Review of International Geographical Education | RIGEO | 2020

RIGEO

ISSN: 2146 - 0353

Review of International GEOGRAPHICAL EDUCATION

www.rigeo.org

Investigations on Predicting Global Climate Change using Machine Learning Models

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Abstract

Historically, climate prediction models have simulated the dynamics of the climate system by using intricate physical equations; however, these models frequently need large computer resources and lengthy calculation times. Machine learning approaches have demonstrated significant promise for pattern detection and prediction in recent years. In particular, machine learning models' benefits in handling massive datasets have made them a popular area of study in the field of climate science. In this work, we present a convolutional neural network-based (CNN) model that can process and analyse multi-dimensional climatic data, such as temperature, air pressure, humidity, and CO2 concentration, from large-scale satellite datasets. Historical climate data is used as the input. The convolutional layer extracts the spatial features, while the fully connected layer performs feature fusion and produces the final forecast output. Last but not least, we trained the model using historical climate data collected across a variety of time periods. The findings demonstrate that CNN-based models outperform traditional physical models in terms of accuracy and prediction errors when it comes to forecasting changes in the world's average temperature, precipitation, and extreme weather occurrences.

1 Introduction

The term "climate change" is defined differently by various organisations and scholars. Climate change is defined by climatologists as statistically significant variations in the mean global or local climate brought on by natural or man-made sources [1]. Thus, the term "climate change" refers to variations in the average climate state brought on by a variety of natural external forcing factors as well as internal low-frequency oscillations of the climate system and its statistics over a range of time scales. It also includes variations in the global and local climate states brought on by direct or indirect changes in the composition of the atmosphere brought on by human activity.

Global climate change refers to long-term and significant changes in meteorological factors such as temperature, precipitation, wind speed and wind direction in the earth's climate system on a global scale. This change spans decades or even millions of time scales and involves multiple systems on Earth, including the atmosphere, oceans, glaciers, terrestrial ecosystems, and human societies. At present, global climate change has become one of the most pressing environmental issues facing the world today, and its impact is extensive and farreaching, covering changes in the natural environment, biodiversity loss, the increase of extreme weather events, and various challenges to global economic and social development.

Global climate change prediction is a highly complex and interdisciplinary research field, and the use of machine learning models to predict climate change has become a research hotspot in recent years. Research on the impact of climate change began in the late 70s of the 20th century, and was jointly promoted by international organizations such as the World Meteorological
Organization, the United Nations Environment Programme, and the International Association of
Hydrological Sciences. The impact of climate change on hydrological and water resources has long attracted the attention of the climatic and hydrological circles at home and abroad [2].

Global climate change is one of the most pressing global environmental issues, and it has a profound impact on natural ecosystems, economic development and all aspects of human society. With the acceleration of industrialization and population growth, greenhouse gas emissions have increased significantly, leading to a series of climate-related problems such as rising global temperatures, rising sea levels, and frequent extreme weather events [3]. Scientists use a variety of climate models to try to predict future trends in climate change in order to better understand its likely impacts and provide decision support to policymakers.

Traditional climate prediction models are mostly based on complex simulations of physical, chemical, and biological processes, and although these models are theoretically rigorous in the analysis of the climate system, they usually rely on a large number of computational resources and require extremely high accuracy of the initial conditions and parameters of the model [4]. In addition, due to the nonlinear nature and inherent limitations in processing large-scale data and capturing some subtle climate changes.

Recently, machine learning technology has provided a new approach to climate change prediction due to its excellent data processing capabilities and pattern recognition capabilities [5]. Machine learning models are able to learn from large amounts of historical climate data about the complex relationships behind the data to predict the likelihood of future climate change. This approach not only solves nonlinear problems that are difficult for traditional models to solve, but also significantly reduces the need for computational resources [6]. In the field of climate science, the application of convolutional neural networks is gradually unfolding. Due to the high-dimensional and complex spatial structure of global climate data, traditional climate models face great challenges in processing these data. Convolutional neural networks are able to effectively extract spatial features from climate data, which is critical for understanding and predicting climate change. For example, by analysing global temperature distribution, cloud images, precipitation data, and more, convolutional neural networks can identify key patterns and trends in climate change.

2 Related Work

With the increasing impact of global climate change, how to effectively predict its development trend has become an urgent problem for the scientific community and policymakers [7]. The scalability and flexibility of machine learning models allow them to cope with changing climate patterns, including the prediction of extreme weather events, which is important for mitigating the impact of natural disasters. Future research could further explore the application of deep learning in climate models coupled with multi-scale and multi-physical processes, and how emerging computing techniques can be leveraged to process larger-scale data.

