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Environmental Science and Climate Modeling Using Neural Networks

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ABSTRACT—

This research examines into the potential of using networks to gain an understanding of climate and environment. Concerns, about climate change and its impact on our planet's future are significant. Traditional methods of studying climate often struggle to capture the interactions that drive changes. In this study we investigate whether neural networks can aid in comprehending these processes effectively. Neural networks help as problem solving tools of uncovering patterns in data when they are not immediately apparent. Leveraging their capabilities may enhance climate predictions. Improve our understanding of the environment. We explore approaches, to computing these networks and utilizing data to optimize their simulation and predictive abilities regarding environmental occurrences. By using a lot of information and smart learning techniques, neural network models might be able to make climate predictions and understand environmental changes better. Our results show that neural networks could really help improve climate modeling and environmental science. As these tools get better, they could help us understand how the environment is changing and come up with better plans to deal with these changes.

Keywords- *Climate change, neural networks, environmental effects, climate predictions, data pattern*

1. INTRODUCTION

Temperature forecasting is important but becomes less accurate as the forecast range increases due to the chaotic nature of the atmosphere and errors in measuring initial conditions. Neural networks are powerful tools for capturing complex input-output relationships and acquiring knowledge through learning, like the human brain. In a neural network-based algorithm for temperature prediction that can approximate a large class of functions and capture complex relationships between factors contributing to temperature. The proposed algorithm is tested using real-time datasets and shows improvement over guidance forecasts from numerical models and official local weather service forecasts. The paper presents a neural network-based algorithm for temperature prediction using the Back Propagation Neural Network (BPN) technique. The BPN neural network method is advantageous as it can approximate a large class of functions and capture complex relationships between factors contributing to temperature. The algorithm employs robust data pre-processing techniques to handle missing values, outliers, and ensure the quality of input features, enhancing the overall model performance. Feature selection methods are applied to identify the most influential factors affecting temperature, helping to streamline the input variables and improve the efficiency of the neural network. The algorithm is designed to capture temporal patterns in weather data, enabling it to recognize and learn from historical trends and seasonality for more accurate long-term temperature predictions. The model incorporates uncertainty estimation methods, providing confidence intervals for temperature predictions. This helps stakeholders gauge the reliability of the forecast and make informed decisions. The algorithm is parallelized to efficiently handle large datasets and expedite the training process, making it scalable and practical for real-world applications. Data supplied to the system during the training phase includes temperature, wind speed, humidity, and other factors. The algorithm determines the nonlinear relationship that exists between this historical data and makes predictions based on it.The algorithm further incorporates feature selection methods, strategically identifying the most influential factors affecting temperature. This not only streamlines input variables but also enhances the neural network's efficiency. Designed to capture temporal patterns in weather data, the algorithm excels at recognizing and learning from historical trends and seasonality, thereby improving the accuracy of long-term temperature predictions. A noteworthy addition to the algorithm is the incorporation of uncertainty estimation methods, providing stakeholders with confidence intervals for temperature predictions. This feature enhances the forecast's reliability, enabling informed decision-making. To accommodate large datasets and expedite the training process, the algorithm is parallelized, ensuring scalability and practical applicability in real-world scenarios. During the training phase, the system is supplied with diverse data, including temperature, wind speed, humidity, and other relevant factors. The algorithm adeptly discerns the nonlinear relationships inherent in this historical data, utilizing them to make accurate predictions. In essence, this comprehensive approach underscores the algorithm's robustness, adaptability, and potential to significantly advance the field of temperature forecasting.

