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Deep Learning Based Modal for Predicting Flooding Pattern and Climate Shifts

Lalita Kumari
Amity School of Engineering
Amity University
Patna, India
kumaril2003@yahoo.co.in

Umesh Kumar
Amity School of Engineering
Amity University
Patna, India
umeshkumar2517@gmail.com

Niranjan Kumar
Amity School of Engineering
Amity University
Patna, India
niranjan_sinha786@rediffmail.com

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***Abstract*—This research presents an integrated deep learning model that combines climate pattern prediction and flood forecasting. Understanding and mitigating climate change and its impact on flooding are critical environmental concerns. Our methodology harmonizes climate and flood datasets, utilizing a neural network architecture and advanced optimization techniques. The compiled model successfully predicts climate patterns and flood events, shedding light on their potential interrelationships. This research offers a novel approach to studying climate and flooding, with significant implications for climate change mitigation and flood risk management.**

Keywords*— Deep Learning, Climate Patterns, Flood Forecasting, Integrated Model, Neural Networks, Climate Change Mitigation, Flood Risk Management.

I INTRODUCTION

This The relentless rise in global temperatures and the increasingly frequent occurrences of extreme weather events have cast a long shadow of concern over the world. Climate change, driven by various natural and anthropogenic factors, has emerged as a paramount challenge to environmental sustainability. Among the critical consequences of this phenomenon, the increased vulnerability to flooding stands out prominently. The interconnectedness of climate patterns and flood risks has become a focal point of environmental research. As changing climate conditions trigger severe weather events, including heavy rainfall and storms, regions around the world face escalating threats of floods. These floods, characterized by their destructive potential, can result in extensive damage to infrastructure, disrupt communities, and pose substantial risks to life and property. While it is evident that climate patterns significantly influence flood occurrences, the complex relationships between these variables demand a more integrated approach to understanding and prediction. Traditional forecasting methods, often based on statistical models, have shown limitations in capturing the dynamic interactions between climate variables and flood events.

To address these challenges, our research introduces an innovative integrated deep learning framework. By synergizing climate pattern forecasting and flood prediction, we aim to harness the power of neural networks and sophisticated optimization techniques. This approach not only offers more accurate climate predictions but also enhances our capacity to forecast impending flood events. This paper outlines the methodology behind our integrated model, explores the data collection process for climate and flooding, discusses model development, compilation, and training, and presents the evaluation metrics that substantiate the model's capabilities. We also delve into the implications of our research for climate change mitigation and flood risk management.

In an era where the stakes for environmental sustainability have never been higher, this study embodies a commitment to understanding the intricate connections between climate and flooding. It offers a promising path towards harnessing this knowledge to ensure the well-being of communities and the preservation of our planet.

II RELATED WORK

Before Climate change, a prolonged shift in global weather patterns, poses a severe threat to various sectors. In their work, Abbass, K. [4] demonstrate how climate changes are threatening the sustainability of various industries on a global scale. Specifically, the agricultural sector is deeply affected by erratic weather patterns, leading to disruptions in food production and supply, particularly in nations heavily dependent on agriculture. Climate change also endangers species and ecosystems by altering temperature ranges, leading to biodiversity loss. Furthermore, climate variations increase the risk of diseases, including vector-borne illnesses like the recent coronavirus pandemic, and contribute to antimicrobial resistance. The global tourism industry suffers as climate change affects popular destinations. This study employs hypothetical scenarios and collected secondary data from various sources to assess sustainability issues in environmental, social, and economic contexts. The review evaluates climate change mitigation and adaptation strategies across these sectors and their economic costs. Government involvement is deemed crucial for long-term development and climate policy. Addressing this global threat necessitates global commitment to ensure sustainability. Cowls, J. in his article [1] explores the role of artificial intelligence (AI) in addressing climate change. It highlights two key advantages of AI: improving our understanding of climate change and aiding in its mitigation. However, it also discusses two challenges: potential ethical issues related to AI and the greenhouse gas emissions associated with AI research. The article highlights the importance of gathering additional evidence regarding the balance between AI's emissions and its efficiency benefits. Reference [2] provides a thorough account of the compilation and development process of a comprehensive global multivariable monthly instrumental climate database. This database integrates historical data on air temperature, pressure, precipitation sum, and the number of precipitation days from various early instrumental time