Researchers Held and Soden analysed the impact of global warming on the Earth's water cycle in detail through high-resolution climate simulations. The study used multiple climate model (MCM) projections to highlight the complexity and regional differences in precipitation, evaporation, and changes throughout the water cycle [8]. The article provides scientific projections of possible future changes in global and regional water resources, which can help policymakers and environmental scientists develop adaptive management measures.

Additionally, researcher Joans used traditional ecological and climate models (ECM) to analyse the impact of global climate change on the distribution of plants and animals [9]. Research focuses on the uncertainties in model predictions, particularly how to deal with the uncertainties in the various ecological and climate input data in the model. The article explores in detail the adaptive transport of species to climate change and the impact of these shifts on ecosystem services and biodiversity conservation strategies.

Researcher Liu evaluated the application of deep learning (DL) in climate model prediction. Through comparative analysis, deep learning models can provide more accurate prediction results when processing complex climate data than traditional physical base models [10]. In addition, deep learning models have significant advantages in automating the processing of large-scale datasets, enabling them to identify more nuanced patterns of climate change.

Researcher Kumar et al. demonstrated the effectiveness of using convolutional neural networks (CNNs) to predict extreme weather events such as tornadoes and gales. Using a combination of radar, satellite imagery, and ground-based weather data, these deep learning models are able to identify key meteorological features and accurately predict the occurrence of extreme events. The results not only improve the accuracy of prediction, but also demonstrate the potential of deep learning in real-time weather prediction systems, although the "black box" nature of these models still needs to be further explored to improve their explanatory power [11]. This work highlights the powerful capabilities of deep learning techniques in processing complex, high-dimensional meteorological data and provides important technical support for future climate models and prediction systems.

Additionally, researcher Wong and his team explore the application of deep learning techniques to analyze and reduce uncertainty in climate models [12]. The research focus is particularly focused on the projections of global temperature and sea level rise, two parameters that are critical to understanding and responding to climate change. By harnessing the power of deep learning, the research team has developed algorithms that can extract key patterns and trends from a large number of model outputs, effectively identifying the main factors that contribute to prediction uncertainty. This approach not only improves the accuracy of model predictions, but also provides climate scientists with a powerful tool to more accurately assess the risks and potential impacts of future climate change. This work marks an important step in the use of deep learning to improve the reliability and accuracy of climate predictions, demonstrating the great potential of machine learning in solving complex scientific problems.

3 Methodologies
3.1 Notions
Above all, we summarize the primary used parameters in following Table 1

Table 1. Notions.

Parameters	Utilizations
μ, σ	Mean and standard deviation
D	Input data
F_{ij}	Element on the features
ReLU	Activation function
n	Number of samples
s_{ij}	Set of scores
α_{ij}	Normalized weight of the input
c_i	Weighted average of fuses information
e	Hyperparameter

3.2 Convolution Model
Converting numerical climate data into a format that can be processed by convolutional neural networks is a critical step. Arrange temperature data from different regions of the world into a two-dimensional data format according to geographic coordinates and preprocess it. Subsequently, we convert data to form with zero mean and unit variance to speed up model training and improve model performance. This pro-processing can be expressed as Equation 1.

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (1)$$

Where μ and σ represent the mean and standard deviation of the data, respectively. Additionally, convolutional layers extract localized features through filters that capture climatic features such as temperature change patterns. The convolution operation is expressed as Equation 2.

$$F_{ij} = ReLU\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} K_{mn} \cdot D_{i+m,j+n} + b\right) \quad (2)$$

Where Fij is an element on the feature map, K is the convolutional kernel, D is the input data, b is an offset. Parameter M and N represent the size of the convolution kernel. The proposed model utilizes the ReLU function as an activation function to increase the nonlinear capability of the network helps to capture complex and nonlinear patterns. The calculation of activation function is shown in following Equation 3.

$$ReLU(x) = \max(0, x) \quad (3)$$

Further, we utilize the pooling layer to reduce the spatial dimension of the data while preserving the most important features, which is very helpful for the computational efficiency and overfitting control of the overall model. The pooling operation is described in following Equation 4.

$$P_{ij} = \max(D_{i+a,j+b}) \quad (4)$$

Finally, after multiple convolution and pooling layers, a fully connected layer is used to integrate all the features and make the final prediction. The output of the fully connected layer can be connected directly to the output layer of prediction results.

