Thesis Report

Climate Forecasting in Bangladesh Using Distinct Artificial Intelligence Techniques

RESEARCH SUPERVISOR

Dr. Md. Ashikur Rahman Khan

Professor and Chairman

Department of ICE, NSTU

SUBMITTED BY

Jannatul Naim

Roll No: BKH2111MSc103F

Session: 2020-2021

Year II, Term I

Department of ICE, NSTU

DEPARTMENT OF INFORMATION AND COMMUNICATION ENGINEERING

NOAKHALI SCIENCE AND TECHNOLOGY UNIVERSITY

2 OCTOBER ,2024

A Thesis Report on

Climate Forecasting in Bangladesh Using Distinct Artificial Intelligence Techniques

JANNATUL NAIM

BKH2111MSc103F

INFORMATION & COMMUNICATION ENGINEERING

NOAKHALI SCIENCE AND TECHNOLOGY UNIVERSITY

DECLARATION

This thesis paper is submitted to the Department of Information & Communication Engineering, Noakhali Science & Technology University, Noakhali – 3814, in partial fulfilment of the requirements for having the M.Sc. degree in ICE. This is also needed to certify that the research work is under the M.Sc. degree in ICE under the course entitled "ICE – 5312'. So, I, here by, declare that this thesis paper has not been submitted elsewhere for the requirement of any kind of degree, diploma or publication.

Jannatul Naim

M.Sc. Student of ICE, NSTU

Roll No: BKH-2111MSc103F

Year : 2, Term - 1

Session: 2020-2021

ACCEPTANCE

This Thesis paper is submitted to the Department of Information and Communication Engineering, for the partial fulfilment of M Sc. in ICE degree and is not copied from any other research work.

Dr. Md. Ashikur Rahman Khan

Chairman and Professor

Department of ICE

NSTU, Noakhali-3814

Bangladesh

Climate Forecasting in Bangladesh Using Distinct Artificial Intelligence Techniques

ABSTRACT

In Bangladesh, a nation that is primarily dependent on agriculture and is extremely vulnerable to weather-related dangers, weather forecasting is of utmost importance. This research paper aims to develop accurate weather prediction models for rainfall, flood, temperature, and drought using distinct artificial intelligence regression techniques, including Support Vector Regression (SVR), Decision Tree, Random Forest, k-Nearest Neighbours (KNN), and Multilayer Perceptron Neural Network (MLPNN). Additionally, the optimization algorithms Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are sequentially applied to enhance the performance of these models. We utilized historical weather data from 1980 to 2022 provided by the Bangladesh Meteorological Department (BMD). Splitting the data into 80% for training and 20% for testing, we evaluated model accuracy using Root Mean Square Error (RMSE) and Mean Squared Error (MSE). Among the techniques tested, Random Forest showed the best performance, demonstrating its efficacy in weather prediction. Therefore, we will use Random Forest to predict the temperature and rainfall for the next 10 years (2023 - 2033). From our research, we have found that over the next 10 years, the average temperature in the country will increase by approximately 0.5 degrees Celsius, and the summer season will be longer. The winter season will be shorter, and the average temperature during winter will increase compared to previous years. The annual average rainfall in the country will decrease, and this reduced rainfall, coupled with higher temperatures, will nearly double the risk of drought. Additionally, due to climate change, the frequency of floods is expected to increase suddenly in the coming years, and there is a possibility of over flood in some years. The results of this study will advance the field of weather forecasting in Bangladesh by giving insight into the effectiveness of various AI regression approaches and optimization algorithms. Accurate weather forecasting can have a substantial positive impact on a number of industries, including agriculture, disaster relief, and public safety.

Keywords - Weather Prediction, Artificial Intelligence, Regression Techniques, Support Vector Regression (SVR), Decision Tree, Random Forest, k-Nearest Neighbours (KNN), Multilayer Perceptron Neural Network (MLPNN), Optimization Algorithms, Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), Weather Data.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATION

SVM	Support Vector Machines
DT	Decision Tree
RF	Random Forest
KNN	K-Nearest Neighbors
MLP	Multilayer Perception
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
RMSE	Root Mean Squared Error
MSE	Mean Squared Error

CHAPTER - 1

INTRODUCTION

1.1 Introduction

Climate pertains to the extended duration of weather observations in a particular geographical area, encompassing factors like temperature, humidity, precipitation, wind patterns, and atmospheric conditions. It represents the consistent and enduring patterns of weather over an extended period, typically ranging from decades to centuries. Climate provides a sense of stability by reflecting the average weather conditions and fluctuations in a specific region.

Long-term changes to the Earth's climatic patterns are referred to as "climate change," particularly when they involve large shifts in temperature, precipitation, wind patterns, and other weather indicators over time. The effects of climate change on the Earth's systems including human societies are extensive on a worldwide scale. The average temperature is gradually rising across the globe due to global warming.----- Hurricanes, floods, cyclones, droughts, and wildfires are just a few examples of the extreme weather events that are becoming more often and severe due to climate change. These incidents cause substantial financial losses, infrastructural damage, and fatalities. Climate change can have a detrimental impact on agricultural output, resulting in crop failures, lower yields, and food shortages. It can also change rainfall patterns and increase the frequency of extreme events.

One of the nations most impacted by climate change is Bangladesh, which is dealing with a number of serious effects that pose serious problems for its people and economy. Bangladesh is extremely vulnerable to sea level rise due to its low-lying topography and long coastline. Storm surges, tidal flooding, and erosion are more likely to occur in coastal areas, increasing the danger of community displacement, losing agricultural land, and infrastructure damage. In Bangladesh, climate change is a factor in the increased frequency and severity of cyclones, flooding, and excessive rainfall. Increasing temperatures, altered rainfall patterns, and pest outbreaks all cause disruptions in agricultural operations as a result of climate change. Crop production, food availability, and rural incomes are all at stake because of this.

1.2 Justification of the Research

I. The Temperature is Increasing Every Year: Bangladesh had faced severe heatwaves in recent years, with temperatures exceeding 40 degrees Celsius. Between 1976 and 2019, Bangladesh experienced a rise in average temperatures, with an overall increase of 0.5°C. The eastern side saw a more significant climb of 0.9°C compared to the 0.6°C to 0.9°C in the west, while the central region recorded an increase of less than 0.5°C. This temperature hike has contributed to making Bangladesh notably hotter over the years, with varying degrees of impact across different regions of the country. People are really feeling the heat, making daily life tough. The extreme temperatures are causing problems for everyone, from health concerns to everyday activities. [1]

II. Decreasing Rainfall Day by Day: The rain is declining day by day. Bangladesh, were expected to see a 50% decline in rain-fed agriculture yields by 2020. Between June and August, the average monthly rainfall during the peak monsoon period has decreased by around 60 mm, while there has been an increase of 43 mm in mean monthly rainfall for September and October from 1901 to 2019. Additionally, from 1980 to 2019, the southern part of Bangladesh has witnessed a drying trend, with rainfall declining from an average of 175mm to 140mm, indicating a shift towards drier conditions over time in this region [1].

III. The Salinity of the Water is Rising: The salinity of the water is rising, which has a direct impact on rice production. If the sea rises by a meter, Bangladesh could lose 12-16% of its land. The current weather shift is negatively affecting crop yielding and reducing the overall area of arable land because agricultural productivity is strongly correlated with temperature and rainfall. When the maximum temperature rises by 1 degree Celsius during different growth stages of Aman rice, production drops by 2.94, 53.06, and 17.28 tons during vegetative, reproductive, and ripening stages, respectively.

IV. Natural Calamities are Increasing More Than in the Past: Floods, droughts, salinity in the soil and water, cyclones, and storm surges are other frequent constraints. Climate change is causing the north-eastern districts to experience greater spikelet sterility, higher levels of insect and disease infestation, a lack of water and soil moisture due to an increased rate of evapotranspiration, and decreased agricultural production (rice, wheat, pulses, rape seed, and coconut). On the other hand, the southern coastal belt will experience flooding and be more susceptible to salinity intrusion, which will reduce crop productivity.

V. Rising Temperatures and Shifting Rainfall Patterns Affecting Public Health: There are several ways that climate change affects human health. The geographic spread of Rising temperature and humidity elevate the risk of respiratory illnesses: each 1°C temperature hike increases infection likelihood by 5.7%, while a 1% humidity rise raises it by 1.5% [2]. Vector-borne illnesses like dengue or malaria fever is influenced by changing weather patterns. The degree of anxiety disorders rises with humidity and temperature.

VI. Biodiversity is Under Threat: The Sundarbans mangrove forest and other distinctive ecosystems in Bangladesh are under threat from climate change. Extreme weather, sea level rise, and rising temperatures all threaten biodiversity.

VII. Economic Loss in Many Sectors: Climate change significantly impacts Bangladesh's economy through various channels. The natural calamities damage infrastructure, agricultural lands, and homes, leading to significant economic losses. Changing weather patterns impact agriculture, the backbone of Bangladesh's economy, leading to reduced crop yields and food insecurity. Major cities such as Dhaka and other coastal portions of the nation are at risk of flooding, which would have an impact on urban areas, transportation systems, and industrial zones. This has a negative impact on trade, business, and the economy as a whole.

Due to all of this, Bangladesh will need to get ready for long-term adaptation. So future weather prediction is very important for Bangladeshi people.

Huge amounts of previous climate data can be processed by AI algorithms to find intricate patterns and relationships. Algorithms that can identify patterns can shed light on long-term climatic trends like temperature variations, precipitation patterns, or atmospheric conditions. AI systems, especially those that use machine learning (ML) methods, may create complex climate models. Algorithms that use machine learning (ML) can learn from past climate data and apply that knowledge to forecast future climate conditions. In our work, we used several machine learning algorithms for climate prediction of Bangladesh.

1.3 Problem Statement

Bangladesh is one of the nations most exposed to the consequences of climate change, making it a crucial problem. At the 2020 edition of German Watch's Climate Risk Index, it came in seventh place among the nation's most severely impacted by climate disasters between 1999 and 2018[3]. Natural disasters that happen frequently, a lack of infrastructure, a large population density (166 million people live in an area of 147,570 km2), an extractives' economy, and social inequalities make the nation more vulnerable to the world's changing climate.

Intelligent weather prediction systems can, to some extent, assist us in making wise judgments that can occasionally save priceless lives, times, and property. Over the years, technology and science have grown to a new level, and the discovery of weather patterns has garnered more attention. The traditional forecasting techniques have been superseded by numerical and computer models. The accuracy and effectiveness of forecasts are being increased through the use of artificial intelligence (AI). Large amounts of weather data from many sources, including weather stations, satellites, radar systems, and weather buoys, are analysed using AI algorithms.

Specifically, for rainfall, flood, drought, temperature, and cyclone events, Bangladesh's variable and dynamic climate present considerable obstacles for precise weather forecast. The intricate interactions & non-linear patterns that are present in these weather occurrences are frequently difficult to depict using conventional weather forecasting techniques. Because of this, it is necessary to investigate and assess various artificial intelligence methods, such as Decision Trees, KNN, SVM, MLPNN, and Random Forests, in order to improve the precision and dependability of weather prediction models in Bangladesh. The project attempts to solve the drawbacks of conventional approaches and create a more reliable and effective weather prediction system by utilizing the capabilities of these cutting-edge algorithms.

We collected data from the Bangladesh Meteorological Department between 1980 and 2022 to forecast the future weather conditions, especially regarding temperature, rainfall, floods, droughts, and cyclones using various machine learning algorithms like Multilayer Perceptron Neural Network, Decision Tree, Support Vector Machines, KNN, and Random Forests. We forecasted weather data for the next 10 years, from 2023 to 2033, and found that the Random Forests algorithm provided the best output, offering the most accurate predictions. Through this forecasting, we acquired information about the future conditions of temperature rise, overall rainfall, floods, and droughts in Bangladesh for the upcoming years, which will aid in understanding the country's weather situations. Additionally, it will help us determine strategies for managing agriculture, industries, disaster management, and other relevant sectors related to weather to mitigate losses and ensure better economic stability.

1.4 Research Objectives

This research paper will work on weather prediction using distinct artificial intelligence techniques. The main purposes of this research are the following:

I. To analysis the data of temperature, rainfall, flood and drought in Bangladesh perspective.

II. To illustrate the impact of climate change in Bangladesh.

III. To find out the impact of climate change in Bangladesh.

IV.To develop distinct models for weather prediction or forecasting.

V.To compare the distinct developed models and to identify the best model in weather prediction.

1.5 Contribution of this Research

This research delves into various sectors that have not been explored by previous researchers in Bangladesh. It involves forecasting temperature, rainfall, floods, and droughts while also analyzing historical data to understand weather trends. Moreover, the study applies sequential optimization with artificial algorithms for weather attribute forecasting, a novel approach in Bangladeshi weather forecasting. Additionally, the research aims to identify the impacts of climate change and propose potential solutions. The paper makes several significant contributions, which are outlined below:

I. In this thesis, we have used 5 machine learning algorithms. To improve the effectiveness of these algorithms, we have utilized sequential optimization of GA and PSO, which has not been used in any climate-related thesis work in Bangladesh so far. Furthermore, we have compared the results between without optimization and with optimization, demonstrating that with optimization provides better accuracy.