2. Literature Survey

This study explores how artificial neural networks (ANN) and IHACRES models predict the impacts of climate change on river flow or discharge. The Mean Observed Temperature-precipitation (MOTP) approach and the change factor method were utilized. The first means to lessen doubts about climate models; the latter helps adjust the climate data. The IHACRES model and the multi-level ANN model were utilized. They gauged the influence of rain and temperature on the¬ river flow. With the scikit-learn library's MLP technique, we modeled the flow of Malaysia's Kalantan River using artificial neural networks [1]. Temperature forecasting is the application of science and technology to predict the state of the temperature for a future time in a given location. Due to the chaotic nature of the atmosphere, forecasts become less accurate as the difference in current time and the time for which the forecast is being made increases. The use of ensembles and models helps narrow the error and pick the most likely outcome. Neural networks are powerful data modelling tools that can capture and represent complex input-output relationships. Neural networks acquire knowledge through learning, resembling the human brain in this aspect [2]. The development of a bias correction approach using artificial neural networks (ANNs) to reduce biases in climate variables over northern South America. The study utilizes inputs such as air and skin temperature, specific humidity, and net longwave and shortwave radiation for bias correction of temperature, and precipitation at different lags and standard deviation of precipitation for bias correction of monthly precipitation. The ANN model outperforms linear regression in improving estimation error and correlation of the variables, even with low temporal consistency between the model data and targets. The developed method can be used to produce bias-corrected climate variables for hydrological and ecological models [3]. The paper discusses the use of convolutional neural networks (CNNs) for classifying, identifying, and predicting patterns in climate and environmental data. An effective auto-labeling strategy based on using an unsupervised clustering algorithm to label thousands of daily large-scale weather patterns over North America. The effects of architecture and hyperparameters on the performance of CNNs are examined and discussed. The paper also mentions the development of two CNNs, one with two convolutional layers (CNN2) and another with four convolutional layers (CNN4) and compares the performance of CNN4 with logistic regression [4]. The development of a deep learning-based model using convolutional neural networks to identify climate patterns during floods and determine flood-induced climate patterns. The study uses sea surface temperature anomaly as the learning data and classifies them into four cases based on spatial extent. Also mentions the selection of data for flood non-occurrence days to match the ratio of flood occurrence to non-occurrence days. To identify the circum global teleconnection (CGT) pattern affecting the occurrence of domestic floods in the Korean peninsula using deep-learning techniques [5]. The paper introduces the concept of neural diffusion equations in climate modeling. It also mentions the use of neural ordinary differential equations and diffusion equations in the context of climate modeling. The authors provide a comprehensive review of the relevant literature on climate modeling with neural diffusion equations, highlighting the importance of incorporating neural networks into traditional diffusion equations for improved climate predictions. The paper builds upon previous research in the field and presents a novel approach to climate modeling using neural diffusion equations. The authors discuss the potential applications and benefits of this approach, emphasizing the need for further exploration and validation of neural diffusion equations in climate modeling [6]. The authors propose the use of neural networks (RNN) to accurately and stably parameterize subgrid atmospheric processes. The paper highlights the importance of physically consistent parameterization and good performance at reduced precision. The authors emphasize the need for stable and accurate parameterization methods to improve the representation of subgrid processes in atmospheric models. The paper provides insights into the application of neural networks in atmospheric modeling and their potential to improve the accuracy and stability of parameterization schemes [7]. The authors propose a method to optimize the tunable parameters of the NN using a kriging method, without the need for any new learning procedure. The paper focuses on tuning the long-term statistical properties of the NN-based model. The authors mention the use of a "reference" data set consisting of a long time-series generated by integrating L63 equations with specific parameters. The length of the time-series is 3000 MTU, which is considered as "infinite" length for the study. The L63 equations and their parameters are used as an example in the paper [8]. Recent advances in artificial intelligence (AI) techniques have provided new challenges in the development of theory-based numerical weather-climate prediction models .The post-processing of numerical model outputs is the most typical example of AI application to numerical weather and climate forecasting .The NN emulator outputs contributed to slight RMSE improvements for the LW flux, SW flux, and precipitation, while no significant change was found for skin temperature .NN-WRF produced more realistic distributions with lower RMSEs for the LW flux, SW flux, and skin temperature compared to WRF60 [9]. The evolution of the climate field by analyzing the leading combined empirical orthogonal functions of temperature, precipitation, and climate moisture index. The study extends the neural-network approach to combined fields of input, providing a method for nonlinear and multi-variable analysis of the forced response. The neural networks are trained on climate model data and can also be applied to observational data. The study highlights the utility of combining variables when identifying patterns of the forced response and the need for methods that are both complex and explainable in multivariate climate analyses [10]. Bias correction of the CNRM-CM5 model output using the gridded near-surface temperature data developed by the Indian Meteorological Department The trained GRNN model is shown to improve the biases of the GCM output with significant accuracy and captures the seasonal variation in near-surface temperature over the Indian mainland .The paper also mentions the process of bias correction, which involves removing systematic biases in GCM modelled output parameters with reference to observed data for the historical period and applying the developed model for bias correcting future data. The future projections are obtained from the same GCM for the time period 2006-2100 for the emission scenarios of RCP4.5 and RCP8.5 [11]. It demonstrates successful approaches in incorporating physics and domain knowledge into ML models. Physics-informed machine learning (PIML) to a neural network (NN) emulator of convection for climate modeling, focusing on the prediction of cloud processes' effects on climate. The work shows the successful characterization of uncertainties in a surrogate model using Bayesian deep learning (BDL) and provides data-driven approaches to model extreme events. The importance of enforcing strict constraints for the conservation of physical quantities in climate modeling, which improves generalizability and guarantees physical consistency. The potential for estimating uncertainty in PIML models using the stochastic nature of generative adversarial networks (GANs) and statistical tests for extreme events [12]. The developments in hybrid deep learning models that combine statistical models with neural network components to improve forecasting methods .The outline ways in which deep learning can facilitate decision support with time-series data .The paper mentions that deep neural networks learn predictive relationships by using nonlinear layers to construct intermediate feature representations in time-series settings .It notes that the same components can be extended to multivariate models without loss of generality. The survey acknowledges that there is a rich body of literature on automated approaches to time-series forecasting, including automatic parametric model selection, kernel regression, support vector regression, Gaussian processes, and older models of neural networks [13]. The paper introduces a novel climate model called the neural advection-diffusion equation (NADE) that combines the concepts of neural ordinary differential equations (NODEs) and the advection-diffusion equation. It aims to learn an appropriate latent governing equation for climate datasets and outperforms existing baselines in experiments with real-world and synthetic datasets. The paper provides a literature review that introduces several base concepts, including neural ordinary differential equations, diffusion equations, advection equations, advection-diffusion equations, and climate modelling [14]. The paper provides a comprehensive review of artificial neural network (ANN)-based approaches for air temperature forecasting during the period of 2005-2020. The reviewed studies are categorized based on their inputs into univariate and multivariate models. Various ANN models such as recurrent neural network (RNN) and long short-term memory (LSTM) for air temperature forecasting. They concluded that ANN models can be promising tools for air temperature forecasting due to their fast computing speed and ability to handle complex problems. However, there is no consensus on the best existing method [15].