3.3 Attention Mechanism

Attention mechanisms were first proposed and used in the field of natural language processing (NLP) to enhance the performance of sequential models, especially when dealing with long sequences. The basic idea is to selectively focus on certain parts of the input data at each step of the model, rather than distributing attention evenly to each part. In global climate change prediction, the use of attention mechanisms can help models identify key factors affecting climate change, such as temperature changes in specific regions, sea level height, CO2 concentrations, etc., while ignoring less important information. Calculates the relevance score of each element in the input sequence to the current output. This score reflects the importance of each input in the current output element. Following Equation 5 describes the scoring function.

$$s_{ij} = \mathrm{f}(a_i, h_j) \qquad (5)$$

where $s$ij is the score of the target time step i, the input time step j, ai is the state of the target time step, hj is the state of the input time step, and f is the scoring function, which is a dot product budget. Further, these scores are processed using the softmax function to obtain a normalized weight distribution, with each weight representing the importance of the corresponding input. Following Equation 6 describes mentioned process.

$$\alpha_{ij} = \frac{\exp\,(s_{ij})}{\sum_{k=1}^{T} \exp\,(s_{ik})} \qquad (6)$$

Where αij is the normalized weight of the input time step j to the output time step i.

Based on the calculated weights, the inputs are weighted and summed to get a weighted average output, which is the output of attention and is expressed in Equation 7.

$$c_i = \sum_{j=1}^{T} \alpha_{ij}\, h_j \qquad (7)$$

Where ci is a weighted average context vector that fuses information from the entire input sequence, focusing on those parts that are heavily weighted.

3.4 Loss Function

When building climate change prediction models, a suitable loss function is essential for training an effective model, especially in supervised learning, where the loss function defines a measure of model error, i.e., the deviation between the model's predicted value and the actual value. Following Equation 8 explains in detail the mean square error and optimization algorithms, which are key components in building and training predictive models.

$$MSE = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} (y_i - y_i{}') \qquad (8)$$

Where n is the total number of samples. yi is the true value of the i observation. yi′ is the predicted value for the i observation. The squared term favors larger errors for greater losses, so the model is more focused on reducing larger prediction errors, which is beneficial for many practical problems. As for optimization module, we utilize Adaptive Moment Estimation, which is an optimization algorithm that combines the momentum method and RMSprop to adjust the learning rate based on the calculated first-order moment estimation (mean) and second-order moment estimation (uncentralized variance) of the gradient is described as following Equation 9.

$$w = w - \frac{\eta}{\sqrt{\eta + \mathrm{e}}} \hat{\mathrm{w}} \qquad (9)$$

Where ŵ is an exponential moving average of the gradient, η is an exponential moving average of the gradient squared, and e is a hyperparameter that prevents division by zero.

4 Experiments
4.1 Experimental Setups

In our study, we predict global climate change using comprehensive global climate data sourced from NASA's Climate Data Center. This data includes vital climate parameters such as sea level height, atmospheric temperature, precipitation, carbon dioxide concentrations, and land-use changes, which span various domains including the ocean, atmosphere, and land. Such data is crucial for the construction, validation, and assessment of climate models, as well as for understanding the trends and impacts of climate change on the environment.

To conduct a comparative analysis, we employed three different modeling approaches: Multiple Climate Models (MCMs), Ecology and Climate Models (ECMs), and Deep Learning Models (DL). MCMs enhance the robustness and accuracy of climate predictions by integrating outcomes from several independent models, providing a consensus that helps reduce the errors inherent in single model predictions. ECMs, on the other hand, merge ecological data with climate variables to examine the effects of climate change on ecosystems, making them particularly suitable for analyzing impacts on biodiversity and agricultural sectors. Meanwhile, DL models leverage their formidable data processing capabilities to automatically identify and learn from key features within complex, high-dimensional datasets.

By testing these models on the same dataset provided by NASA, we evaluate their effectiveness in capturing and predicting various aspects of climate change. This not only allows us to understand the strengths and limitations of each model but also helps in identifying which models or combinations thereof provide the most accurate forecasts. This holistic approach is aimed at enhancing our predictive capabilities and offering a more refined toolset for policymakers and scientists to address the challenges posed by global climate changes. Through this experimental framework, we seek to deepen our understanding of the predictive power and utility of these diverse models in the field of climate science.