II. We have predicted the average temperature of Bangladesh for the next 10 years and found that the temperature is on a rising trend. The mean temperature will rise by at least 0.5 degrees Celsius in the next 10 years. Additionally, we have analyzed the temperature data of the last 43 years, showing temperature conditions in Bangladesh at 10-year intervals and 5-year intervals. We have presented the mean temperature conditions for summer and winter as well as the rising trends over the past 43 years.

III. In our research, we have identified a consistent rise in monthly temperatures each year. We have analyzed the monthly temperature data of the past 40 years to illustrate this trend. Furthermore, we have projected how monthly temperatures will continue to increase in the future. Through our research, we have observed the lengthening of summers and the shortening of winters over time.

IV. Our research indicates a consistent decrease in rainfall each year based on previous data, with projected average rainfall for upcoming years falling below 200 millimetres. Additionally, we have observed a decline in total rainfall during the rainy season, accompanied by an increase in rainfall after the rainy season.

V. From our research, we have discovered that in the future, the frequency of droughts will significantly increase compared to previous years. Additionally, Bangladesh will continue to experience a considerable number of floods.

VI. The continuous rise in temperature and declining rainfall in previous years will have significant impacts on both people's lives and the environment. We have endeavoured to identify the effects of this climate change on Bangladesh and its inhabitants. Additionally, we provide suggestions on how to mitigate the impact of climate change and outline necessary steps to safeguard our environment.

1.6 Research Hypothesis

The accuracy and dependability of weather forecasting in Bangladesh can be improved by the implementation of various artificial intelligence approaches. It is anticipated that the forecast of weather patterns, such as rainfall, temperature, and cyclones, are more accurate by applying AI algorithms and machine learning models. The idea is that by applying several artificial intelligence approaches, it will be possible to analyse and understand meteorological data more effectively, improving forecasts for Bangladesh's weather. Additionally, it expects that the application of these algorithms delivered localized weather forecasts in a timely manner, assisting with efforts to prepare for and mitigate disasters. The adoption of various artificial intelligence techniques, according to the hypothesis, is revolutionizing weather forecasting in Bangladesh and providing invaluable information for efficient planning and decision-making in a variety of fields, including agriculture, transportation, and disaster management.

1.7 Scope of this Research

Bangladesh's vulnerability to climate change underscores the critical need for accurate climate prediction models. This paper explores the scope of climate forecasting in Bangladesh, focusing on sectors like agriculture, health, industry, disaster management, and infrastructure. By anticipating future climate conditions, these models enable informed decision-making and effective adaptation strategies, fostering resilience and sustainable development in the face of climate challenges.

Future climate forecasting in Bangladesh will provide valuable insights for the agricultural sector, including crop selection, planting schedules, and irrigation management. Climate prediction models will empower farmers with timely and localized weather forecasts, enabling them to make informed decisions regarding planting, harvesting, and crop protection measures. Access to accurate climate information will enhance agricultural productivity, reduce crop losses due to adverse weather conditions, and improve livelihoods in rural communities.

Climate prediction in Bangladesh will support the industrial sector by informing infrastructure planning, energy demand projections, and supply chain management strategies. Climate prediction in Bangladesh will inform infrastructure planning and development projects, including roads, bridges, housing, and urban infrastructure.

Future climate forecasting in Bangladesh aids the health sector by enabling early detection and prevention of climate-related health risks. It anticipates changes in temperature, humidity, and disease vectors, informing interventions like heatwave preparedness, vector control, and disease surveillance.

Climate prediction models will play a crucial role in disaster management in Bangladesh by improving early warning systems, risk assessment tools, and emergency response strategies. Forecasting extreme weather events, such as floods, cyclones, and landslides, will enable authorities to evacuate vulnerable populations, pre-position relief supplies, and coordinate disaster response efforts effectively.

climate prediction in Bangladesh covers agriculture, health, industry, disaster management, infrastructure, ecosystem services, and livelihoods. It enhances resilience, fosters sustainable development, and safeguards people and ecosystems against climate change.

1.8 Thesis Structure

This thesis report is structured as follows:

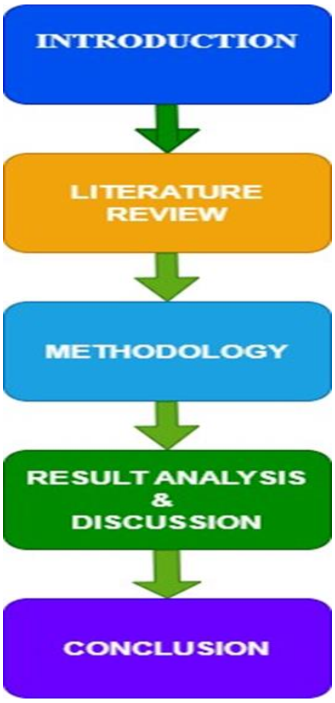

Figure 1.1: Structure of the thesis paper

Chapter 2: Literature Review offers an overview of recent works in the field of weather, climate change, and future climate prediction.

Chapter 3: Methodology describes the steps that are used in the proposed system.

Chapter 4: Result Analysis and Discussion presents the future climate conditions that we have found from our research and also presents the impact of climate change on Bangladesh.

Chapter 5: Conclusion includes the conclusions and scopes of future work.

CHAPTER - 2

LITERATURE REVIEW

2.1 Introduction:

In this section, we provide a comprehensive review of previous research on weather prediction, detailing the contributions of various researchers and comparing their work. This section is structured into four parts. The initial part features a summarized table showcasing related work in this field. Subsequently, Global Weather Research Across Countries, the weather-related work of researchers in Bangladesh, and Papers Relevant to Comparative Analysis of Machine Learning Algorithms delve into distinct aspects of the reviewed literature.

Table -2.1: Related Works at a Glance

SN	Paper	Author And year	Data Collection	Implemented Methods	Findings
1	Atmospheric Temperature Prediction using Support Vector Machines	Y. Radhika et. al 2009[40]	University of Cambridge	SVM, MLP	Maximum Temperature
2	Artificial intelligence Models for prediction of monthly rainfall without climatic data for meteorological stations in Ethiopia	Abebe et. al [39]	Meteorological stations (Ethiopia)	MLP Gradient Descent	Rainfall
3	A Bayesian Deep Learning Approach to Near-Term Climate Prediction	Xihaier Luo et. al 2022[12]	Communy Earth System Model (CESM)	CNN BDL	Temperature
4	A canonical model for seasonal climate prediction using Big Data	M. P. Ramos et. al 2022 [13]		MPRECLIS. PINSERTR, PEXTRACTOR and P-PRECLIS	
5	Drought forecasting using new machine learning methods	Anteneh BELAYNEH et. al 2013 [16]		ANN SVR WA-ANN	Drought

6	Weather Forecasting Using Artificial Neural Network	Dires Negash Fente et. al 2018 [15]	national climate data center (NCDC)	LSTM	Wind, temperature pressure, humidity
7	Artificial Intelligence-Based Model for Drought Prediction and Forecasting	Amandeep Kaur et.al 2019[17]		IOT, ANN GA, SVD	Drought
8	Comparison of Different Artificial Intelligence Techniques to Predict Floods in Jhelum River, Pakistan	Fahad Ahmed Et. al 2022 [18]		LLR, DLLR TLBP, CG BFGS	Flood
9	Prediction of Flood in Bangladesh using k-Nearest Neighbors Algorithm	Noushin Gauhar et. al 2021[19]	BMD	K-NN	Flood
10	Prediction of Temperature and Rainfall in Bangladesh using Long Short-Term Memory Recurrent Neural Network	Mohammad Mahmudur Rahman Khan et. al [20]	BMD	RNN LSTM	Temperature Rainfall
11	Tropical cyclone prediction over Bay of Bengal: a comparison of the performance of NCEP operational HWRF, NCAR ARW, and MM5 models	D. V. Bhaskar Rao et. al 2012 [21]			Cyclone
12	Flood Prediction Using Machine Learning Models	Miah Mohammad Asif Syeed et. al 2022 [22]	BMD	KNN Logistic Regression	Flood
13	An Overview of Weather Forecasting for Bangladesh Using Machine Learning Techniques	Atik Mahabub et. al 2019 [23]	BMD	SVR, LR, GB XGBoost CatBoost AdaBoost KNN, DTR	Rainfall, Temperature Humidity, wind, Wrongfoot
14	Flood susceptibility mapping in Brahmaputra floodplain of Bangladesh using deep boost, deep learning neural network, and artificial neural network	Naser Ahmed et. al 2022 [24]	versatile national & international sources	Deep learning neural network, and artificial neural network	Flood
15	Monthly Weather Forecasting through ANN Model: A Case Study in Barisal, Bangladesh	S.M. Taohidul Islam et. al 2016 [37]		ANN MATLAB	

16	Weather Forecasting for the North-Western region of Bangladesh: A Machine Learning Approach	Md. Arif Rizvee et. al 2020 [25]	BMD	ELM ANN	
17	Predicting cyclone tracks in the north Indian Ocean: An artificial neural network approach	M. M. Ali et. al 2006 [38]		ANN	Cyclone
18	Application of Weather Forecasting Apps for Agricultural Development in Bangladesh	Md. Nakibul Hasan Khan et. al 2018 [27]			Temperature, humidity, Rainfall and wind
19	A comprehensive statistical assessment of drought indices to monitor drought status in Bangladesh	Md. Jalal Uddin et.al 2020 [36]	BMD		Drought
20	Weather Prediction Using Clustering Strategies in Machine Learning.	Sravani Nalluri et al. 2019 [42]		Simple k means, Hierarchical Density based clustering, Filtered clustering and Farthest first Clustering.	
21	Application of Artificial Neural Networks for Temperature Forecasting	Mohsen Hayati et al. 2007 [41]	IMD	Heuristic technique And numerical optimization techniques	

2.2 Global Weather Research Across Countries

Over the past few decades, there has been a significant amount of research dedicated to exploring the application of artificial intelligence (AI) in automated weather prediction. Several research projects have focused on this area, delving into various methodologies and techniques to enhance forecasting accuracy. These methodologies include expert systems, fuzzy logic, data mining, machine learning (ML), and deep learning. Researchers have utilized these approaches to develop innovative models and algorithms capable of analysing weather data and generating predictions. The integration of AI technologies has opened up new possibilities for improving the accuracy and efficiency of weather forecasting systems, paving the way for advancements in the field.

Tae-wong et al. [4] introduced the Space-Time model, which effectively represented the daily rain event's temporal and geographic characteristics, providing visualizations of short-term weather conditions over time. Air temperature prediction has been the subject of several research endeavours, with Chevalier et al. [5] utilizing Support Vector Regression (SVR) as a methodology for this purpose. Devi et al. [6] developed a temperature forecasting model based on Artificial Neural Networks (ANN), leveraging real-time quantitative data to capture the current state of the atmosphere. Olaiya and Adeyemo et al. [7] conducted a study that explored the application of Artificial Neural Networks (ANN) and decision trees for classifying various meteorological data parameters, including maximum, minimum, and mean temperature, precipitation, evaporation, and wind speed. The data used in the study was collected from Nigeria. Luminto et al. collaborated on this research endeavour. A weather forecasting model specifically tailored for Indonesia was developed by Luminto et al. [8], employing a Linear Regression model to predict the optimal rice cultivation time.

In a separate study, Navin et al. [9] focused on creating site-specific prediction models for solar power generation using various machine learning (ML) techniques. Multiple regression strategies, such as linear least squares and support vector machines with multiple kernel functions, were compared in their research. The research conducted by Nishe et al. [10] resulted in the development of a comprehensive system for gathering precise weather updates and forecasts. They developed an Android application and an Arduino-based device integrated with a GPS system, which allowed for the collection of micro-level data from thousands of users. The research conducted by Krasnopolsky et al. [11] demonstrated the practicality of employing Neural Network (NN) techniques in numerical weather modeling and prediction. They presented a model that utilized NN as a statistical or machine learning (ML) approach to develop highly accurate and efficient emulations for computationally-demanding model physics components, thereby enhancing the overall performance of the system.

Xihaier Luo et al. [12] focused on the use of feedforward convolutional networks in A Bayesian Deep Learning Approach to Near-Term Climate Prediction. They discovered that, in terms of predicting capability, a feedforward convolutional network using a Densenet layout can outperform a convolutional LSTM. The probabilistic (Bayesian) formulation of the same network utilizing Stein variational descent gradients was then taken into consideration, and it was discovered that in addition to offering practical measures of predictive uncertainty, it outperformed its predictable counterpart in terms of predictive skill. M. P. Ramos et al. [13]. The development of a canonical model with approaches, techniques, metrics, equipment, and Big Data was suggested with the purpose of improving dynamism, speed, conciseness, and adaptability in the area of seasonal climate forecast.