3. Methodology

3.1 Artificial Neural Network:

Identification of unit Hydrographs and Component flows from Rainfall, Evaporation and Stream flow data (IHACRES) model and multi-layer Artificial Neural Network (ANN):

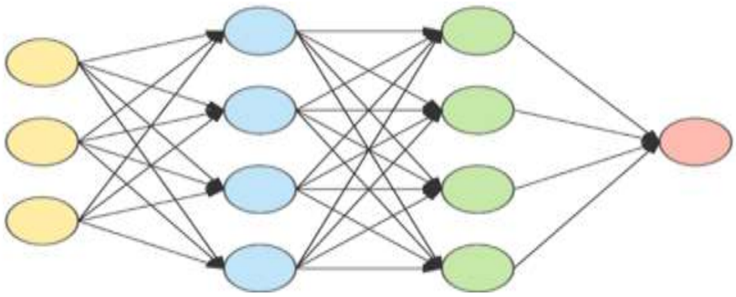

Fig.-1: Working of ANN model[1]

The IHACRES model is calibrated by the usage of observational facts of temperature, precipitation, and month-to-month discharge inside the base length. After calibration, Coupled Model Intercomparison Project Phase 5(CMIP5) the version predicts month-to-month runoff inside the basin with the aid of introducing downscaled temperature and rainfall data from weather models for future durations. The version performance is evaluated and compared with other fashions, which includes the artificial neural network version, to assess its accuracy and efficiency. Different variables are taken into consideration in the ANN model, such as monthly precipitation, monthly precipitation of previous months, monthly discharge, monthly discharge of previous months, and monthly temperature. The performance of the ANN model is compared with the IHACRES model in terms of calibration and validation phases, using standards that includes Root Mean Square Error (RMSE), Mean Absolute Error (MAE).

To gauge the accuracy and efficiency of the IHACRES model, a comprehensive evaluation is conducted, comparing its performance with other established models, including the artificial neural network (ANN) model. The ANN model incorporates a diverse set of variables, encompassing monthly precipitation, the precipitation of previous months, monthly discharge, discharge of previous months, and monthly temperature. This multi-faceted approach allows the ANN model to capture complex relationships and dependencies within the hydrological system. The evaluation process involves scrutinizing the performance of both models during calibration and validation phases. Key metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are employed as standards for comparison. These metrics provide quantitative measures of the disparities between model predictions and observed data, facilitating a robust assessment of each model's predictive accuracy. By systematically comparing the IHACRES model with the ANN model, this study aims to discern the strengths and weaknesses of each approach in simulating hydrological processes. The incorporation of CMIP5 downscaled data further enriches the analysis, enabling a forward-looking perspective on potential changes in basin runoff under future climate scenarios. This comprehensive evaluation contributes valuable insights to the field of hydrological modeling, aiding in the refinement and selection of models for effective water resource management and climate impact assessment.