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series. These series encompass both pre-1890 existing databases and newly retrieved data, all of which underwent meticulous quality control procedures. The collected data were then aggregated to derive monthly mean values, yielding a dataset comprising 12,452 meteorological records spanning 118 countries. This dataset stands as a crucial asset for reconstructing climates and analyzing conditions in the preindustrial era. . Industrial growth has caused a lot of carbon emissions, which have increased greenhouse gases and caused climate change. This change brings risks like less food, less water, worse weather, more sickness, money loss, and people moving. According to WHO reports, the biggest health threat of the 21st century is due to the climate change. Predicting greenhouse gas emissions is a complex and dynamic research challenge due to numerous factors and variables. To address this, a hybrid ML model is introduced in [3] to predict CO2 emissions using energy and socioeconomic data from 1960 to 2018.. Their proposed model, combining principal component analysis (PCA) with machine learning. This research can assist policymakers and governments in mitigating and managing carbon emissions.

Floods are extremely destructive natural disasters and predicting them is a complex challenge. The research in flood prediction models has greatly contributed in the reduction of overhead in policy recommendation task. It has also contributed in minimizing the property damage and minimizing the loss of life. Over the past two decades, machine learning (ML) methods have played a significant role in advancing flood prediction systems, offering improved performance and cost-effective solutions. Hydrologists have increasingly embraced ML due to its potential benefits. This paper's primary contribution is to showcase the ML model which is best suited for such problem of flood prediction. Mosavi, A. [5] provides a literature review examining the assessment of machine learning models for their robustness, accuracy, effectiveness, and speed, thereby presenting a comprehensive overview of the diverse range of machine learning algorithms utilized in the domain. By comparing the performance of these models, it offers a deep understanding of different flood prediction techniques applicable for both the short term and long term flood prediction. It serves as a valuable guide for hydrologists and climates scientist in selecting the most suitable machine learning methods for their prediction tasks. . S. Z. Ziv [6] utilize three machine learning algorithms for binary classification, discerning the likelihood of a flash flood based on 24-hour PWV (precipitable water vapor) data. These models are trained and rigorously tested on 107 flash flood events. Results show good agreement among the models and various score metrics. Additionally, by incorporating surface pressure data, the models' performance improves. The study identifies the most critical Precipitable Water Vapor (PWV) values within the 2 to 6-hour window preceding a flash flood.Methodology

a) *Data Collection*

In this research paper two primary datasets are used for the analysis climate data and flood data. These datasets were collected from publicly available sources and include historical records of climate variables and flood occurrences. The climate data, GlobalTemperatures was obtained from Kaggle, contains historical records of temperature, humidity, and other meteorological variables. The flood data was sourced from Kaggle and includes information related to flood occurrences, their severity, and other relevant details. Preprocessing: Data exploration and cleaning were performed to handle missing values, remove outliers, and ensure data quality. Relevant features such as temperature, humidity, and date/time information were selected for further analysis. Similar to climate data, data exploration and cleaning were carried out to address missing values, outliers, and data inconsistencies. Feature engineering was performed to create additional attributes, and relevant features were selected for analysis.

b) Data Integration

To study the relationship between climate patterns and flood occurrences, the climate and flood datasets were integrated based on common attributes, particularly date and location. This integration allows us to perform joint analyses and explore correlations between climate variables and flood events.