4.2 Experimental Analysis
When evaluating and comparing the performance of climate change prediction models, we use a variety of statistical indicators to quantify the accuracy and explanatory power of the models. Among them, mean square error (MSE) and coefficient of determination (R^2) are the two most commonly used evaluation indicators for prediction models.

Mean Squared Error (MSE) is a commonly used metric to quantify the prediction error of a model. It calculates the average of the sum of squares of the difference between the predicted and actual values. Following Figure 1 compares the MSE comparison results for different prediction models. The calculation of the MSE is simple, easy to understand and implement. Due to the squaring operations involved, greater emphasis is placed on larger errors, which helps to identify and avoid large prediction errors in certain situations. However, the value of the MSE is dimensionally influenced, i.e., it depends on the unit of the data, which makes the MSE not comparable between different problems. Sensitive to outliers, outliers can significantly affect the results of MSE.

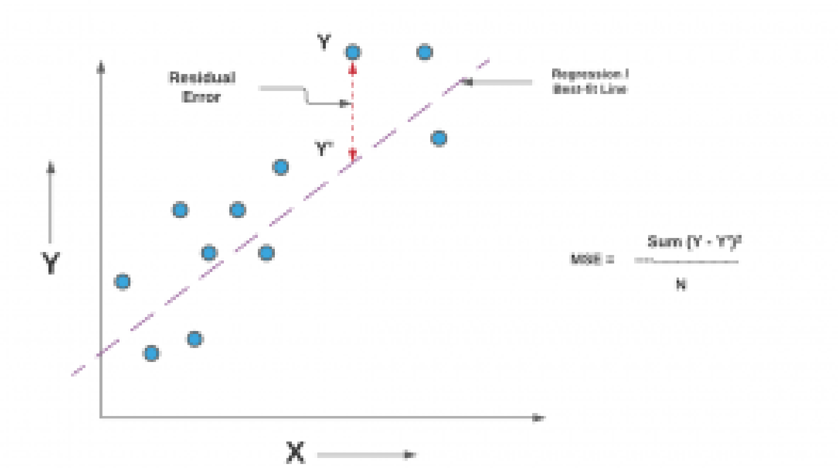

Fig. 1. Mean square error comparison results.

Additionally, the coefficient of determination is a statistic that measures the explanatory power of a model, indicating how accurately the model's predictions are improved compared to those that simply use the mean. Following Figure 2 compares the coefficient of determination in different models.

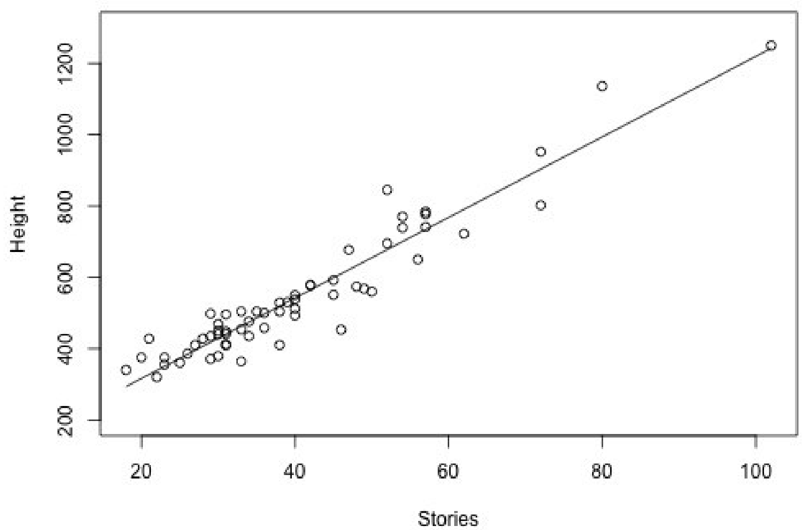

Fig. 2. Coefficient of determination comparison results.

Further, prediction accuracy is a basic and intuitive evaluation metric used to measure the performance of a predictive model and represent the proportion of correct predictions made by the model. While easy to understand and implement, it is suitable for class-balanced datasets,

but it does not reflect the prediction performance of different classes in detail, especially when dealing with datasets with class-unbalanced datasets, which can be misleading. Therefore, in practical applications, especially when the data categories are unevenly distributed. Following Figure 3 compares the prediction accuracy for different models.