3.2 Back Propagation:

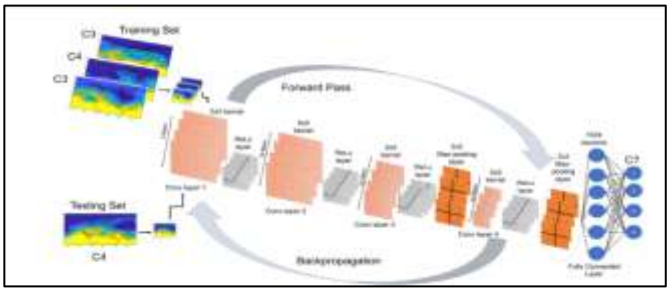

Fig.- 2: Working of Back Propagation [2]

The paper makes use of the Back Propagation Neural Network (BPN) method for temperature prediction. The backpropagation method in this paper involves 2 phases: propagation and weight update. In the propagation phase, the input is forwarded via the neural network to generate output activations, and the output activations are then back propagated using the education sample's goal to generate the deltas of all output and hidden neurons. In the burden replace segment, the gradient of every weight is calculated by multiplying its input activation and output delta, and the weight is up to date inside the contrary path of the gradient with the usage of a learning charge. This process is repeated till the network's performance is first-rate. It is used to predict the state of temperature for a future time and region.

Back Propagation Neural Network (BPN) method employed in this paper represents a fundamental yet powerful approach for temperature prediction. The method is structured into two pivotal phases: propagation and weight update. During the propagation phase, the input data traverses the neural network, producing output activations. Subsequently, these output activations undergo a backward propagation process, utilizing the educational sample's target values to compute the deltas for all output and hidden neurons. In the weight update segment, the gradients of each weight are determined by multiplying their respective input activations with the corresponding output deltas. The weights are then updated in the opposite direction of these gradients, incorporating a learning rate to regulate the magnitude of adjustments. This iterative process continues until the network achieves optimal performance in predicting temperature states for future times and locations.

The weight update segment, a pivotal component of the BPN method, introduces a dynamic mechanism for refining the neural network. Here, the gradients of each weight are meticulously computed, leveraging the product of their respective input activations and output deltas. These gradients serve as guides for adjusting the weights in the opposite direction, a process vital for optimizing the network's predictive capabilities.

The network refines its predictions continuously until a state of excellence is attained, ensuring accurate forecasts of temperature states for future times and locations. In essence, the Back Propagation Neural Network method emerges as a fundamental yet powerful tool, bridging the realms of theory and application to enhance our ability to foresee temperature dynamics.

3.3 Convolution Neural Network:

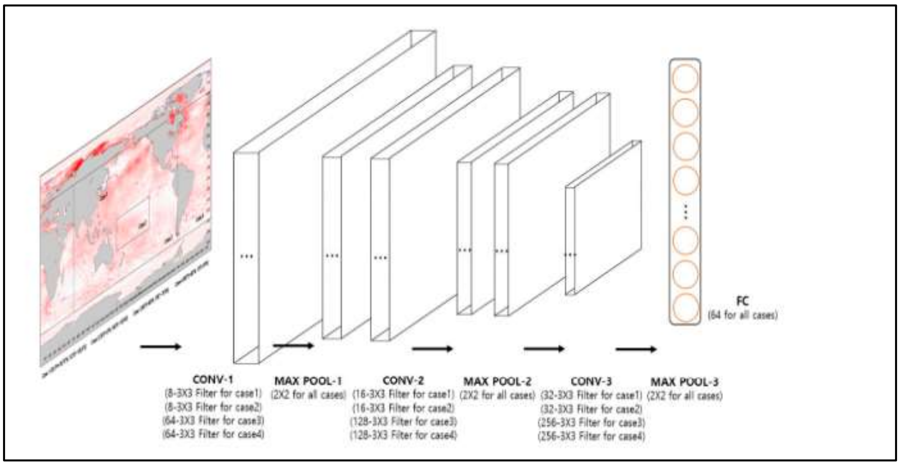

Fig.- 3: Working of Convolutional Neural Network [5]

The examination utilized a deep learning-primarily based version, mainly a convolutional neural community (CNN), to become aware of climate styles for the duration of floods and determine flood-prompted weather styles. Seafloor temperature anomaly (SSTA) data become used because the gaining knowledge of information for the model. The spatial volume of the SSTA facts was labeled into four instances to evaluate and assess the applicability of the category version. The CNN model shape is used to create a type version by extracting functions from -dimensional facts, in particular for figuring out worldwide flood-prompted climate patterns. The version's performance was evaluated with the use of a confusion matrix, a common method for performance assessment of predictive models.