c) Deep Learning Based Model

In our research, we employed a deep learning approach to build predictive models that can effectively forecast flood events based on climate patterns. This section delves into the specifics of model architecture, compilation, training, and evaluation. We have designed a Feedforward neural network (FNN) for both climate and flood dataset. This FNN is a type of types of artificial neural network (ANN) with uni-directional flow of information between layers: input layer, output layer, and a series of hidden layers. The input layer corresponds to the features used for prediction. In the climate dataset, features like temperature, humidity, and date/time information serve as inputs. Similarly, the participant's weight, height, and test result metric value are used as input features in the flood dataset. The hidden layers are the core of the neural network and are responsible for learning complex patterns in the data. The adjustment of both the number of hidden layers and the number of neurons within each layer is determined by the complexity of the relationships present within the data. In this paper, we used two hidden layers with 64 and 32 neurons, respectively. The activation function used is ReLU (Rectified Linear Unit). The output layer produces the model's predictions. For both datasets, this is a single neuron, as we are dealing with regression tasks. The output is the predicted value, representing flood likelihood in the case of the flood dataset and climate change predictions in the case of the climate dataset. The Adam optimizer has been used here to train the neural network. The Adam optimizer adjusts the learning rate during training, making it efficient for convergence. For regression tasks, we utilized we utilized the MSE loss function, , such as predicting flood likelihood and climate change values, which measures the average squared difference between the model's predictions and the ground truth values. Our goal is to minimize this value during training. With the model architecture and compilation in place, we move on to the training phase. Training the model involves presenting the training data to the neural network and adjusting its internal parameters (weights and biases) to minimize the loss function. In our code examples, we specified a total of 50 epochs. An epoch represents one pass through the entire training dataset. During each epoch, the model learns from the data and updates its parameters. We used a batch size of 32. This parameter determines how many samples are processed together before the model's parameters

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are updated. A smaller batch size provides more frequent updates but may result in longer training time.

