© June 2025 | IJIRT | Volume 12 Issue 1| ISSN: 2349-6002

A Review on Deep Learning Models for Predicting Climate Change Trends

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***Abstract*—Accurate climate change prediction is essential for anticipating and mitigating the adverse effects of global warming. While traditional climate modeling approaches offer foundational insights, they often face limitations when dealing with the high dimensionality and complexity of climate data. In recent years, deep learning has gained prominence as a transformative approach for modeling climate dynamics, owing to its capacity to process large-scale datasets and uncover complex, non-linear patterns. This review explores the application of various deep learning architectures—including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GANs)—in forecasting climate change trends. We analyze their effectiveness, data dependencies, and adaptability to different climate variables such as temperature, rainfall, and extreme weather phenomena. Additionally, the review highlights key challenges in deploying deep learning for climate modeling, including issues related to data quality, interpretability, and computational scalability. The objective is to synthesize current progress in this field and outline promising research directions to enhance the precision, robustness, and practical applicability of deep learning models in climate science.**

***Index Terms*—climate change, prediction, machine learning, neural network, temperature data**

I INTRODUCTION

Federated Climate change is one of the most pressing issues facing humanity today, with far-reaching impacts on ecosystems, weather patterns, and socio-economic systems. Accurate prediction of climate trends is essential for developing effective mitigation and adaptation strategies. Traditional climate models, such as General Circulation Models (GCMs), rely on physical and mathematical representations of the Earth's climate system. While these models are sophisticated and have been instrumental in understanding climate dynamics, they often face challenges in handling the complexity and vastness of climate data, leading to limitations in their predictive capabilities. In recent years, deep learning has emerged as a revolutionary tool in the field of data science, offering powerful methods for analyzing large and complex datasets. Deep learning models, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GANs), have shown remarkable success in various domains such as image recognition, natural language processing, and autonomous driving. These models excel at capturing intricate patterns and dependencies in data, making them promising candidates for climate change prediction.

This review aims to evaluate the application of deep learning models in predicting climate change trends. We will explore the different types of deep learning architectures used in climate science, assess their performance and data requirements, and discuss their suitability for predicting various climate variables, including temperature, precipitation, and extreme weather events. Additionally, we will address the challenges and limitations associated with these models, such as data quality, interpretability, and computational demands. By providing a comprehensive overview of the current state of deep learning in climate change prediction, this review seeks to highlight the potential of these advanced techniques to improve our understanding and forecasting of climate trends. We will also identify future research directions to enhance the accuracy and reliability of deep learning models in this critical field.

Climate change prediction is vital for anticipating environmental impacts and guiding effective mitigation strategies. Traditional models often struggle with the complexity and volume of climate data. Deep learning has emerged as a powerful alternative, capable of capturing intricate spatial and temporal patterns. This study explores the application of deep learning models—including CNNs, LSTMs, RNNs, and GANs—for forecasting climate trends. It also addresses the challenges of data quality, interpretability, and computational demands, aiming to enhance predictive accuracy in climate science.

II REVIEW SCOPE AND OBJECTIVES:

This survey aims to comprehensively evaluate the efficacy and accuracy of deep learning models in predicting climate change trends. it will cover a broad spectrum of models, including convolutional neural networks (cnns), recurrent neural networks (rnns), long short-term memory networks (lstms), and generative adversarial networks (gans). the review will assess their performance based on criteria such as prediction accuracy, computational efficiency, and scalability. additionally, it will examine the datasets used, feature extraction methods, and evaluation metrics. the survey will also identify key challenges and limitations in the current models, highlighting areas for future research. by synthesizing findings from various studies, this review aims to provide insights into the state-of-the-art in deep learning applications for climate trend prediction and inform the development of more robust predictive models.

III 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.

Authors [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] proposes 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 applies 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.

IV FINDINGS OF THE SURVEY

The survey reveals significant advancements and challenges in using deep learning models for predicting climate change trends.
Model Performance: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated considerable success in capturing spatial and temporal patterns in climate data. Long Short-Term Memory networks (LSTMs) are particularly effective in handling time-series data, while Generative Adversarial Networks (GANs) show promise in simulating future climate scenarios with high fidelity.
Datasets and Data Quality: The quality and quantity of datasets play a crucial role in model performance. High-resolution climate datasets, such as those from satellite observations and reanalysis projects, have significantly enhanced model accuracy. However, issues like data sparsity and inconsistencies remain prevalent, impacting the reliability of predictions.
Feature Extraction and Engineering: Effective feature extraction and engineering are vital for improving model performance. Techniques such as dimensionality reduction and data augmentation have been employed to enhance the predictive capabilities of deep learning models. However, the complexity of climate systems necessitates further advancements in this area.
Evaluation Metrics: Standardized evaluation metrics are essential for comparing model performance. Metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and correlation coefficients are commonly used. However, there is a need for more comprehensive metrics that can capture the multifaceted nature of climate predictions.
Challenges and Limitations: Key challenges include the high computational cost of training deep learning models and the interpretability of complex models. Additionally, the inherent uncertainty in climate projections and the need for integrating domain knowledge into model development are significant hurdles.
Future Directions: The survey highlights the importance of developing hybrid models that combine the strengths of different deep learning approaches. It also underscores the potential of incorporating physics-based models and enhancing model interpretability to improve the robustness and reliability of climate predictions.
This survey provides a roadmap for future research and development in the application of deep learning to climate change prediction.

V CONCLUSION

This review underscores the growing potential of deep learning models in forecasting climate change trends, emphasizing their capability to manage complex, high-dimensional datasets with improved predictive accuracy. Advanced architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GANs) have demonstrated considerable promise in capturing the non-linear dependencies and intricate temporal-spatial patterns characteristic of climate systems. While traditional climate models continue to offer valuable insights, deep learning approaches provide a powerful alternative that complements and enhances existing methodologies. However, the application of deep learning in climate science is not without challenges. Key limitations include issues related to data availability and quality, high computational requirements, and the often-opaque nature of model interpretability. Furthermore, uncertainties inherent in long-term climate prediction and the complexity of environmental interactions pose additional barriers. As such, future research must prioritize the development of hybrid architectures, the incorporation of physical domain knowledge into model design, and the enhancement of interpretability and evaluation frameworks. Addressing these challenges will be crucial for fully harnessing the capabilities of deep learning in climate modeling. With continued innovation, deep learning can play a transformative role in supporting more accurate and actionable climate forecasts, ultimately informing effective policy-making, adaptation strategies, and global efforts to mitigate the impacts of climate change.

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] [14] Zavala, V.M.; Constantinescu, E.M.; Krause, T. On-line economic optimization of energy systems using weather forecas 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