Wondmagegn Taye Abebe et al. [14] they made an effort to look at the usage of artificial intelligence (AI) models to forecast monthly rainfall at 92 meteorological stations in Ethiopia. Using geographic and periodicity component (longitude, latitude, and altitude) data gathered from 2011 to 2021, the usefulness of Artificial Neural Networks (ANNs) with Adaptive Neuro-Fuzzy Inference System (ANFIS) models in forecasting long-term monthly precipitation was examined. Dires Negash Fente et al. [15] in this study, several meteorological parameters were gathered from the national climate data centre, after which the neural network was trained for various combinations using the Long-Short Term Memory (LSTM) technique. The neural network used in LSTM weather prediction is trained using various combinations of meteorological parameters, including temperature, precipitation, wind speed, pressure, dew point, visibility, and humidity. The forecasting for upcoming weather is completed after the LSTM model has been trained using these parameters.

Anteneh BELAYNEH et al. [16] proposed a new model combining ANN and SVR named WANN. This coupled wavelet-neural network (WANN) models were found to provide the best results for forecasts of SPI 3 and SPI 6 in the Awash River Basin. Amandeep Kaur et al. [17] this study suggests an IOT-enabled fog-based architecture for drought forecasting and prediction. Utilizing singular vector decomposition, the overall dimensions of the information are reduced at the fog layer. The Holt-Winters approach is used to forecast future drought conditions. Drought severity categories are assessed for the given event using artificial neural networks with genetic algorithm classifiers. The suggested system is put into practice utilizing datasets from government organizations, and it successfully determines the level of drought severity.

2.3 The Weather-Related Work in Bangladesh

As Bangladesh is a disaster-prone country and one of the most vulnerable nations to climate change impacts, researchers in our country have been conducting research in this field for a long time. Below some of their research findings are highlighted.

Noushin Gauhar et al. [19] , in this study, they used the k-nearest neighbors (k-NN) method to predict floods using various correlation coefficients for feature selection. The thorough study of the results reveals that we used the k-NN machine learning algorithm to achieve a very high checking accuracy of 94.91%, an average precision of 92.00%, and an overall recall of 91.00%. Mohammad Mahmudur Rahman Khan et al. [20], their forecasting model can be used to analyse seasonal diseases in Bangladesh whose incidences are influenced by local temperature and/or rainfall as well as variations in weather patterns. D. V. Bhaskar Rao et al. [21], used NCEP, HWRF, NCAR, ARW and MM5 for predicting cyclone in the bay of bangle and HWRF gave the best accuracy. Miah Mohammad Asif Syeed et al. [22], used Binary Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), Decision tree Classifier and Stacked Generalization for predicting flood in Bangladesh.

Atik Mahabub et al. [23], in order to effectively predict the weather parameters for Bangladesh, regression-based Machine Learning (ML) models have been proposed in this study. Numerical modeling of the environment has been subject to a practical use of ML approaches. The raw data set was gathered from the Bangladesh Meteorological Division (BMD), and it contains information on rainfall, temperature, humidity, wind speed, and other variables for Bangladesh for the previous five years. Support Vector Regression (SVR), Linear Regression, Bayesian Ridge, Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), Category Boosting (CatBoost), Adaptive Boosting (AdaBoost), k-Nearest Neighbors (KNN), and Decision Tree Regressor (DTR) are a few of the regression algorithms that have been used. Regression approach results have been compared to the output of the current forecast-based models, demonstrating that models based on machine learning are more reliable than conventional methods.

Naser Ahmed et al. [24], the current study aims to evaluate the Brahmaputra floodplain's sensitivity to flooding. Using Artificial Neural Network, Deep Learning Neural Network, and Deep Boost. Flood inventory maps were mostly created using fieldwork and classification of satellite images. In order to run the models and validate the models, the flood areas were randomly divided into 70% training samples and 30% validation samples. Md. Arif Rizvee et al. [25], the Bangladesh Meteorological Department (BMD) provided thirty years' worth of historical weather data for this experiment, including information on temperature, rain, wind, and humidity from seven meteorological stations in the northwest. Compared to artificial neural networks, the Extreme Machine Learning (ELM) system performs better and has a 95% accuracy rate. In their study, Zaman et al. [26], focused on developing a machine learning (ML)-based rainfall prediction system specifically for Bangladesh. The researchers employed multiple regression algorithms and compared their performance to assess their effectiveness in predicting rainfall patterns. In their research, Nasimul et al. [27], developed a weather analysis model based on machine learning for the Los Angeles weather dataset. They utilized the C4.5 learning algorithm to classify different weather events, such as normal conditions, rain, and fog. This classification technique facilitated the accurate categorization of these weather patterns. Mohammadi et al. [28], developed a predictive model to anticipate the dew point temperature on a daily basis, incorporating various atmospheric conditions. They employed machine learning algorithms and utilized five fundamental atmospheric features, namely mean air temperature, relative humidity, atmospheric pressure, vapor pressure, and horizontal global solar radiation, as predictors in their model.

Based on Support Vector Regression (SVR) methods, Nasimul et al. [29], developed a rainfall prediction model for Bangladesh. When used with Bangladesh-specific weather data, the suggested method proved to be more accurate than traditional ones.

2.4 Papers Relevant to Comparative Analysis of Machine Learning Algorithms

Many researchers have compared various machine learning methods to determine the most effective ones for forecasting. Below are descriptions of some papers that have highlighted the best-performing methods.

Fahad Ahmed et al. [18], in the Jhelum River, Punjab, Pakistan, they sought to create and assess multiple data-driven flood forecasting models. They used Local Linear Regression (LLR), Dynamic Local Linear Regression (DLLR), Two Layer Back Propagation (TLBP), Conjugate Gradient (CG), and Broyden–Fletcher–Goldfarb–Shanno (BFGS). For all the training and validation periods, the LLR model outperformed the competition and can be used to forecast floods in the Jhelum River. Additionally, the model offers a starting point for the creation of a flood early warning system in the study region. A flood prediction model using the NARX structure of an Artificial Neural Network (ANN) model is provided in the research paper [30]. Multiple upstream river water levels are included in the model as input variables due to their importance in the occurrence of floods. A portion of the samples are used for the model's training, while the remainder are used for the model's validation. The model has a 73.54% success record in foretelling floods five hours in advance.

The utilization of the NARX neural network in modeling and predicting flood water levels is discussed in the research paper [31]. The model incorporates four variables, namely upstream river water levels, water levels at the flood site, and differences in water levels. The dataset is divided into training and testing data, which are then utilized to train the NARX model. The authors highlight an impressive accuracy rate of 87% achieved by the model when forecasting flood water levels. In recent years, a research study conducted in India [32] explored the use of various machine learning algorithms to predict floods. This study considered variables such as rainfall, humidity, temperature, and water velocity. Specifically, the research compared the accuracy and error rates of Deep Neural Network (DNN) with other machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naïve Bayes. The study utilized temperature and rainfall as parameters and employed a confusion matrix to determine the most effective approach for flood detection. The results indicated that DNN achieved the highest accuracy rate of 91.18%, followed by Naïve Bayes with 87.01%, SVM with 85.57%, and KNN with 85.73% accuracy.

A different study [33] used an artificial neural network called a back propagation neural network (BPN) to predict flood levels. Data on water levels from numerous stations in Johor, Malaysia, were used to train the BPN model. Although the preliminary results were not totally satisfactory, Extended Kalman Filter (EKF) was added to improve accuracy. The paper claims that the accuracy was increased when the BPN model and EKF were combined. Additionally, a study [34] explores the use of the EKF algorithm for flood water level prediction. The paper details the EKF method's two-stage process, involving prediction and update steps. In the prediction stage, previous data estimations are utilized, and the update stage incorporates feedback correction to refine the forecasted values. The dataset employed in this research consists of water level data, which is utilized for the purpose of forecasting flood levels. As mentioned in the paper, the algorithm achieves a Root Mean Square Error (RMSE) of 0.9236 m based on calculations. A comparative analysis of SVM and ANN for flood forecasting accuracy, using datasets of flood occurrences in Bangladesh, is presented in a research paper [35].

The study reveals that SVM demonstrates comparable prediction accuracy to ANN and sometimes outperforms ANN for longer lead times. The research employed water level data from five stations in Bangladesh to train and validate the SVM model. It was observed that ANN is more time-consuming, requiring extensive trial and error, compared to the SVM architecture. The limited availability of data also affects the accuracy of predictions made using the ANN model. In contrast, SVM yields better results within a shorter time frame and with limited datasets, which is crucial for effective flood prediction. The paper also highlights the computational advantages offered by SVM, such as its ability to represent input variables in dual form, which can be particularly advantageous in real-time forecasting scenarios involving substantial data handling.

2.5 Summary

In our work, we used several machine learning algorithms to predict the climate of Bangladesh. We used real data for this prediction. Utilizing artificial intelligence techniques for weather forecasting in Bangladesh is the main goal of this study. This study distinguished itself from other works using a variety of strategies, with a heavy emphasis on achieving unique and new results. The study focused on Bangladesh in particular, taking into account the nation's unique geographical features, diverse climatic patterns, and regionalized weather occurrences. The project attempts to provide weather forecasts that are extremely accurate and contextually relevant to the region by tailoring the analysis to address the particular conditions and difficulties found in Bangladesh. The study used modern artificial intelligence methods, such deep learning models, to improve the precision and accuracy of weather predictions. The substantial historical weather data, which includes temperature, humidity, precipitation, wind patterns, and other pertinent meteorological factors, were used to train these advanced algorithms. Additionally, the project concentrated on creating a clear and accessible interface that communicates weather forecasts to a variety of stakeholders, such as farmers, disaster management authorities, and the general public. This will guarantee that the study's findings have real-world applications.

CHAPTER -3

METHODOLOGY

3.1 Introduction

In this research works we aimed to predict the future climate of Bangladesh. For this, we have assessed the weather conditions for the next 10 years in Bangladesh. Alongside, we have compared previous data to see how the climate of Bangladesh has changed over the past 43 years and in what state it will be in the future. We have used various algorithms to predict temperature, rainfall, drought, and flood accurately based on historical data. Furthermore, the capability of making these predictions has significantly increased through the use of optimization algorithms.

3.2 Proposed Model of Climate Prediction

The process of climate prediction is briefly outlined in Figure 3.1. Initially, we collect data from the Bangladesh Meteorological Department (BMD) spanning the years 1980 to 2022. Subsequently, we apply min-max normalization and randomization to the dataset during the preprocessing stage. Following preprocessing, we employ five algorithms. Initially, these algorithms are applied without optimization. Then, the same algorithms are utilized with sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms. This optimization process enhances the accuracy of the results. Next, we divide the dataset into 80% for training and 20% for testing, applying the algorithms accordingly. Finally, we assess performance using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to evaluate algorithm performance. Through comparative analysis, we identify the algorithms that perform best with this dataset. Subsequently, we employ these selected algorithms to predict future rainfall and temperature. These predicted rainfall and temperature values are then utilized for forecasting future flood and drought conditions.

The overall diagram of the work in given below:

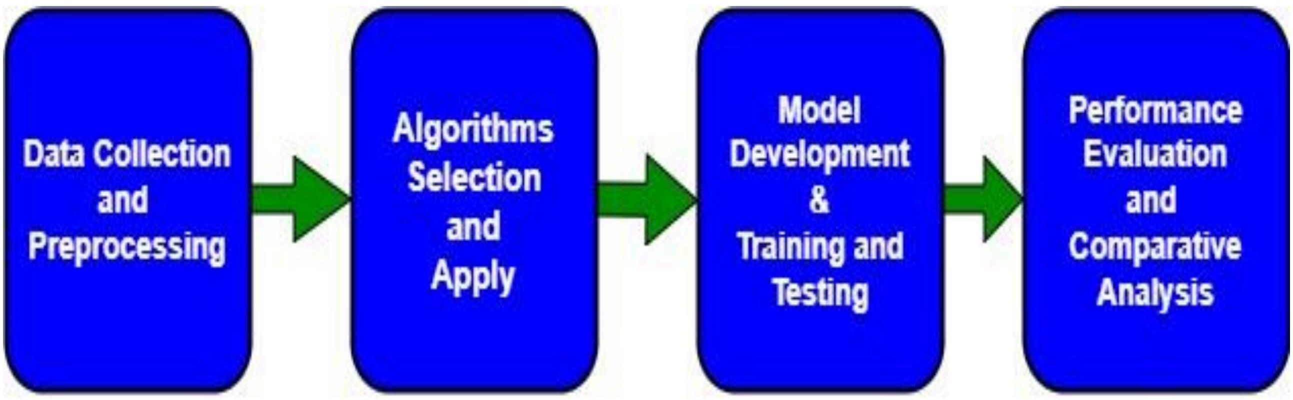

Figure 3.1: Workflow Diagram of Climate Prediction Model

For Climate predictions the following steps will be adopted:

3.2.1 Attributes: Determine the features or characteristics that are most important for each meteorological phenomenon in Bangladesh (rainfall, flood, temperature, and drought). The subset of attributes that have the greatest influence on each unique weather occurrence can be identified via statistical analysis, domain expertise, or feature selection algorithms. For climate predictions, evaluating the main attributes of climate is necessary. It is found that the attributes of climate are Temperature, Rainfall, Wind Speed, Wind Directions, Humidity, Precipitation, Pressure, Cloud Coverage, Sunshine, Radiation, Evaporation, Moisture of Soil, Dew Point and Water Level of River etc.