The model's performance was rigorously evaluated through the implementation of a confusion matrix, a widely adopted method for assessing the efficacy of predictive models. The confusion matrix provided a detailed breakdown of the model's predictive accuracy, allowing for the examination of true positives, true negatives, false positives, and false negatives. This comprehensive evaluation facilitated a nuanced understanding of the CNN model's ability to correctly identify and classify flood-induced weather patterns across diverse spatial contexts. By employing deep learning techniques and specifically the CNN model, this research aimed to contribute to the understanding of the complex relationships between floods and climate patterns.. This approach enhances our understanding of climatic responses to flooding and holds promise for improving early warning systems and disaster preparedness efforts by providing a data-driven means of recognizing and classifying critical meteorological conditions associated with flood events

3.4 Layer-wise Relevance Propagation:

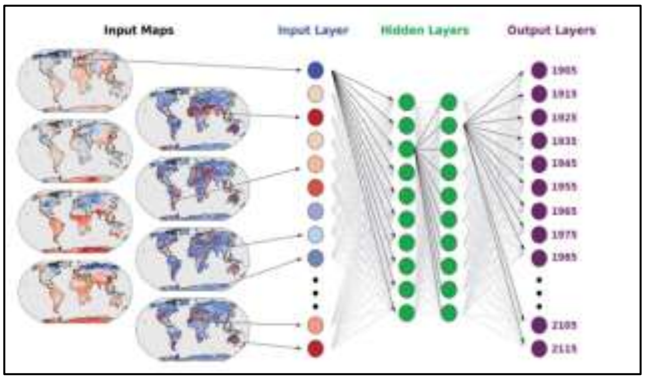

Fig.- 4: Working of Layer-wise Relevance Propagation [10]

The focus of the paper is on the use of explainable neural networks and the application of LRP (Layer-wise Relevance Propagation) to detect forced changes within combined climate fields. The neural network architecture used in the study is not specifically referred to as an MLP. The paper discusses the training of the neural network on various input vectors and the use of clustering techniques in combination with neural network explainable methods. While MLPs are a type of neural network architecture commonly used in machine learning.

While Multilayer Perceptrons (MLPs) are a prevalent choice in the machine learning landscape, the deliberate omission of this specific designation in the paper suggests a departure from conventional architectures. Instead, the focus is directed towards the application of Layer-wise Relevance Propagation, showcasing a commitment to employing cutting-edge techniques for enhanced interpretability in the context of climate science. This nuanced approach aligns with the evolving landscape of neural network applications, where the choice of architecture is tailored to the specific needs and complexities of the problem at hand. By embracing the explainability provided by LRP and combining it with training on diverse input vectors and clustering techniques, the study pioneers a comprehensive methodology for detecting forced changes in combined climate fields, contributing to the growing body of research at the intersection of neural networks and climate science.3.

3.5 LSTM and Recurrent Neural Network:

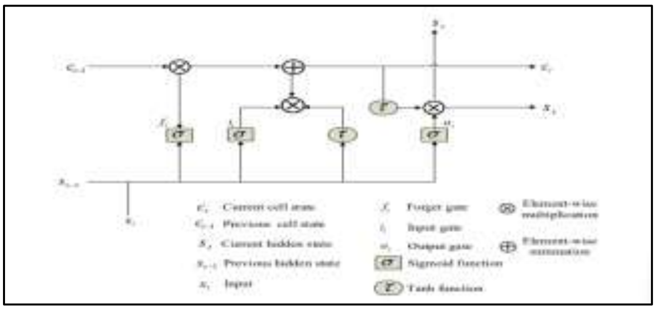

Fig.- 5: Structure of LSTM [15]

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to overcome certain limitations of traditional RNNs, which struggle with learning and remembering long-term dependencies in sequential data. LSTMs were introduced by Hochreiter and Schmidhuber in 1997 and have since become a popular choice for various applications, especially in tasks involving time-series data, natural language processing, and speech recognition. The key innovation of LSTM lies in its ability to selectively remember or forget information over long sequences, preventing the vanishing gradient problem that often occurs in standard RNNs.