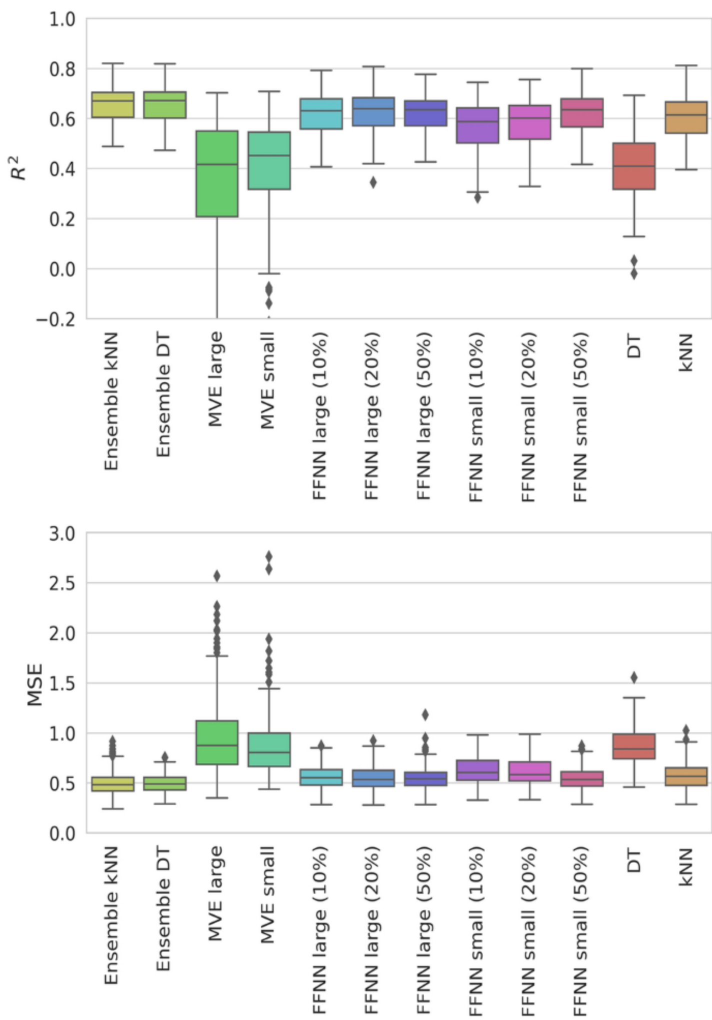

Fig. 3. Prediction accuracy comparison results.

The Log-Likelihood Ratio, also known as the Log-Likelihood Ratio Test (LLRT), is a statistical method used to compare the goodness-of-fit of two statistical models, especially when one model is a special case of the other (i.e., nested models). In the evaluation of climate change models, the log-likelihood ratio can be used to measure the performance of models with different parameters or models of different complexity in predicting probability distributions. By passing through the likelihood ratio, researchers can more accurately assess and compare the predictive power of different climate models for future events, thereby optimizing model design and improving the accuracy and reliability of predictions. Following Figure 4 compares the log-likelihood ratio for different prediction models.