3.2.2 Data Collection and Pre-processing: we Collected detailed weather data (1980–2022) from Bangladesh Meteorological Department (BMD), including rainfall, flood incidents, temperature fluctuations, drought conditions, and cyclone events.

The Bangladesh Meteorological Department (BMD) is the national meteorological organization of Bangladesh. It operates under the Ministry of Defence of the Government of Bangladesh and is also known as the Abohawa Office or Weather Office. The BMD's history dates back to 1867 when meteorological activities began with the establishment of an observatory in Satkhira, a district in Southwestern Bangladesh. The BMD is responsible for maintaining a network of surface and upper air observatories, radar and satellite stations, agrometeorological observatories, geomagnetic and seismological observatories, and the meteorological telecommunication system of Bangladesh. They closely monitor and issue forecasts and warnings for various meteorological extreme events, including tropical cyclones, severe thunderstorms, tornadoes, heavy rainfall, droughts, cold waves, and heatwaves. The BMD provides round-the-clock daily routine forecasts and plays a vital role in ensuring public safety and preparedness for weather-related hazards in Bangladesh.

Pre-process the data by cleaning, handling missing values, and resolving inconsistencies or outliers to ensure its reliability and suitability for analysis. Then we applied min max normalization on the dataset. We also randomized the data to train the model properly.

The description of dataset for the proposed work has been described in table- 3.1.

Table -3.1: Description of attributes

Attributes	**Description**
Minimum Temperature	Minimum temperature of air (°C)
Maximum Temperature	Maximum temperature of air (°C)
Average Temperature	Average temperature of air (°C)
Heat index	The temperature feels like (°C)
Rainfall	Total amount of rainfall (mm)
Wind Speed	Velocity of Wind (km/hour)
Wind Direction	Direction from which the wind emanates in radius degree (0-360)

Humidity	Amount of water vapor in a mixture of air and water (%)
Precipitation	Total amount of rainfall (mm)
Pressure	Pressure by the surrounding air (Pascal)
Cloud Coverage	The amount of Cloud (Oktas)
Sunshine	Sunshine Duration (Hour)
Dew Point	Total Dew point in Degree Celsius (°C)
Evaporation	Precipitation Evaporation Index (PEI)
SPEI	Drought prediction tool

3.2.3 Dataset Preparation: We used a total of 3 datasets to predict 4 things: rainfall, flood, temperature, and drought. Using the first dataset, we predict the next 10 years' data for rainfall and temperature. The attributes available in this dataset are Minimum Temperature, Maximum Temperature, Average Temperature, Rainfall, Wind Speed, Wind Direction, Humidity, Precipitation, Pressure, Cloud Coverage, Sunshine, Dew Point, and Evaporation. These data encompass weather conditions for each day over 43 years, from 1980 to 2022. Based on this data, a forecast is made for the weather situation in Bangladesh for the next 10 years. We've collected data over many years and included multiple attributes to ensure accurate weather forecasting. Additionally, weather doesn't rely on a single attribute but rather on several, hence why this dataset comprises various attributes to provide accurate predictions. Afterward, this data is normalized using max-min normalization to bring them within a specific range.

The next dataset is for flood forecasting. It contains the total monthly rainfall amounts over 43 years for 34 weather stations in Bangladesh. Based on this rainfall data, forecasting of rainfall for the next 10 years on a monthly basis has been conducted. Excessive rainfall during the monsoon season primarily causes flooding in Bangladesh. Hence, the forecasting of rainfall for the upcoming years aims to identify the possibility of over flood occurrence in certain future years.

The third dataset primarily focuses on providing drought forecasts. Drought predictions are made based on several factors, namely SPI, SPEI, PDSI, and PSI. Among these, SPI and SPEI are used for hydrological drought prediction. We've utilized SPEI because it offers a comparative advantage, potentially providing more effective drought forecasts than SPI, utilizing new methodologies. This dataset includes attributes such as mean temperature, average rainfall, SPEI3, SPEI6, and SPEI12. SPEI3, SPEI6, and SPEI12 assess the likelihood of drought occurrences after 3, 6, and 12 months, respectively, based on mean temperature and average rainfall. By calculating SPEI3, SPEI6, and SPEI12, we've forecasted the potential drought situation for the next 10 years across 34 stations in Bangladesh, considering both mean temperature and average rainfall as factors contributing to drought conditions.

3.2.4 Algorithms for Climate Predictions: Accurate weather prediction is essential for understanding and mitigating hazards caused by changing weather patterns. In cyclone and flood-prone Bangladesh, precise forecasting is crucial for effective disaster management and resource allocation. This study aims to explore and evaluate the adaptability and effectiveness of modern AI algorithms tailored to Bangladesh's unique climatic conditions for improved weather forecasting.

This research will use distinct Artificial Intelligence techniques such as:

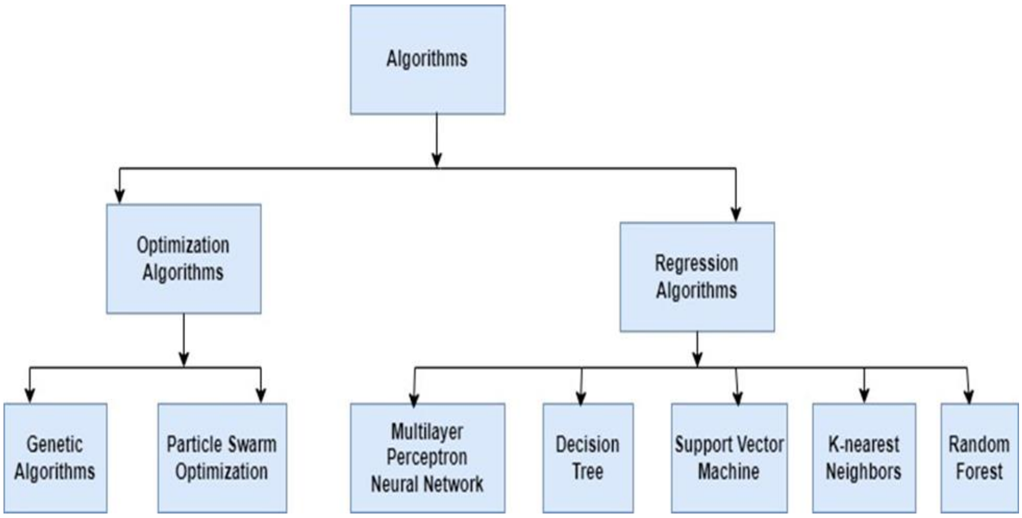

Figure 3.2: List of the algorithms that have been used in the model

A. Optimization Algorithms

AI optimization algorithms enhance model effectiveness and performance by systematically exploring a solution space to find optimal solutions for challenging tasks. They enable AI models to converge towards better outcomes through iterative improvement of viable solutions, modifying weights, setups, or parameters based on predefined standards or goals. Optimization algorithms empower AI systems to handle complex tasks more efficiently. In this work, we used sequential optimization of Genetic Algorithms and Particle Swarm Optimization Algorithms.

I. Genetic Algorithms: A genetic algorithm is a search heuristic that is inspired by Charles Darwin's theory of natural evolution [43]. Genetic algorithms (GAs) are optimization algorithms that take inspiration from natural selection and genetics. Their purpose is to iteratively explore and locate the most optimal solution for a given problem. GAs commences by establishing an initial population of potential solutions, typically represented as chromosomes or binary strings. The fitness function plays a vital role in assessing the quality or suitability of each solution within the population.

Genetic algorithms rely on genetic operators as their fundamental concept. These operators, including selection, crossover, and mutation, replicate the reproductive and genetic variation processes found in nature. Selection favors solutions with superior fitness values to serve as parents for the next generation. Crossover combines genetic material from chosen parents, resulting in offspring with a blend of their traits. Mutation introduces random alterations or diversifications in the genetic makeup of the offspring, facilitating exploration of novel regions within the solution space [43].

Genetic algorithms improve their outcomes over repeated generations. Finding optimal or nearly optimal solutions is more likely when the population is fitter because fitter people are more likely to pass on their genes to the following generation. GAs more effectively explores the solution space and adjust to the needs and limits of the problem by using selection, crossover, and mutation iteratively.

II. Particle Swarm Optimization: Particle Swarm Optimization was proposed by Kennedy and Eberhart in 1995[44]. The optimization algorithm known as Particle Swarm Optimization (PSO) was influenced by the group behaviour of fish schooling or bird flocking. It provides a potent method for resolving challenging optimization issues in artificial intelligence. PSO simulates a population of particles travelling through a multidimensional search space to perform its operations. Each particle denotes a possible solution, and it moves according to both its own and the swarm's overall best-known positions.

Initially, particles are placed randomly in the search space. They undergo iterative updates to their positions, which depend on two key factors: their previous velocity and the influence of their own best-known position as well as the globally known best position. By incorporating cognitive and social components, particles adjust their velocities accordingly. The cognitive component ensures particles retain knowledge about their own best-known position, while the social component enables them to learn from the best-known position of the entire swarm.

Throughout the iterations, particles actively explore the search space in pursuit of the optimal solution. Through communication and information exchange, they collectively guide the swarm towards regions that show promise. As particles make progress towards the optimal solution, they gradually converge towards a shared best-known position, which signifies the currently identified global best solution [44][45].

III. Sequentially Optimizing between Genetic Algorithms (GA) and Particle Swarm Optimization (PSO): Sequential optimization of optimization algorithms means making an optimization method better step by step. One can do this by changing its parts like settings or rules, one after another, to make it work even better for the problem one’s solving. It's like tweaking a recipe to make it taste just right – one keeps adjusting until its perfect.

Using optimization methods like PSO and GA involves using one method first, then switching to the other to improve finding solutions. Picture starting with GA to explore various possibilities, then switching to PSO to enhance those possibilities further. GA acts like evolution, trying out different combos, while PSO is like friends aiding each other to find the right way. Blending these methods helps explore broadly and refine solutions for the best answers to tough problems.

We have used GA and PSO here to enhance the performance of the model. If we had only used GA or PSO, the performance we would have achieved would have been less than what we have achieved by using GA and PSO sequential optimization. As a result of this, the performance of our model has improved, and machine learning algorithms are now able to make predictions even more accurately.

Since weather forecasting is a very complex process and this forecast relies on many factors simultaneously, it is essential to optimize machine learning algorithms so that they can predict accurately. And GA and PSO sequential optimization primarily enhances the performance of optimization algorithms (RF, SVM, MLPNN, KNN, DT) so that they can further improve their ability to predict accurately.

B. Regression Algorithms

Regression algorithms are a part of machine learning algorithms. Regression algorithms are crucial in AI for assessing and predicting continuous numerical data. They model the relationship between input and target variables, enabling accurate value estimation and predictions. Methods like decision trees, support vectors, linear and polynomial regression use statistical ideas and optimization to minimize the discrepancy between expected and actual data. AI systems benefit from regression algorithms in diverse sectors, enhancing decision-making processes with improved data-driven insights.

I. Multilayer Perceptron Neural Network: The field of artificial neural networks is often just called neural networks or multi-layer perceptron's after perhaps the most useful type of neural network. A perceptron is a single neuron model that was a precursor to larger neural networks. It is a field that investigates how simple models of biological brains can be used to solve difficult computational tasks like the predictive modeling tasks we see in machine learning. The goal is not to create realistic models of the brain but instead to develop robust algorithms and data structures that we can use to model difficult problems.

The Multilayer Perceptron is composed of a set of sensorial units organized in three or more layers. The first layer is the input layer, which does not perform any computational task. Then there are one or more hidden (intermediate) layers and an output layer, all composed of computational nodes. In a typical MLP network, all the nodes from a layer are connected with every node from the previous and from the next layer. The non-computational nodes in the input layer use an identity function, while the computation nodes in the intermediate and the output layers use a sigmoid function. In our work we have used the MLPNN which has two hidden layers but the number of neurons in each layer is randomly generated between 1 and 100.

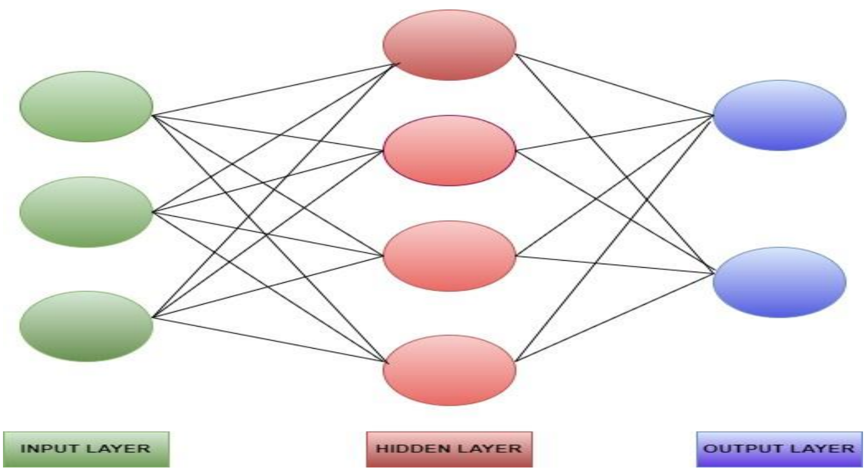

Figure 3.3: The Structure of the MLPNN

II. Decision Tree: Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, the decision tree algorithm can be used for solving regression and classification problems too. The goal of using a Decision Tree is to create a training model that can use to predict the class or value of the target variable by learning simple decision rules inferred from prior data (training data).