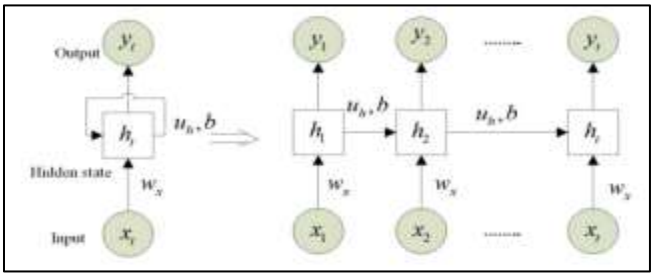

Fig.- 6: Structure of RNN [15]

Recurrent Neural Network and Long Short-Term Memory:

Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) are used in this neural network fashions for air temperature forecasting. RNN is designed to procedure sequential data via making use of remarks connections, allowing statistics to persist over time. LSTM is a sort of RNN that addresses the vanishing gradient problem and can seize long-term dependencies in the data. In air temperature forecasting, RNN and LSTM fashions are trained in the use of ancient temperature records and different relevant meteorological variables as inputs. The fashions research the patterns and relationships inside the data to make predictions about future temperature values. The overall performance of RNN and LSTM models is evaluated based totally on their ability to appropriately forecast air temperature, considering the non-linear and chaotic nature of temperature data.

4. Case Study

4.1. Case Study-1

Development of Technology for Identification of Climate Patterns during Floods Using Global Climate Model Data with Convolutional Neural Networks. Water, 14(24), 4045.

Convolutional Neural Networks:

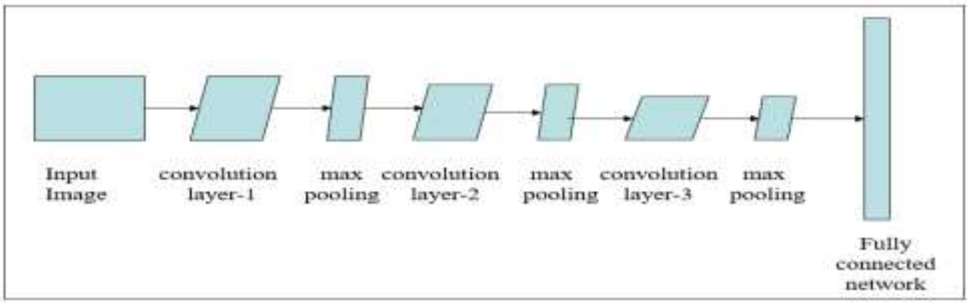

Fig.- 7: flow diagram of CNN

The model takes the image of the particular region where the flood may occur. The image is convoluted in the 1st layer by a filter in it and then it is max pooled it will continuous until the necessary data come. Finally, it will be converted into a flatten array. From there it will be made into fully connected network to predict the output. Epochs made the output more accurate. The developed deep learning-based model can be applied in real-time flood prediction systems. By utilizing global climate model data and identifying flood-induced climate patterns, the model can help in predicting floods by recognizing climate patterns of flood precursors. The model's accuracy in determining flood-induced climate patterns, with an accuracy of >90% in all cases, makes it a valuable tool for real-time flood prediction.

The real-time applicability of this deep learning model in flood prediction systems is a noteworthy feature. By harnessing global climate model data and discerning climate patterns indicative of impending floods, the model becomes a valuable asset in proactive flood prediction. Its capability to recognize climate patterns associated with flood precursors positions it as a robust tool for anticipating and mitigating the impact of floods.

Comparison Table:

Table -1: Comparison table for different reference papers

Ref no	Title	year	Objectives	Limitations	Advantages	Performance metrics
1	Prediction of Discharge Using Artificial Neural Network and IHACRES Models Due to Climate Change**.**	2021	To forecast future precipitation and temperature using climate models and simulate and optimize their runoff with suitable models.	Limitations in the accuracy and reliability of IHACRES and the ANN models.	Does not consider other factors that may influence river discharge, such as land.	MAE:1.23 RMSE:1.3 R score:0.99
2	An Efficient Weather Forecasting System using Artificial Neural Network.	2010	To present a neural network-based algorithm for predicting temperature and demonstrate its potential for successful application to temperature forecasting.	The accuracy of temperature forecasts decreases as the time difference between the current time and the forecasted time increases	Determining the nonlinear relationship between historical data and making predictions based on that relationship	RMSE: 0.26
3	Bias Correction of Climate Modeled Temperature and Precipitation Using Artificial Neural Networks	2017	To develop a bias correction approach using artificial neural networks (ANNs) to reduce biases in climate variables.	The ANN model to perform well with new and unseen data may also be a potential limitation	Modify the probabilistic structure of the climate variables, enhancing their representation of the underlying climate patterns	MSE:2.58 BIAS:1.24 Correlation coefficient (ρ):0.76
4	Predicting clustered weather patterns: A test case for applications of convolutional neural networks to spatio-temporal climate data.	2020	To explore the use of convolutional neural networks (CNNs) for classifying, identifying, and predicting patterns in climate and environmental data.	Chance of overfitting.Time-consuming and may discourage the use of CNNs for new problems	CNNs can handle the inherent complexities of spatiotemporal climate data, which are often chaotic and non-stationary	Accuracy over 90 %. RMSE: 0.1%-0.3%
5	Development of Technology for Identification of Climate Patterns during Floods Using Global Climate Model Data with Convolutional Neural Networks	2022	Develop a deep learning-based model using convolutional neural networks to identify climate patterns during floods and determine flood-induced climate patterns	Chance of over fitting. Did not analyze the specific impacts of climate patterns on flood occurrence, but rather focused on identifying and classifying the patterns.	Recognizing climate patterns of flood precursors, the model can help predict floods and contribute to flood management.	Accuracy over 95%. Precision: 0.97. Recall: 0.99. F1 Score: 0.98.
6	Climate Modeling with Neural Diffusion Equations	2021	To improve the accuracy of climate predictions by incorporating neural networks into traditional diffusion equations.	Limitations of using neural diffusion equations	The advancement of differential equation-inspired deep learning	Hidden dimension size:32. Forecasting errors 51% less.

