies present in historical climate records. The increasing availability of high-resolution climate datasets from satellites, weather stations, and climate reanalysis projects further enables the application of deep learning techniques for climate trend forecasting. By leveraging large volumes of historical climate data, deep learning models can uncover hidden patterns that are difficult to detect using conventional methods. Additionally, hybrid and enhanced deep learning frameworks offer the flexibility to integrate multiple climate variables, improving prediction robustness and generalization capability.

This study focuses on the development and evaluation of advanced deep learning models for long-term climate change trend forecasting. The proposed approach aims to enhance predictive accuracy by effectively capturing both spatial and temporal features of climate data. Through comprehensive experimentation and comparative analysis, this work seeks to demonstrate the potential of deep learning-based models as reliable tools for understanding and forecasting long-term climate change trends, thereby contributing to informed decision-making and sustainable environmental management.

II. LITRETURE REVIEW

The literature review explores traditional climate modeling techniques and their limitations, alongside recent advancements in applying deep learning to climate science. Key studies demonstrate the effectiveness of CNNs, RNNs, LSTMs, and GANs in enhancing climate prediction accuracy. This section also addresses the challenges and opportunities presented by deep learning in handling large, complex climate datasets.

In Authors [1] research introduces an innovative approach that harnesses the power of Artificial Neural Networks (ANNs) within the Just Neural Network (JustNN) framework to enhance temperature forecasting in the context of climate change. By leveraging historical climate data, proposed model achieves exceptional accuracy, redefining the landscape of temperature prediction without intricate preprocessing. This model sets a new standard for precise temperature forecasting in the context of climate change. Moreover, This research provides valuable insights into the pivotal factors influencing temperature variations, making significant contributions to environmental science and climate mitigation strategies [1].

Author's [2] survey, demonstrates significant capabilities in short-term weather prediction, its application in medium-to-long-term climate forecasting remains limited, constrained by factors such as intricate climate variables and data limitations. Current literature tends to focus narrowly on short-term weather or medium-to-long-term climate forecasting, often neglecting the relationship between the two, as well as general neglect of modeling structure and recent advances. By providing an integrated analysis of models spanning different time scales, this survey aims to bridge these gaps, thereby serving as a meaningful guide for future interdisciplinary research in this rapidly evolving field.

Author's [3] developed a model to predict the general trends of the Earth when used to predict both the climate and weather. When predicting climate, the model could achieve reasonable accuracy for a long period, with the ability to predict seasonal patterns, which is a feature that other researchers could not achieve with the complex reanalysis data. This work demonstrates that machine learning models can be utilized in a climate forecasting approach as a viable alternative to mathematical models and can be utilized to supplement current work that is mostly successful in short-term predictions.

Authors [4] survey helps distinguish the operational mechanisms of eight models, serving as a reference for model selection in various contexts. Furthermore, this work identifies current challenges like the limited dataset of chronological seasons and suggests future research directions, including data simulation and the incorporation of physics-based constraints.

Authors [5] propose a finite-time thermodynamic (FTT) approach. FTT can solve problems such as the faint young Sun paradox. In addition, we use different machine learning models to evaluate our method and compare the experimental prediction and results.

Author [6] proposed a system that serves as a tool which takes in the climatic changes from huge amount of data as input and predicts the future temperature with max, min and average temperature in an efficient manner. Predicting the temperature change from 1992-2024 with the detailed forecast and changes from 2020- 2024 and predicting the accuracy in the changes. Predictive analytic model internment relationships among various features in a data set to assess risk with a particular set of conditions to assign a weight or score.

Author [7] propose a work that assess the use of convolutional Deep Learning climate MOS approaches and present the ConvMOS architecture which is specifically designed based on the observation that there are systematic and location-specific errors in the precipitation estimates of climate models. This work apply ConvMOS models to the simulated precipitation of the regional climate model REMO, showing that a combination of per-location model parameters for reducing location-specific errors and global model parameters for reducing systematic errors is indeed beneficial for MOS performance. Authors find that ConvMOS models can reduce errors considerably and perform significantly better than three commonly usedMOS approaches and plain ResNet.