Classification trees are tree models where the target variable can take a discrete range of values. In these tree structures, the leaves correspond to class labels, and the branches to the attributes combine to form those class labels. Regression trees are decision trees when the target variable can take continuous values (usually real numbers).

Regression models can be built in the form of a tree structure using DTR (Decision Tree Regression). Initially, a dataset is broken into small and smaller subsets and at the same time, an associated decision tree is developed in the incremental order which results in decision nodes or leaf nodes. Usually, a decision node has two branches, each representing values for the attribute tested. Whether the leaf node represents a decision on the numerical target. The topmost decision node in a tree which is referred to as the best predictor is called the root node.

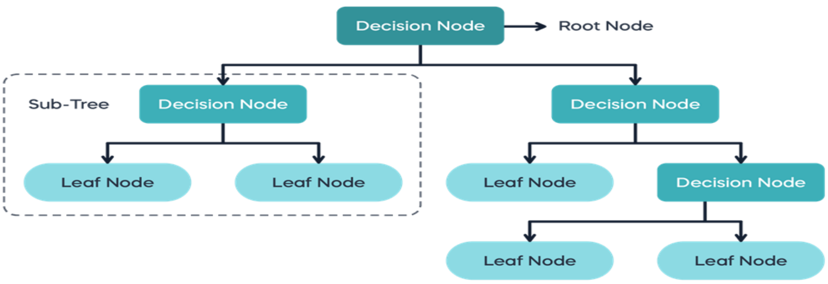

Figure 3. 4: The Structure of the Decision Tree [46]

III. Support Vector Machine: Support Vector Machine (SVM) is a powerful machine learning algorithm used for linear or nonlinear classification, regression, and even outlier detection tasks. The main objective of the SVM algorithm is to find the optimal hyperplane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin between the closest points of different classes should be as maximum as possible.

Support Vector Regression (SVR) is a type of machine learning algorithm used for regression analysis. The goal of SVR is to find a function that approximates the relationship between the input variables and a continuous target variable, while minimizing the prediction error.

Unlike Support Vector Machines (SVMs) used for classification tasks, SVR seeks to find a hyperplane that best fits the data points in a continuous space. This is achieved by mapping the input variables to a high-dimensional feature space and finding the hyperplane that maximizes the margin (distance) between the hyperplane and the closest data points, while also minimizing the prediction error. SVR can handle non-linear relationships between the input variables and the target variable by using a kernel function to map the data to a higherdimensional space. This makes it a powerful tool for regression tasks where there may be complex relationships between the input variables and the target variable.

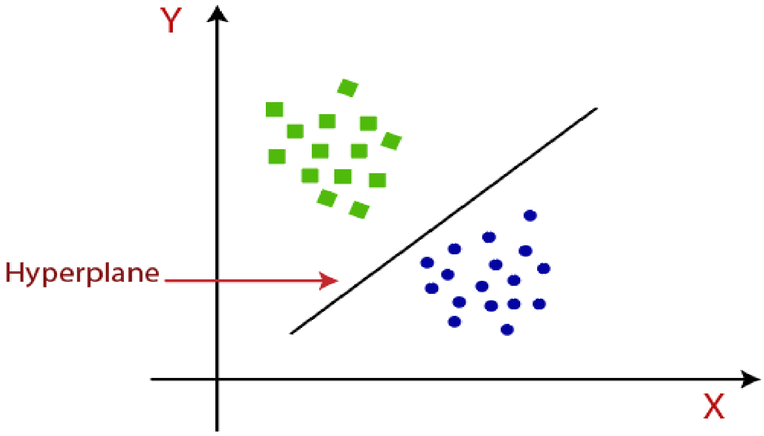

Figure 3.5: The Structure of the SVM [47]

IV. K-Nearest Neighbors(KNN): K-Nearest Neighbors is one of the simplest Machine Learning algorithms based on Supervised Learning technique. K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories. K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.

K-Nearest Neighbors or KNN is a non-parametric method which is used for both classification and regression-type problems. In the case of KNN regression, the output is the property value for the object. This value is the average of the values of K-Nearest Neighbors. It is a sort of instance-based learning or lazy learning, where the functions are only predicted locally and all the computations are deferred. It is supposed to be the simplest of all ML algorithms. The KNN algorithm is used for estimating continuous variables.

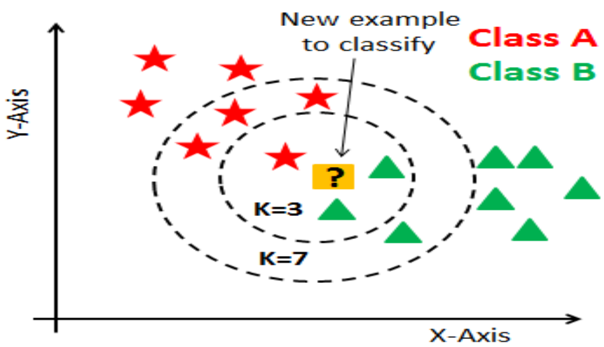

Figure 3.6: The Structure of the KNN [48]

It uses a weighted average of the K-Nearest Neighbors, weighted by the inverse of their distance. First of all, the Euclidian or Manhattan distance is computed from the query example to the labeled examples. Then the labeled examples are ordered by increasing distance. To the next step, it is tried to find a heuristically optimal number of K-Nearest Neighbors, based on the values of Root Mean Squared Error (RMSE). This is done using cross-validation. In the end, an inverse distance weighted average is calculated with the K-Nearest Multivariate Neighbors.

V. Random Forest: The very effective and adaptable machine learning method Random Forest that builds a group of decision trees to provide predictions based on their aggregate actions. It combines two important ideas bagging & random feature selection.

Random feature selection requires choosing a random subset of attributes at each split, whereas bagging entails training a number of decision trees on various subsets of the training data. The first step of the method is to build a predetermined number of decision trees, each using a different subset of the training data. To find the best split, a random subset of attributes is selected at each node. Using the bootstrap aggregating (bagging) method, which involves sampling the initial training data with replacement, the trees are trained independently.

The algorithm aggregates all of the trees' predictions throughout the prediction phase and outputs the most common forecast as the final outcome. This ensemble technique improves the model's generalization capabilities and reduces overfitting. The method provides diversity across the trees by introducing randomness into the process, which lowers the possibility of correlated errors and increases overall predictive power.

The random forest technique is remarkably adaptable and may be used for both regression and classification tasks. It exhibits robustness against unstable data and outliers, giving it a solid option for practical applications. Furthermore, it successfully handles huge datasets that have high dimensionality, a problem that many other algorithms struggle with.

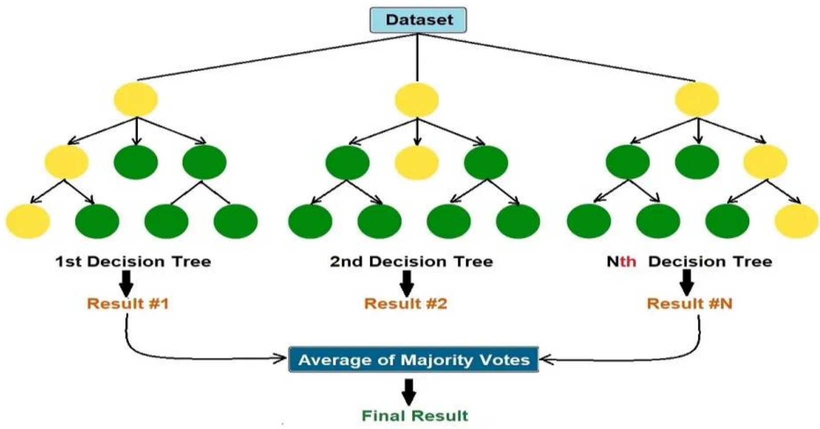

Figure 3.7: The Structure of the Random Forest [49]

3.2.5 Model Training and Testing: Train AI models using pre-processed meteorological data, dividing it into training and testing sets. The 70% of the total data will be used for training and 30% data will be used for testing.

Create strong models using this split: 70% for learning from the data and 30% for checking how well the models predict new info. This way, models learn a lot but also get tested on new stuff. It makes sure they're good at predicting real-world weather situations. This split helps make accurate models that work well with different weather scenarios.

3.2.6 Performance Analysis and Comparative Analysis:

A. Performance Analysis: The main goal of this study is to evaluate the effectiveness and practicality of using various artificial intelligence techniques for weather prediction by building models**.** We used measures like Mean Squared Error, Root Mean Square Error and R-Squared Value to see how accurate the predictions are. These measures showed us how well the models work for weather forecasts. We explored if AI can actually make weather predictions more accurate. By using these measures, we aimed to figure out how dependable and precise these models are in predicting weather conditions, ultimately striving to improve the quality and reliability of weather forecasts.

I. Mean Squared Error: Mean Squared Error (MSE) is a metric that is frequently used in statistics and machine learning to evaluate the efficacy of a predictive model. The average squared variance between expected and actual values is measured. The mean of all squared discrepancies between anticipated and actual values is used to calculate MSE. When larger errors need to be punished more severely, this metric is especially helpful because squaring the differences magnifies the impact of larger errors.
Averaging the squared deviation of estimates from the actual data serves as the foundation for MSE interpretation. A lower MSE implies a more accurate model since, on average, the predictions are more in line with the actual data. MSE is frequently used in regression issues to assess how well models perform at forecasting continuous numerical values.

The capacity of MSE to take into account error magnitude and offer a measurement of error dispersion is one of its benefits. Due to the squaring procedure, it penalizes greater errors more severely, emphasizing the importance of these deviations. Because of this characteristic, MSE works well in applications where the significance of major mistakes needs to be highlighted.

Formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

MSE = mean squared error
y_i=observed values
$\hat{y}_i$ =predicted values
n= number of data points [50].

II. Root Mean Square Error: Root Mean Square Error (RMSE) is a prevalent evaluation metric in the fields of machine learning and statistics, employed to assess the precision of a predictive model. It quantifies the average magnitude of errors by considering both the direction and magnitude of the discrepancies between predicted and actual values. RMSE is computed by taking the square root of the mean of the squared differences between predicted and actual values. This metric is particularly valuable when it is necessary to assign greater weight to larger errors, as the squaring operation magnifies the impact of these deviations.

Since RMSE is the square root of the mean squared deviation of estimates from the actual data, its meaning is straightforward. As predictions are, on average, more accurate when the RMSE is lower, the model is more accurate. In regression issues, the RMSE is frequently used to evaluate how well models perform in predicting continuous values for numbers.

The fact that RMSE takes into account error magnitude and offers a measurement of error dispersion is one of its main benefits. It accounts of both overestimation & underestimation, giving both positive and negative mistakes equal weight. This quality qualifies RMSE for applications where each the amount and direction of errors are important.

Formula:

$$RSME = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{N - P}} \quad (2)$$

y_i is the actual value for the i[th] observation.
$\hat{y}_i$ is the predicted value for the i[th] observation.
N is the number of observations.
P is the number of parameter estimates, including the constant [51].

B. Comparative Analysis: Evaluate the performance of several artificial intelligence methods (Multilayer Perceptron Neural Network, Decision Trees, SVM, KNN, Random Forests) for each individual weather event. Here, we've applied various algorithms (Multilayer Perceptron Neural Network, Decision Trees, SVM, KNN and Random Forests) separately for each weather event. Across all cases, Random Forest has consistently produced superior results compared to others. Hence, we've chosen Random Forest for forecasting the upcoming 10 years' weather events.

3.2.7: Analysis the Historical Data and Predicted Data

In our research, we utilized weather data spanning from 1980 to 2022 to forecast temperature, rainfall conditions, and the likelihood of droughts and floods for the next 10 years. We briefly analyzed historical data to observe a rising trend in temperature. Our analysis involved various time periods, such as 5 or 10-year intervals, to illustrate the temperature rise in Bangladesh. Furthermore, we compared previous data with new data to identify overall temperature trends for the upcoming years. We delved into monthly temperature analysis to examine how monthly temperatures are changing presently and their projected changes in the future. Additionally, we investigated summer and winter temperature patterns. Similarly, we conducted rainfall analysis, scrutinizing past data to discern the declining trend in rainfall and the lengthening of the rainy season. We also studied previous drought conditions in Bangladesh, comparing them with projected future conditions. Moreover, our research encompassed past flood data, where we constructed a curve depicting past and future flood possibilities in Bangladesh. We aimed to determine the likelihood of future flooding events exceeding historical occurrences.

3.3 Summary

This study aims to predict the future climate conditions of Bangladesh. Climate change is rapidly altering weather patterns worldwide, and Bangladesh is among the most severely affected countries. The temperature in Bangladesh is steadily rising, while rainfall is decreasing. As a low-income nation, Bangladesh is particularly vulnerable to the impacts of climate change, losing agricultural land and experiencing declining crop yields each year. Climate-related illnesses are on the rise, and the increasing frequency of floods, droughts, and cyclones is devastating both the economy and livelihoods, leading to loss of life. Therefore, it is crucial for Bangladesh to anticipate its future climate conditions in order to prepare and mitigate the effects of climate change. This study seeks to predict and provide an overview of Bangladesh's future climate conditions.