7	Use of Neural Networks for Stable, Accurate and Physically Consistent Parameterization of Subgrid Atmospheric Processes With Good Performance at Reduced Precision.	2021	To develop a neural network parameterization that incorporates physical constraints and can mimic the climate of a high-resolution simulation when coupled to an atmospheric model	Chance of overfitting Lack of precision	Speed and power requirements for running climate simulations. reducing the computational resources and energy needed to run climate simulations.	Hidden layers: 5 Nodes: 128
8	Calibrate a Dynamical System With Neural Network Based Physics . .	2022	To fit an NN model to approximate the L63 time derivative as a function of the state variable and parameters .	not discuss the computational efficiency or scalability of the proposed method does not address the accuracy of short-term predictions	accurately represent the dynamics of the system and generate validation time series	Nodes: 32 Epochs: 30 R^2 score =0.89
9	Improved Weather Forecasting Using Neural Network Emulation for Radiation Parameterization.	2021	To demonstrate the potential of NN emulators for radiation parameterization in improving computational cost and accelerating numerical forecast models.	Representation errors and overfitting. Deep hidden layers or more complex structures in the NN emulator may not always produce better performance in terms of speedup compared	Accelerate the numerical forecast model by reducing the total computational cost. NN emulators have shown better performance in terms of root mean square error for radiation parameterization.	RMSE: 18%-25% Hidden layer: 39
10	Detection of Forced Change Within Combined Climate Fields Using Explainable Neural Networks	2022	To detect forced changes within combined climate fields using explainable neural networks.	forced change can be accurately captured and learned by the network	The paper addresses the issue of overfitting and collinearity in the interpretation of learned weights through the application of ridge regularization	Signal-to-noise ratio accuracy: 90%
11	A statistical bias correction technique for global climate model predicted near-surface temperature in India using the generalized regression neural network	2022	To assess the accuracy and effectiveness of the trained GRNN model in improving the biases of the GCM output, as well as its ability to capture the seasonal variation in near-surface temperature over the Indian mainland	the assumption of quasi-stationarity of future temperature data for both emission scenarios (RCP4.5 and RCP8.5) may introduce uncertainties in the bias correction process, as future climate conditions	The nature of unseen future temperature data and correct the biases of future data, assuming quasi-stationarity of future temperature data	correlation coefficient (ρ): 0.06-0.67 RMSE: 2.67-4.10

				may deviate from historical patterns.		
12	Physics-informed machine learning: case studies for weather and climate modelling	2021	Incorporating physics and domain knowledge into ML models to improve generalizability, guarantee physical consistency.	can be challenging due to the large number of assumptions, components, and parameters involved	PIML models have the potential to emulate high-order statistics, model uncertainties, and provide alternatives to subgrid-scale closure models	MSE: 156 ± 1.0 × 10^3 Correlation coefficient (ρ): 458 ± 5 × 10^2
13	Time-series forecasting with deep learning	2021	To describe how temporal information is incorporated into predictions by each model and highlight recent developments in hybrid deep learning models.	may be prone to overfitting. limitations in learning long-range dependencies.	Have the potential to improve forecasting performance over existing univariate or multivariate models by explicitly accounting for hierarchical structures and logical groupings in time series data.	Loss function: 0.024
14	Climate modeling with neural advection–diffusion equation	2023	To propose a novel climate model called the neural advection-diffusion equation	It primarily focuses on introducing the NADE model, and the advection-diffusion equation, and its superior performance compared to existing baselines in climate modeling experiments	Utilizes the advection-diffusion equation, which is widely used in climate modeling to describe physical processes involving Brownian and bulk motions in climate systems.	MSE: 0.4435 MAE: 0.031±0.0057
15	A Review of Neural Networks for Air Temperature Forecasting	2023	To predict daily maximum air temperature in Canada. The best predictions were obtained with an ANN having 5 hidden layers, 10 neurons per layer.	Mainly viable for short-term air temperature forecasting. Will not explore multivariate models for air temperature forecasting.	Suitable for capturing the temporal patterns and dependencies in air temperature data.	RMSE: 1.41C MSE: 0.272C R^2 = 0.997