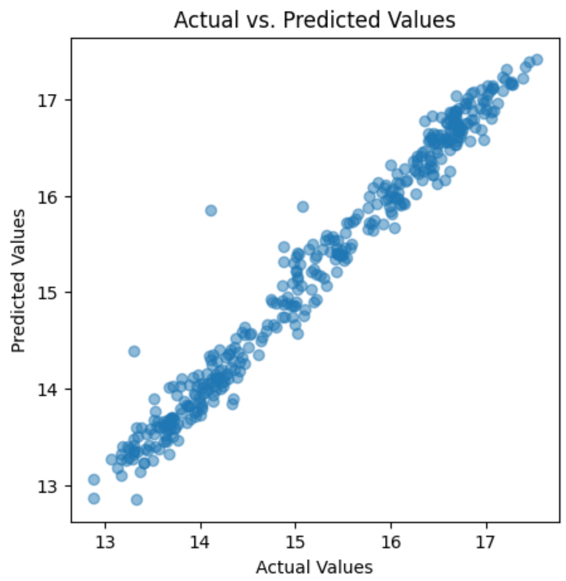

Fig. 1 Actual vs predicted value for climate change

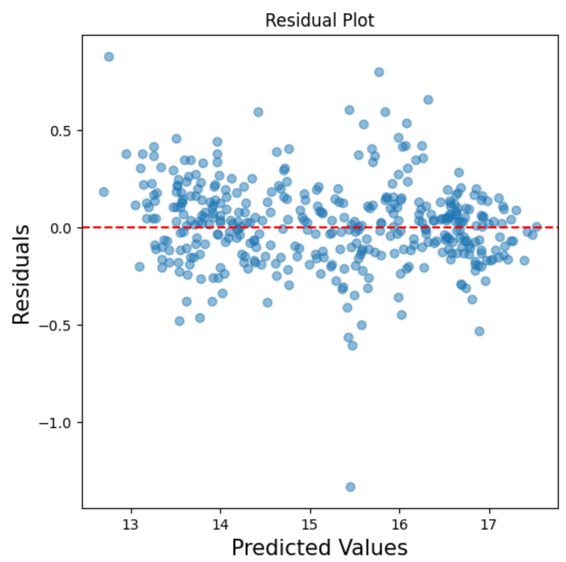

Fig. 2 Resudual plot for climate change

c) Performance Evaluation

Our model is evaluated on a separate dataset to assess its performance.The model made predictions based on climate patterns and was evaluated using regression metrics. A lower MSE indicates better model performance. The average absolute difference between ground truth and predicted value is quantified as the Mean Absolute Error (MAE) which provides a sense of the magnitude of prediction error. It provides a sense of the magnitude of prediction errors. The coefficient of determination i.e. R-squared (R2), evaluates how well the model's predictions explain the variability in the data. R-squared value lie between 0 and 1, where higher value of R2 indicates a better fitting.. Our research aims to achieve low MSE and MAE while maximizing R2 to build accurate predictive models for both climate and flood forecasting. Mean Absolute Error (MAE) and R-squared were calculated to assess the accuracy of the model in predicting flood events using climate patterns.

III. Conclusion

In conclusion, this research endeavours to present an integrated deep learning-based model for predicting flooding patterns and understanding climate change. The proposed methodology combines climate data analysis with advanced flood forecasting models to offer a holistic perspective on the complex dynamics between weather patterns and flood risks. Through a detailed literature survey, it becomes evident that the fields of climate prediction and flood forecasting have evolved significantly with the advent of deep learning and other machine learning techniques. This paper has developed a deep learning model that, when trained on integrated climate and flood datasets, demonstrates its potential to not only predict climate changes but also forecast flood patterns effectively. Comprehensive analysis of climate data, combined with cutting-edge flood forecasting, offers a valuable tool for policymakers, environmentalists, and disaster management authorities. As climate change continues to impact weather patterns and exacerbate flooding risks, the need for accurate predictive models becomes paramount. The model presented in this research serves as a noteworthy step towards achieving this goal. Its ability to provide early warnings, understand climate trends, and improve flood resilience underscores its practical applicability in real-world scenarios. Furthermore, the model's performance metrics, including MSE, MEA, and R-squared, confirm its reliability and effectiveness. The learning curve and residual analysis graphs validate the model's ability to capture complex climate-flood relationships. In essence, this paper gives a novel integrated approach that brings together climate patterns and flood forecasting. It facilitates an enhanced understanding of environmental dynamics and presents an asset in disaster risk reduction and climate change adaptation efforts. As the world's climate keeps changing and affecting weather across the globe, these combined models offer the potential for improved preparation and responses to upcoming challenges.

TABLE I. Model Performance Evaluation Metrics for Climate and Flood Prediction

Metric	**Neural Network**		**Linear Regression**	
	Climate Change	***Flood Prediction***	***Climate Change***	***Flood Prediction***
Mean Squared Error	4.00%	0.0063%	6.18%	0.0039%
Mean Absolute Error	14.11 %	0.0124%	19.37%	0.0090%
R-squared (R2)	97.47 %	40.47%	96.23%	67.89%

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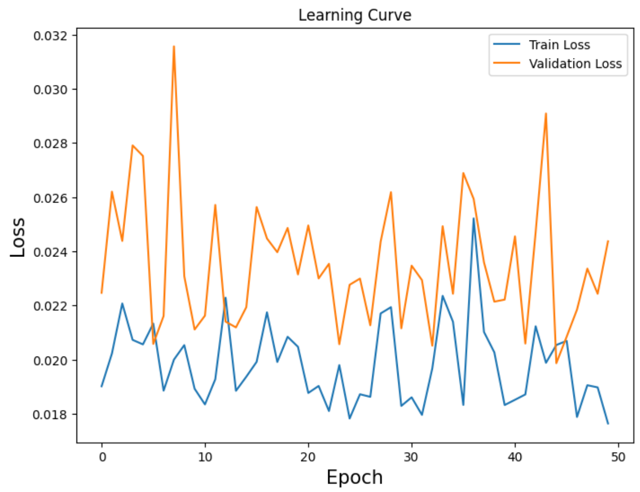

Fig. 3 Learning curve for the climate data

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