CHAPTER -4

RESULTS AND DISCUSSION

4.1 Introduction

In our research, we have used 5 machine learning algorithms: Support Vector Regression (SVR), Decision Tree, Random Forest, K-Nearest Neighbors (KNN), and Multilayer Perceptron Neural Network (MLPNN). With these algorithms, we derived 4 weather attributes: Rainfall, flood, temperature, and drought. We have used sequential optimization of GA and PSO with these algorithms. Prediction has been done once using the algorithms without optimization. Then, prediction has been done again using sequential optimization of GA and PSO. Finally, the algorithm that yielded better results between these two predictions has been selected for that particular algorithm. Among these algorithms, we determined which would provide better results and used that outcome to predict the future states of weather attributes - Rainfall, flood, temperature, and drought.

For this purpose, initially, we collected historical data from BMD spanning from 1980 to 2022. Then, we divided this data into two parts: 80% for training data and 20% for testing data. We gauged accuracy through MSE, RMSE, and R SQUARED VALUE. We also plotted actual and predicted value curves and loss curves. Using these methods, we determined which machine learning algorithm performed well on the given dataset, providing higher accuracy.

Although we obtained the 4 attributes - Rainfall, flood, temperature, and drought, we found that by deriving Rainfall and temperature datasets, we could predict flood and drought. Hence, we applied machine learning algorithms on temperature and rainfall datasets. In both scenarios, Random Forest yielded the best results. Therefore, we used Random Forest for our predictions.

4.2: Temperature Prediction Using Distinct Algorithms

we delve into the comparative analysis of five machine learning algorithms—Support Vector Regression (SVR), Decision Tree, Random Forest, K-Nearest Neighbors (KNN), and Multilayer Perceptron Neural Network (MLPNN)—for predicting temperature trends over the next decade (2023-2032). By evaluating and contrasting the performance of these algorithms, we aim to provide insights into their effectiveness in modelling future temperature dynamics, thereby aiding policymakers, researchers, and stakeholders in making informed decisions to mitigate the effects of climate change.

4.2.1: Using Random Forest (RF): We have performed temperature prediction using Random Forest both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, Random Forest is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from Random Forest with optimization algorithms.

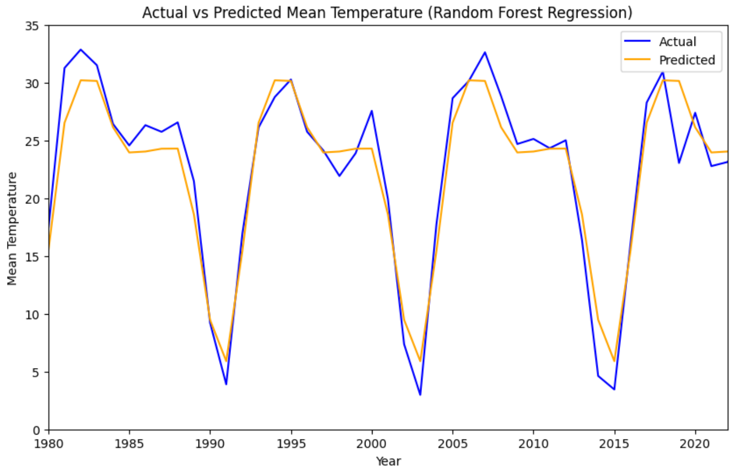

Figure 4.2.1: Actual Vs Predicted Temperature without optimization [RF]

Table 4.2.1: Training & Testing MSE & RMSE Vales for Random Forest Predicted Without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
RF	0.003523	0.004480	0.00095	0.05935	0.06694	0.00758

The table 4.2.1 showcases the Random Forest algorithm's performance in temperature prediction, with Training MSE of 0.003523 and Testing MSE of 0.004480. The minimal difference between Training and Testing MSE (0.00095) indicates balanced model fit and generalization. Additionally, Training RMSE (0.05935) and Testing RMSE (0.06694) reflect the model's effectiveness in capturing data variability, with a consistent performance across datasets evident from the small difference between Training and Testing RMSE (0.00758).

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with Random Forest to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

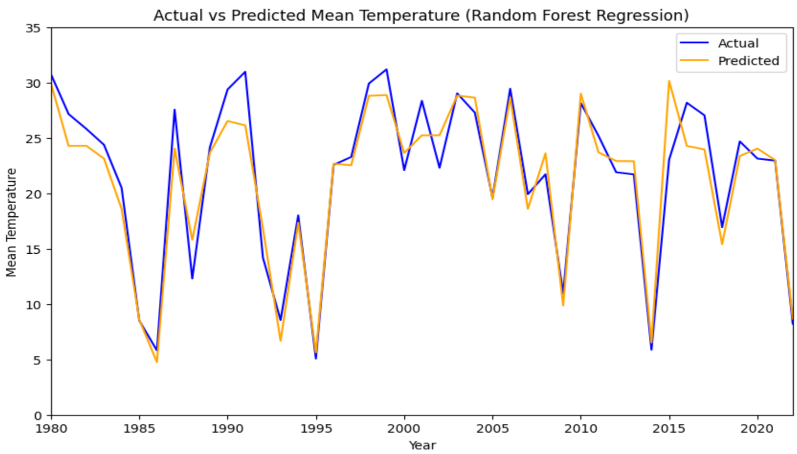

Figure 4.2.2: Actual Vs Predicted Temperature with optimization [RF]

Table 4.2.2: Training & Testing MSE & RMSE Vales for Temperature for RF Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
RF	0.003695	0.004079	0.000384	0.060789	0.063874	0.003085

The table 4.2.2 illustrates the enhanced performance of the Random Forest algorithm with optimization algorithms applied. With Training MSE of 0.003695 and Testing MSE of 0.004079, the model demonstrates improved accuracy compared to the non-optimized version. The minimal difference between Training and Testing MSE (0.000384) suggests effective generalization, while the reduced discrepancy between Training and Testing RMSE (0.003085) highlights enhanced consistency in predictive performance across datasets.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.2.3- Comparison of MSE and RMSE values

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.003523	0.004480	0.00095	0.05935	0.06694	0.00758
With Optimization Algorithms	0.003695	0.004079	0.000384	0.060789	0.063874	0.003085

Lower MSE and RMSE values indicate better performance. Difference in MSE and RMSE (Testing - Training) indicates overfitting or underfitting. Smaller differences suggest better generalization performance. Based on these factors, from the Table 4.2.3 we can see that the approach with optimization algorithms performs better. It achieves lower differences between testing and training MSE/RMSE, indicating improved generalization performance and less overfitting. The optimized model adapts better to unseen data, suggesting it may provide more accurate temperature predictions in future scenarios. Therefore, the approach with optimization algorithms using GA and PSO is preferred for future temperature prediction.

4.2.2: Using Decision Tree: We have performed temperature prediction using Decision Tree both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, Decision Tree is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from Decision Tree with optimization algorithms.

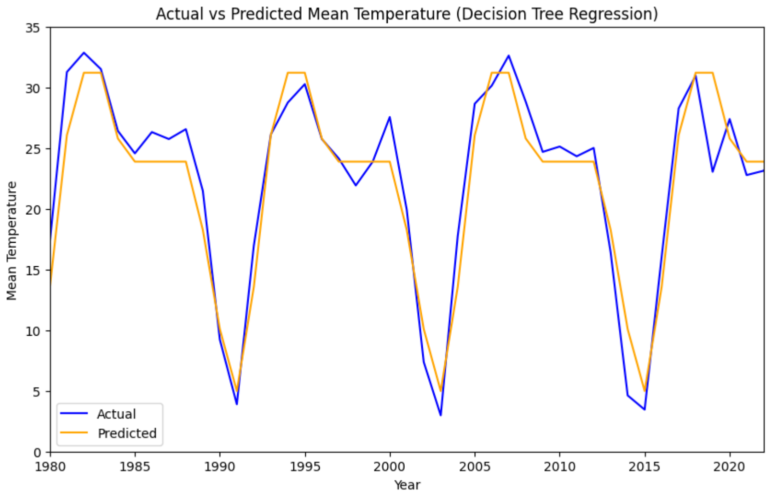

Figure 4.2.3: Actual Vs Predicted Temperature without optimization [DT]

Table 4.2.4 - Training & Testing MSE & RMSE Vales for DT Predicted without Optimization

Algorithm's Name	**Training MSE**	**Testing MSE**	**Training MSE – Testing MSE**	**Training RMSE**	**Testing RMSE**	**Training RMSE – Testing RMSE**
DT	0.00361	0.00562	0.002005	0.06013	0.07498	0.014845

The Table 4.2.4 highlights the performance of the Decision Tree algorithm in temperature prediction. With a Training MSE of 0.00361 and Testing MSE of 0.00562, the model displays effective learning from the training data, albeit with a slightly higher error rate on unseen testing data. The moderate difference between Training and Testing MSE (0.002005) indicates a balanced performance in generalization. Additionally, the noticeable gap between Training and Testing RMSE (0.014845) suggests some variance in predictive accuracy across datasets.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with Decision Tree to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

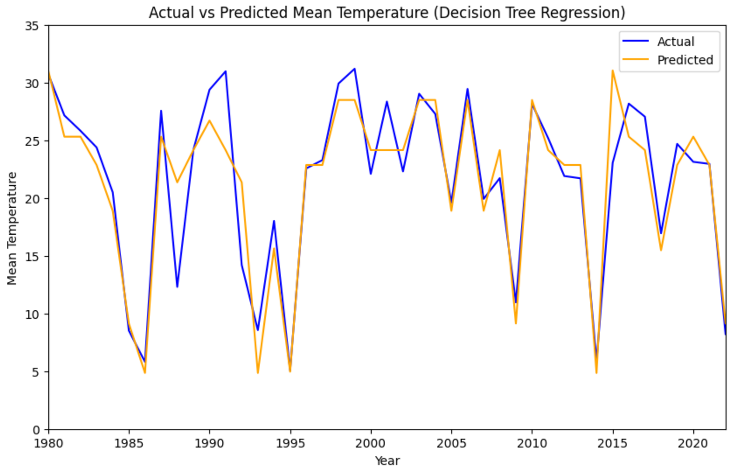

Figure 4.2.4: Actual Vs Predicted Temperature with optimization [DT]

Table 4.2.5: Training & Testing MSE & RMSE Vales for DT Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
DT	0.003434	0.005753	0.002319	0.058602	0.075850	0.017248

The Table 4.2.5 illustrates the enhanced performance of the Decision Tree algorithm with optimization algorithms integrated. With Training MSE of 0.003434 and Testing MSE of 0.005753, the model showcases improved accuracy compared to its non-optimized counterpart. The relatively small difference between Training and Testing MSE (0.002319) suggests effective generalization, while the reduced discrepancy between Training and Testing RMSE (0.017248) highlights enhanced consistency in predictive performance across datasets.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.2.6: Comparison of MSE & RMSE Vales for Temperature for DT Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.00361	0.00562	0.002005	0.06013	0.07498	0.014845
With Optimization Algorithms	0.003434	0.005753	0.002319	0.058602	0.075850	0.017248

From the Table 4.2.6, based on these values, we observe that both approaches exhibit improvements in MSE and RMSE compared to the baseline training without optimization. However, the model with optimization algorithms yields slightly lower Training MSE and RMSE values, indicating better performance in fitting the training data. Nevertheless, the model without optimization algorithms displays a smaller difference between Testing and Training MSE/RMSE, suggesting a better ability to generalize to unseen data.

Therefore, the choice between the two approaches depends on the specific priorities. If the main concern is achieving the best fit to the training data, the model with optimization algorithms may be preferable.

4.2.3: Using K-Nearest Neighbors: We have performed temperature prediction using KNN both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, KNN is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from KNN with optimization algorithms.