The above table consists of 15 different reference papers with published year, objective, advantages, limitations and performance metrics.

5. Graphical Representation

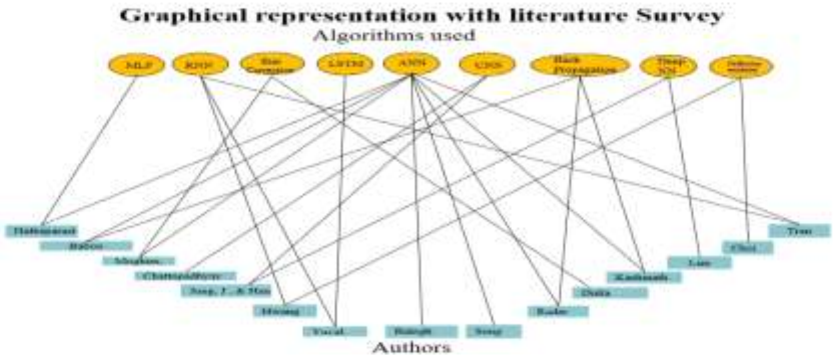

Fig.-8: Diagrammatical Representation of different authors and algorithms

6. Results

Table -2: Results table for 5 reference papers

Reference no	Title	Method	Metrics
1	Prediction of Discharge Using Artificial Neural Network and IHACRES Models Due to Climate Change.	Artificial Neural Network	MAE:1.23 RMSE:1.3
2	An efficient weather forecasting system using artificial neural network.	Back Propagation	RMSE: 0.26
5	Development of Technology for Identification of Climate Patterns during Floods Using Global Climate Model Data with Convolutional Neural Networks.(SSTA)	Convolutional Neural Network	Accuracy over 95%. Precision: 0.97. Recall: 0.99. F1 Score: 0.98.
10	Detection of forced change within combined climate fields using explainable neural networks.	Multi-Layer Perceptron	Accuracy: 90%
15	A review of neural networks for air temperature forecasting.	Recurrent Neural Network, Long short-term memory.	RMSE: 1.41C MSE: 0.272C R^2 = 0.997

7. Conclusion

In conclusion, the Convolutional Neural Network (CNN) emerges as a powerful tool for identifying climate patterns during floods when utilizing global climate model data. Its superiority over the aforementioned algorithms is attributed to its adeptness in leveraging backpropagation and an increased number of epochs, leading to minimized errors in pattern recognition. The inherent capacity of CNNs to analyze vast image datasets contributes to their ability to provide more accurate outputs, particularly in the context of discerning intricate climate patterns associated with flood events. The effectiveness of CNNs is underscored by their proficiency in capturing spatial dependencies within meteorological images. By employing convolutional layers, these networks excel at recognizing intricate features and patterns in large-scale spatial data, enhancing their accuracy in identifying climate variations during floods. The utilization of backpropagation, along with an extensive number of epochs, further refines the model's capacity to discern nuanced patterns within the data, resulting in heightened accuracy. In practical applications, a synergistic approach is often beneficial, and a combination of different neural network architectures may be employed to address the diverse aspects of complex datasets. For instance, a hybrid model could integrate CNNs to capture spatial dependencies in meteorological images and Recurrent Neural Networks (RNNs) to handle temporal dependencies over sequential data. This hybridization enables a more comprehensive analysis, considering both spatial and temporal dimensions, thereby enhancing the overall predictive accuracy of the model. In the broader context, it is worth noting that the choice of neural network architecture depends on the nature of the data and the specific patterns being targeted. The recommendation to use CNNs for image data and RNNs for numerical data reflects a thoughtful consideration of the strengths of each architecture in handling different types of information. This nuanced approach ensures that the model can capitalize on the unique capabilities of each neural network type, ultimately leading to a more accurate and comprehensive understanding of climate patterns during flood events.

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