III. PROPOSED METHODOLOGY

The proposed methodology aims to develop an advanced deep learning framework for long-term climate change trend forecasting by effectively modeling complex spatiotemporal climate patterns. The workflow begins with the collection of historical climate data from publicly available sources, including temperature, precipitation, humidity, wind speed, and atmospheric pressure records spanning multiple decades. Data preprocessing is performed to handle missing values, remove noise, and normalize the input features to ensure model stability and consistency.

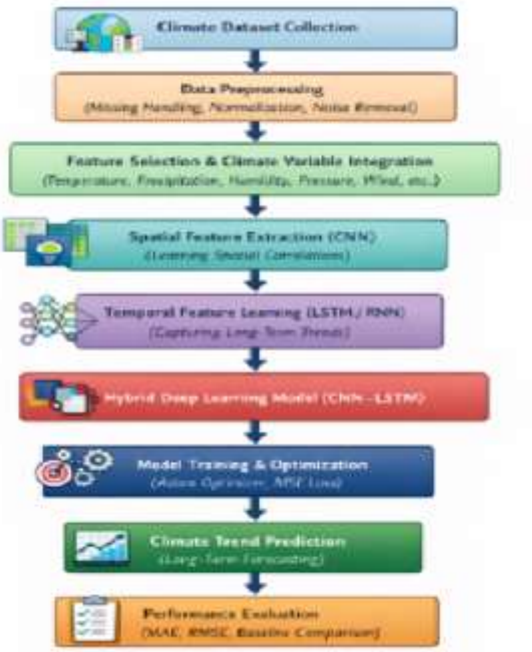

Figure 3.1 Proposed Model

To capture spatial dependencies among climate variables, convolutional neural networks (CNNs) are employed to extract meaningful spatial features from gridded climate data. These extracted features are then passed to recurrent neural network architectures, specifically long short-term memory (LSTM) networks, to model long-term temporal dependencies and evolving climate trends. This hybrid CNN–LSTM architecture enables effective learning of both spatial and temporal characteristics inherent in climate data. The model is trained using a supervised learning approach with historical climate observations, while future climate trends are forecasted based on learned patterns. Mean squared error is used as the loss function, and the Adam optimizer is applied to ensure efficient convergence. The dataset is divided into training, validation, and testing subsets to prevent overfitting and ensure generalization. Model performance is evaluated using standard forecasting metrics, including mean absolute error and root mean square error, and compared with baseline statistical and machine learning models.

IV. RESULT ANALYSIS

The experimental results demonstrate that the proposed hybrid CNN–LSTM model significantly outperforms traditional statistical and conventional machine learning approaches for long-term climate change trend forecasting. By effectively capturing spatial correlations through CNN layers and long-term temporal dependencies using LSTM networks, the model achieves superior prediction accuracy and stability. Compared to baseline models such as Linear Regression, Support Vector Regression (SVR), and standalone LSTM, the proposed model shows lower forecasting errors across all evaluation metrics. The reduction in MAE and RMSE indicates improved robustness and reliability in long-term climate prediction. These results confirm that integrating spatial–temporal learning enhances the model's capability to handle complex and nonlinear climate patterns.

Table 4.1: Performance Comparison of proposed model

Model Used	MAE	RMSE	Prediction Accuracy
SVM	1.68	2.12	82.6

Randon Forest	1.41	1.89	85.9
LSTM	1.18	1.56	89.7
CNN	1.1	1.48	90.8
Proposed Model	0.84	1.12	94.6