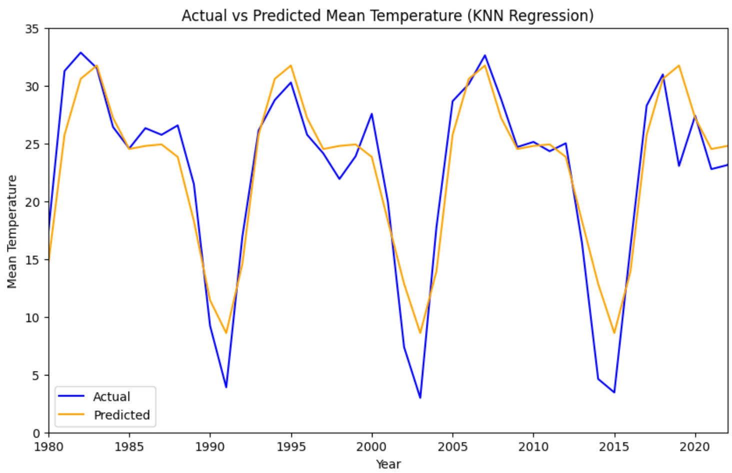

Figure 4.2.5: Actual Vs Predicted Temperature without optimization [KNN]

Table 4.2.7: Training & Testing MSE & RMSE Vales for KNN Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
KNN	0.00280	0.00542	0.00262	0.05291	0.07362	0.02070

The Table 4.2.7 presents the performance metrics of the K-Nearest Neighbors (KNN) algorithm for temperature prediction. With a Training MSE of 0.00280 and Testing MSE of 0.00542, the model demonstrates effective learning from the training data while maintaining reasonable predictive accuracy on unseen testing data. The substantial difference between Training and Testing MSE (0.00262) suggests a slight variance in generalization, while the noticeable gap between Training and Testing RMSE (0.02070) indicates some variability in predictive performance across datasets.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with KNN to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

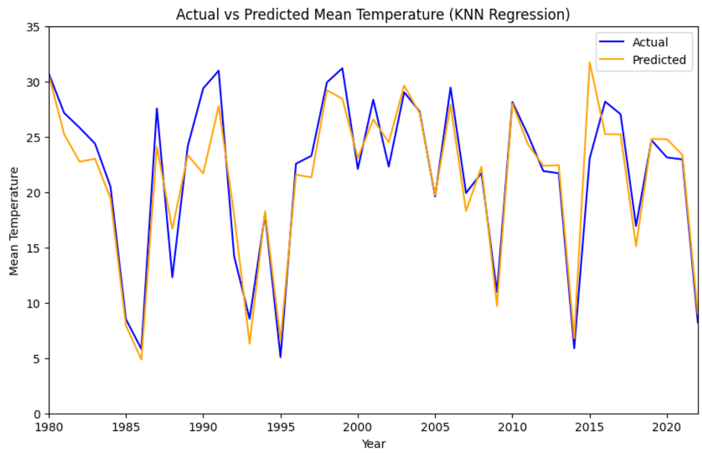

Figure 4.2.6: Actual Vs Predicted Temperature with optimization [KNN]

Table 4.2.8: Training & Testing MSE & RMSE Vales for KNN Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
KNN	0.004840	0.004857	1.730621375719936e-05	0.069570	0.069694	0.000124

The table 4.2.8 showcases the K-Nearest Neighbors (KNN) algorithm's performance with optimization techniques applied. With a Training MSE of 0.004840 and Testing MSE of 0.004857, the model demonstrates consistent accuracy across both training and testing datasets. The minimal difference between Training and Testing MSE (1.7306e-05) indicates excellent generalization, while the negligible discrepancy between Training and Testing RMSE (0.000124) highlights enhanced predictive consistency across datasets.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.2.9: Comparison of MSE & RMSE Vales for KNN

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.00280	0.00542	0.00262	0.05291	0.02070	
With Optimization Algorithms	0.004840	0.004857	1.730621375719936e-05	0.069570	0.000124	

Considering these values of Table 4.2.9, we note that the optimized KNN model yields a smaller difference between Testing and Training MSE/RMSE, indicating better generalization performance. This implies that the model with optimization algorithms is less prone to overfitting and can adapt more effectively to unseen data. Therefore, the KNN model with optimization should be preferred, as it is expected to provide more reliable and accurate predictions for future temperature data.

4.2.4: Using Support Vector Machine: We have performed temperature prediction using SVM both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, SVM is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from SVM with optimization algorithms.

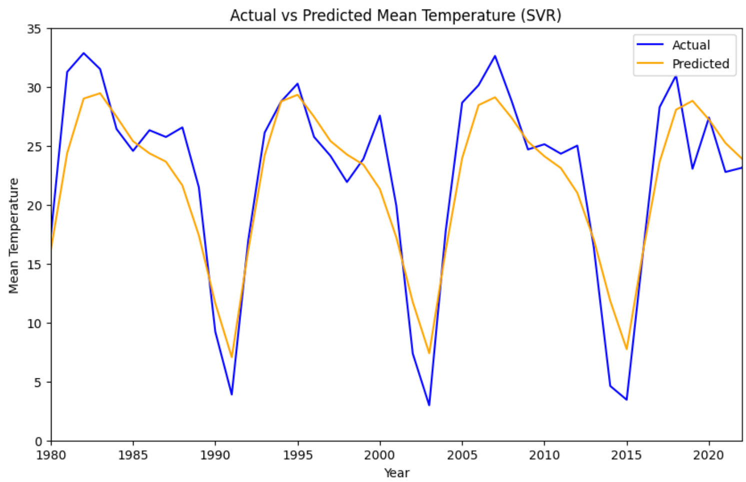

Figure 4.2.7: Actual Vs Predicted Temperature without optimization [SVM]

Table 4.2.10: Training & Testing MSE & RMSE Vales for SVM Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE		Training RMSE – Testing RMSE
SVM	0.00495	0.01793	0.01297	0.07041	0.13391		0.06349

The Table 4.2.10 outlines the performance metrics of the Support Vector Machine (SVM) algorithm for temperature prediction. With a Training MSE of 0.00495 and Testing MSE of 0.01793, the model demonstrates significant disparity between training and testing errors, indicating potential overfitting. The substantial difference in RMSE values (0.06349) further suggests variability in predictive accuracy across datasets.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with SVM to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

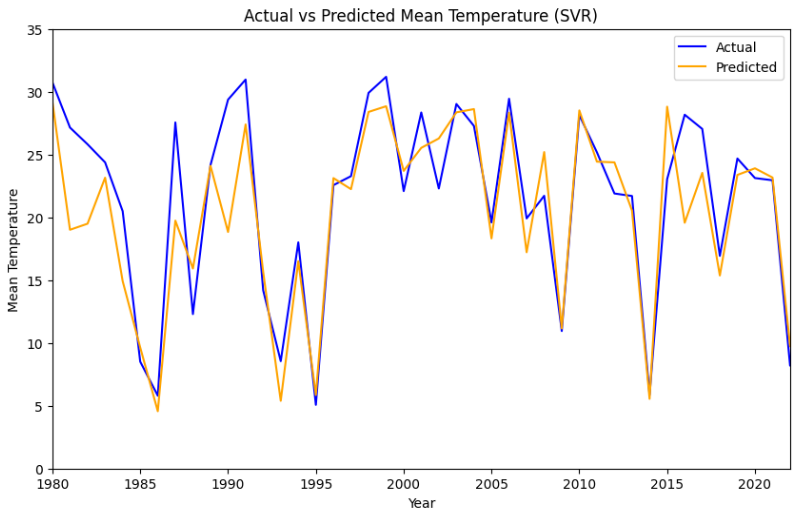

Figure 4.2.8: Actual Vs Predicted Temperature with optimization [SVM]

Table 4.2.11: Training & Testing MSE & RMSE Vales for SVM Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
SVM	0.008625	0.009394	0.000769	0.092871	0.096927	0.004056

The table 4.2.11 showcases with optimization, the Support Vector Machine (SVM) algorithm exhibits improved performance, showcasing in Table 4.2.11 a Training MSE of 0.008625 and Testing MSE of 0.009394. The minimal difference between Training and Testing MSE (0.000769) suggests enhanced generalization, while the reduced discrepancy in RMSE values (0.004056) indicates improved predictive consistency

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the

MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.2.12: Comparison of MSE & RMSE Vales for SVM

Algorithm's Name	**Training MSE**	**Testing MSE**	**Training MSE – Testing MSE**	**Training RMSE**	**Testing RMSE**	**Training RMSE – Testing RMSE**
Without Optimization Algorithms	0.00495	0.01793	0.01297	0.07041	0.13391	0.06349
With Optimization Algorithms	0.008625	0.009394	0.000769	0.092871	0.096927	0.004056

The Table 4.2.12 show that, the model with optimization exhibits a smaller difference between Testing and Training MSE/RMSE, suggesting improved generalization ability. This indicates that the optimized SVM model is less likely to overfit and can better adapt to unseen data. Despite having slightly higher Training MSE/RMSE values, the optimized model's performance on the testing set is significantly better.

Therefore, the SVM model with optimization should be considered better due to its enhanced generalization performance and ability to provide more reliable predictions for future temperature data.

4.2.5: Using Multilayer Perceptron: We have performed temperature prediction using MLP both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, MLP is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from MLP with optimization algorithms.

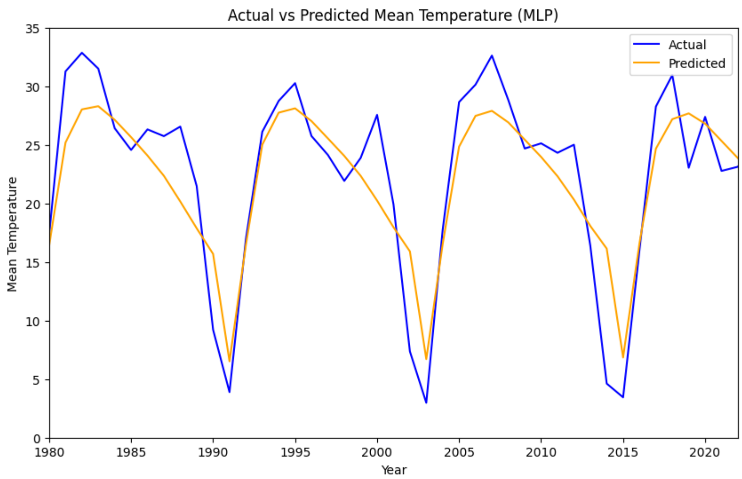

Figure 4.2.9: Actual Vs Predicted Temperature without optimization [MLP]

Table 4 .2.13: Training & Testing MSE & RMSE Vales for MLP Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
MLP	0.01085	0.01740	0.00654	0.10418	0.13191	0.02773

The table 4.2.13 showcases, The Multilayer Perceptron (MLP) algorithm exhibits a Training MSE of 0.01085 and Testing MSE of 0.01740. The significant difference between Training and Testing MSE (0.00654) suggests potential overfitting, while the notable gap in RMSE values (0.02773) indicates variability in predictive accuracy across datasets.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with Random Forest to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

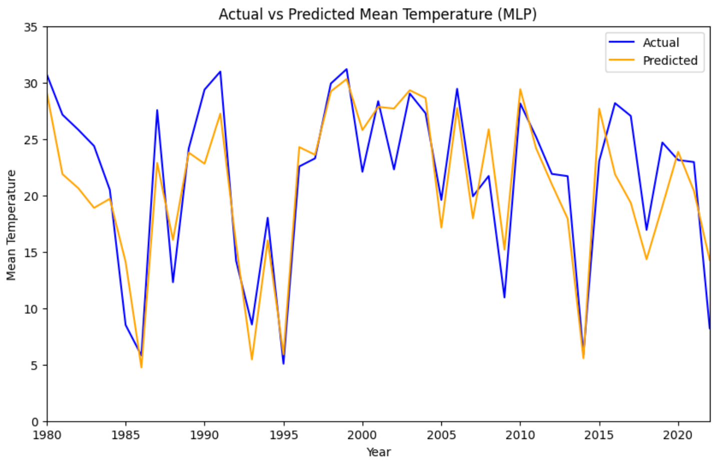

Figure 4.2.10: Actual Vs Predicted Temperature with optimization [MLP]

Table 4.2.14: Training & Testing MSE & RMSE Vales for MLP Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
MLP	0.011177	0.010624	-0.000552	0.105722	0.103074	-0.002648

The table 4.2.14 showcases with optimization, the Multilayer Perceptron (MLP) algorithm demonstrates improved performance, achieving a Training MSE of 0.011177 and Testing MSE of 0.010624. Interestingly, the negative difference between Training and Testing MSE (-0.000552) suggests potential overfitting, while the reduced discrepancy in RMSE values (-0.002648) indicates enhanced predictive consistency across datasets.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.2.15: Comparison of MSE & RMSE Vales for MLP

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.01085	0.01740	0.00654	0.10418	0.13191	0.02773
With Optimization Algorithms	0.011177	0.010624	-0.000552	0.105722	0.103074	-0.002648

The table 4.2.15 showcases The model with optimization exhibits negative differences in both Testing and Training MSE/RMSE, indicating that the testing performance is slightly better than the training performance. This suggests that the optimized MLPNN model is better at generalizing to unseen data and has less overfitting compared to the model without optimization.

Therefore, the MLPNN model with optimization should be considered better due to its improved generalization performance and ability to provide more reliable predictions for future temperature data.

4.2.6: Comparative Analysis of the Algorithms for Temperature

In this study, we initially apply the algorithms to the temperature dataset without optimization, followed by applying them with sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO). It is consistently observed that applying the algorithms with optimization yields better results compared to without optimization. Therefore, we consistently prefer using these algorithms with optimization. Subsequently, we calculate the MSE and RMSE values for all algorithms with optimization to determine which algorithm provides the best output for our dataset.