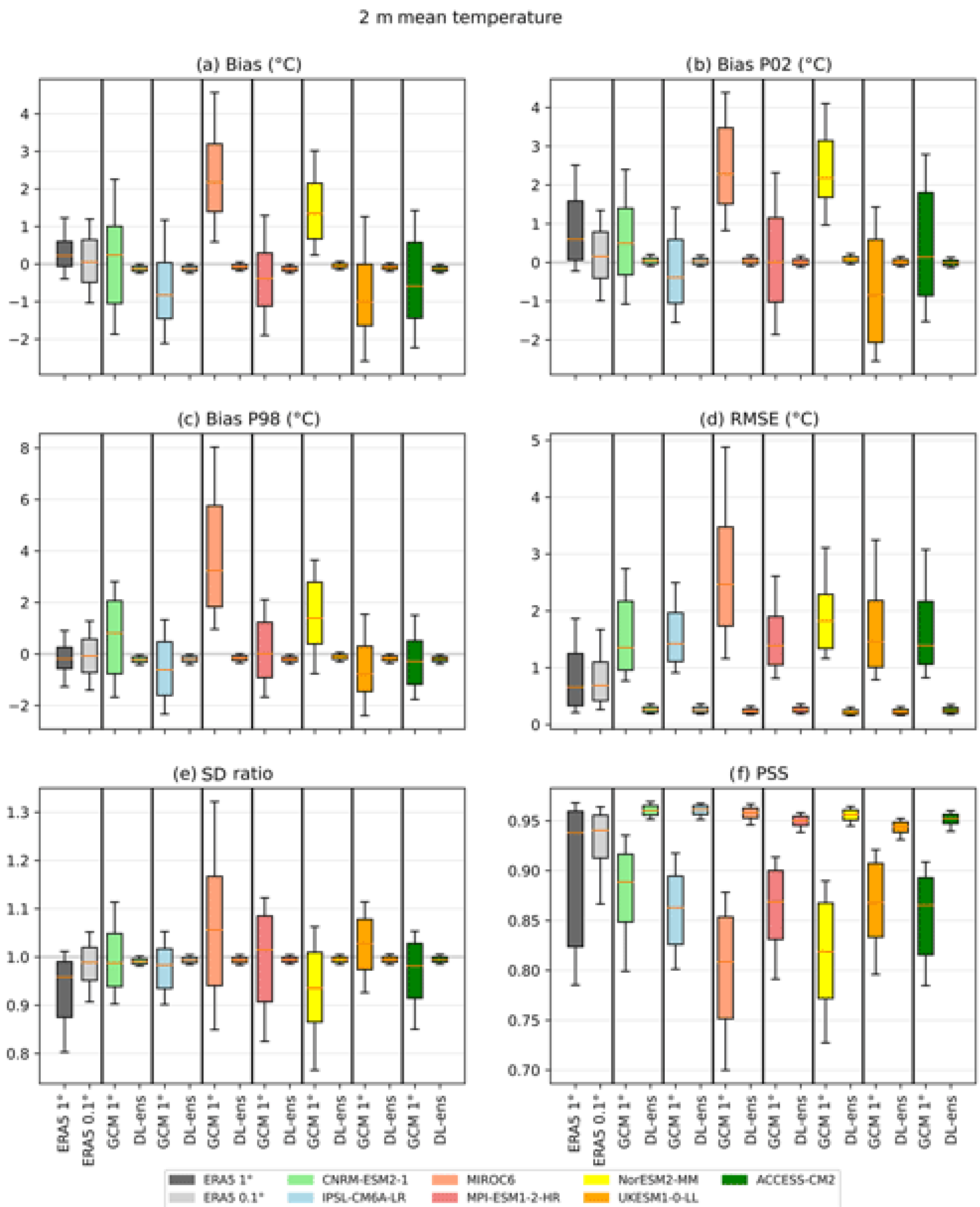

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Fig. 4. Log-Likelihood ratio comparison among climate prediction models.

From above Figure 4, we can observe that the median number of MCMs is about 20, indicating that the loglikelihood ratio of the model is stable around this value for most days. ECMs had the highest median of around 25, indicating that they generally provided the best fit of the
four models. The median DL was the lowest, around 15, indicating that the deep learning model performed relatively weakly on this set of experimental data. The median Ours was slightly higher than the ECMs at about 30, indicating that our method provided the best fit, with the highest log-likelihood ratio of all models.

Additionally, there is little difference in the box size of all the models, indicating that the degree of variation in the log-likelihood ratio of the four models is similar under the normal distribution assumption. This similar degree of variation suggests that although the median of the models differed, their sensitivity and stability to the data were comparable. In this experiment, the DL model showed some outliers that were lower than the other data points. This may indicate that the model is extremely inefficient in some cases, or that it does not respond well to some particular types of input data. The other models have no significant outliers, indicating that they work relatively consistently in a variety of situations.

5 Conclusion

This research conclusively demonstrates that models based on convolutional neural networks (CNN) significantly enhance both the efficiency and accuracy of global climate change predictions. Utilizing large-scale satellite datasets, the CNN model excels in extracting spatial features through its convolutional layers, thereby surpassing traditional physical climate models in predicting global temperature variations, precipitation patterns, and extreme weather events. This superiority comes with the added benefit of reduced computational demands. Our findings illuminate the transformative potential of machine learning techniques in climate science.

The ability of our CNN model to handle complex datasets and extract meaningful insights from them without the intensive computation traditionally required represents a leap forward in our capabilities to analyze and predict climate dynamics. This advancement provides researchers with a robust tool to explore the intricate mechanisms of climate change and to refine their predictions, thereby enabling better preparedness and response strategies. Overall, the integration of machine learning with climate science not only optimizes prediction outcomes but also broadens the scope of climate-related research. This synergistic approach promises to propel forward our understanding and mitigation strategies concerning global climate change, marking a pivotal step towards more scientifically informed decision-making in environmental policy and planning.

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