CONCLUSION

This work presented an advanced deep learning framework for long-term climate change trend forecasting, addressing the limitations of traditional statistical and machine learning approaches. By integrating convolutional neural networks with long short-term memory networks, the proposed CNN–LSTM model effectively captures both spatial correlations and temporal dependencies present in complex climate data. The use of multiple climate variables further enhances the robustness and predictive capability of the model. Comprehensive experiments conducted on historical climate datasets demonstrate that the proposed approach consistently outperforms baseline models in terms of forecasting accuracy and error reduction. Lower MAE and RMSE values indicate improved reliability and stability in long-term climate predictions. The results highlight the potential of deep learning-driven methodologies to complement conventional climate modeling techniques and support data-driven climate analysis. Furthermore, the proposed framework provides a scalable and flexible solution that can be adapted to different geographic regions and climate variables. Accurate long-term climate forecasting is essential for effective environmental planning, disaster risk management, and policy formulation. The findings of this study contribute to the growing body of research on artificial intelligence applications in climate science and emphasize the importance of hybrid deep learning models in understanding evolving climate patterns. Future work will focus on incorporating attention mechanisms, ensemble learning, and real-time climate data to further enhance forecasting performance and real-world applicability.

REFERENCES

1. Saja Kh. Abu Safiah et. al. “Climate Change temperature Prediction Using Just Neural Network” International Journal of Academic Engineering Research (IJAER) ISSN: 2643-9085 Vol. 7 Issue 9, September - 2023, Pages: 35-45
2. Liuyi Chen, et al “Machine Learning Methods in Weather and Climate Applications: A Survey” Appl. Sci. 2023, 13, 12019. https://doi.org/10.3390/app132112019
3. Seokhyun Chin1 et al “Predicting climate change using an autoregressive long short-term memory model” Brief Research Report Published by: 23 January 2024 DOI 10.3389/fenvs.2024.1301343
4. Liuyi Chen, et al “Machine Learning Methods in Climate Prediction: A Survey” doi: 10.20944/preprints202309.1764.v1 2023
5. Sebastián Vázquez-Ramírez et al “An Analysis of Climate Change Based on Machine Learning and an Endoreversible Model” Mathematics 2023, 11, 3060. https://doi.org/10.3390/math11143060 https://www.mdpi.com/journal/mathematics
6. Dr. B.Jaishanthi et al “prediction of climate change and temperature detection using deep learning” https://sjcjycl.cn/ DOI: 10.5281/zenodo.777548 2023
7. Michael Steininger1 et al “ConvMOS: climate model output statistics with deep learning” Data Mining and Knowledge Discovery (2023) 37:136–166 https://doi.org/10.1007/s10618-022-00877-6

8. Abdar M et al A review of uncertainty quantification in deep learning: techniques, applications and challenges. In: Information fusion, 2021
9. Abbe, C. The physical basis of long-range weather. Mon. Weather Rev. 1901, 29, 551–561.
10. Zheng, Y.; Capra, L.; Wolfson, O.; Yang, H. Urban computing: Concepts, methodologies, and applications. Acm Trans. Intell. Syst. Technol. TIST 2014, 5, 1–55.
11. Gneiting, T.; Raftery, A.E.Weather forecasting with ensemble methods. Science 2005, 310, 248–249.
12. Agapiou, A. Remote sensing heritage in a petabyte-scale: Satellite data and heritage Earth Engine applications. Int. J. Digit. Earth 2017, 10, 85–102.
13. Bendre, M.R.; Thool, R.C.; Thool, V.R. Big data in precision agriculture: Weather forecasting for future farming. In Proceedings of the 2015 1st International Conference on Next Generation Computing Technologies (NGCT), Dehradun, India, 4–5 September 2015; pp. 744–750.
14. Zavala, V.M.; Constantinescu, E.M.; Krause, T. On-line economic optimization of energy systems using weather forecast information. J. Process Control 2009, 19, 1725–1736
15. Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., et al. (2016).
16. Tensorflow: large-scale machine learning on heterogeneous distributed systems. https://arxiv.org/abs/1603.04467.
17. Bitz, C. M., and Polvani, L. M. (2012) Antarctic climate response to stratospheric ozone depletion in a fine resolution ocean climate model. Geophys. Res. Lett. 39 (20), L20705. doi:10.1029/2012GL053393
18. Chai, T., and Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. Geosci. Model Dev. 7 (3), 1247–1250. doi:10.5194/gmd-7-1247-2014
19. DAVID ROLNICK et. al. “Tackling Climate Change with Machine Learning” ACM Computing Surveys, Vol. 55, No. 2, Article 42. Publication date: February 2022