Table 4.2.16: Training & Testing MSE & RMSE Vales for Temperature of the Algorithms

Algorithm Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Random Forest	0.003695	0.004079	0.000384	0.060789	0.063874	0.003085
Decision	0.003434	0.005753	0.002319	0.058602	0.075850	0.017248

Tree						
SVM	0.008625	0.009394	0.000769	0.092871	0.096927	0.004056
KNN	0.004840	0.004857	1.730621375 719936e-05	0.069570	0.069694	0.000124
MLP	0.011177	0.010624	-0.000552	0.105722	0.103074	-0.00264

We can see in Table 4.2.16, based on the provided performance metrics, the Random Forest algorithm appears to be the most suitable for future temperature prediction. It demonstrates the lowest Testing MSE (0.004079) and Testing RMSE (0.063874), indicating better predictive accuracy compared to other algorithms. Additionally, it exhibits a relatively small difference between Training and Testing MSE (0.000385) and RMSE (0.003085), suggesting effective generalization and consistency in predictive performance across datasets. Random Forest displays a minimal difference between Testing and Training errors, suggesting robustness against overfitting. While Decision Tree also performs decently, it shows slightly higher Testing MSE and RMSE compared to Random Forest, implying slightly weaker generalization. KNN, despite having a relatively low Training MSE, exhibits higher Testing MSE and RMSE, indicating potential issues with generalization. SVM and MLP, on the other hand, display higher Testing MSE and RMSE, highlighting poorer performance on the test dataset. Therefore, considering the balance between training and testing performance, Random Forest emerges as the most suitable algorithm for this temperature prediction task due to its superior generalization and lower testing error compared to the other models.

4.2.7: Analyzing the Overall Temperature Conditions of Bangladesh

The climate change has brought fundamental changes in weather patterns across the globe. Everywhere, temperatures are rising each year. Global warming is now the primary concern worldwide. Its impact is even more pronounced in South Asia. Every country in South Asia is experiencing severe temperature increases. Among all the countries in the world, Bangladesh is projected to suffer the most from temperature rise. The melting ice in the Polar Regions might lead to submergence of the coastal areas of Bangladesh in the coming years. The yearly temperature rise is visibly affecting our country in a catastrophic manner.

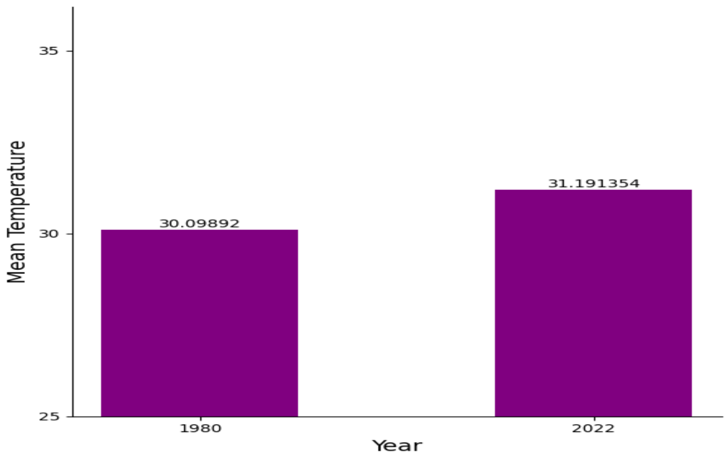

Figure 4.2.11: Mean Temperature difference of 40 years

We have been working on Bangladesh's temperature data for the past 43 years (1980-2022). There are a total of 34 weather stations in Bangladesh. We have calculated the average annual temperature from the temperature records of all these stations for the last 43 years. In Figure 4.2.11 we can see that, in 1980, the average annual temperature in Bangladesh was 30.09892 degrees Celsius. And by 2022, it has risen and stabilized at 31.191354 degrees Celsius. This means that over 43 years, the country's average temperature has increased by 1.10924 degrees Celsius.

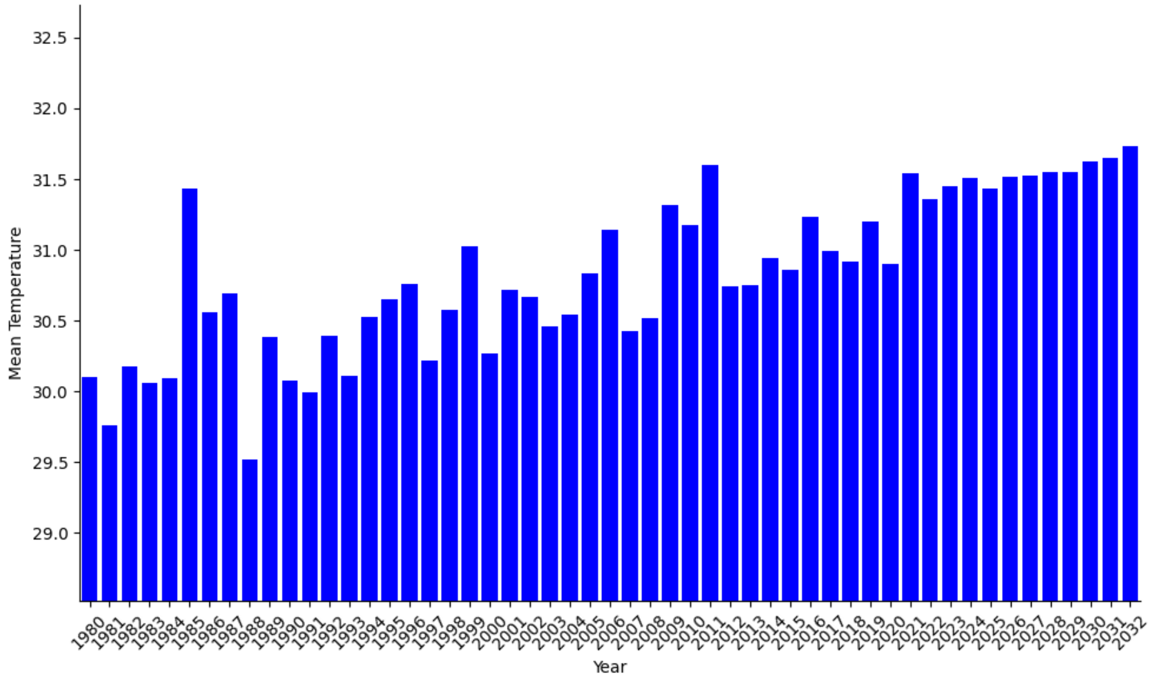

Figure 4.2.12: The mean temperature from 1980 to 2032

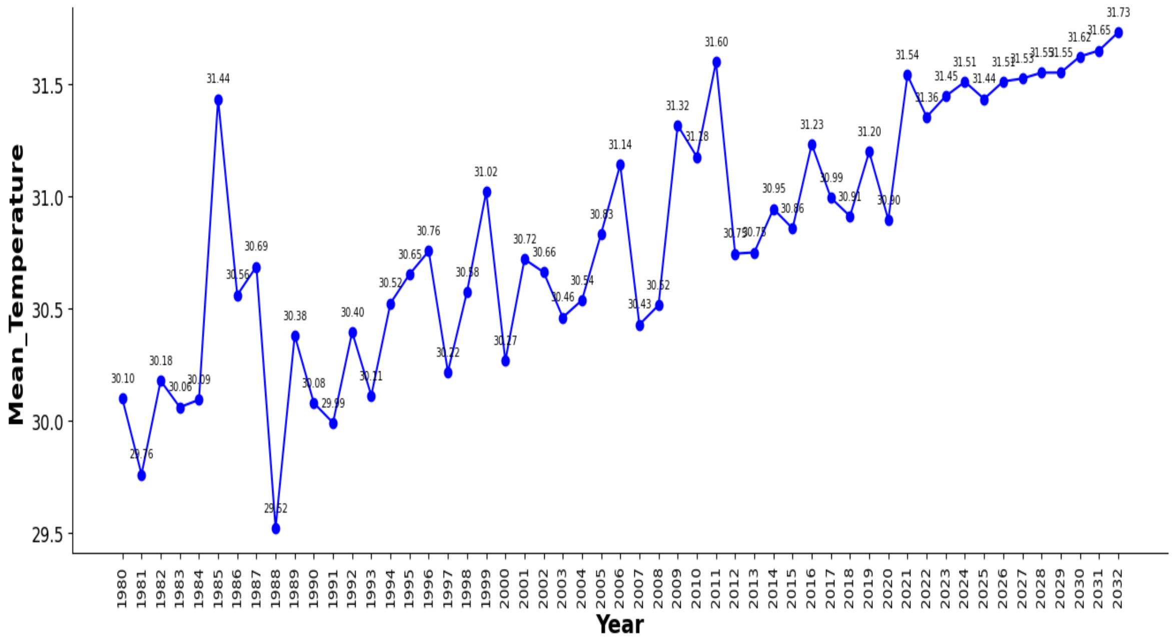

Figure 4.2.13: The flowchart of mean temperature from 1980 to 2032

In our research, we primarily utilized the daily temperatures of past years in Bangladesh. By averaging these maximum temperatures, we have computed the annual mean temperature. Additionally, the predictions we made using this data represent the average of the maximum temperatures expected in the upcoming years. Here, all calculations have been based on using the highest recorded temperatures as the reference.

Using our dataset, we have predicted the temperature in Bangladesh for the next 10 years (2023-2032). We have computed both monthly average temperatures and annual average

temperatures. Observing the temperature trends from the previous 43 years in Bangladesh, we have found that each year experiences a certain increase in temperature. Form the Figure 4.2.12 and 4.2.13 we can see that the average temperature up's and down from 1980 to 2032.The rate of temperature increase appears to be the highest post-2016, with 2022 showing the most substantial rise. The average temperature in the country has seen its most significant surge in 2021 and 2022. Our research indicates that the rate of temperature increase will remain consistent over the next 10 years which also show in the Figure 4.2.12 and 4.2.13. Furthermore, in the upcoming years, this temperature increase is expected to surpass the rates observed in the previous years.

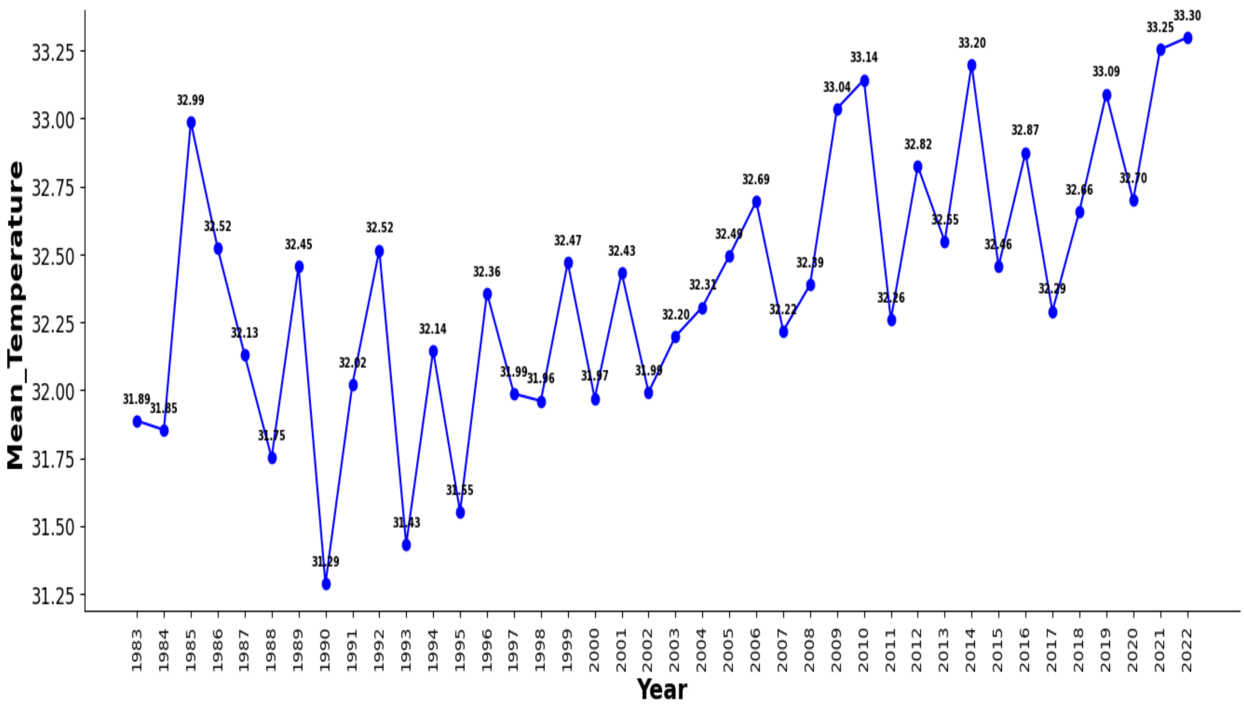

Figure 4.2.14: The flowchart of mean temperature from 1983 to 2022 in Summer Season

In the Figure 4.2.14, we can see that the past four decades depicts a clear and consistent pattern of temperature rise during the summer season in Bangladesh. Commencing from the early 1980s, where the mean temperature hovered around 31.8°C, there has been a discernible upward trajectory in temperatures over the years. Despite minor fluctuations, the trend consistently points towards higher temperatures. By the early 2020s, the average temperature had surged to approximately 33.3°C, indicating a notable increase in just four decades. This temperature rise reflects a concerning trend of warming summers in Bangladesh, which can be attributed to the broader phenomenon of global climate change. As temperatures continue to climb, the impacts are likely to be manifold, including heightened risks of heatwaves, stress on ecosystems and agriculture, and potential challenges for human health and well-being. Mitigating these effects and adapting to the changing climate will be imperative for safeguarding the resilience and sustainability of Bangladesh's environment and society in the coming years.

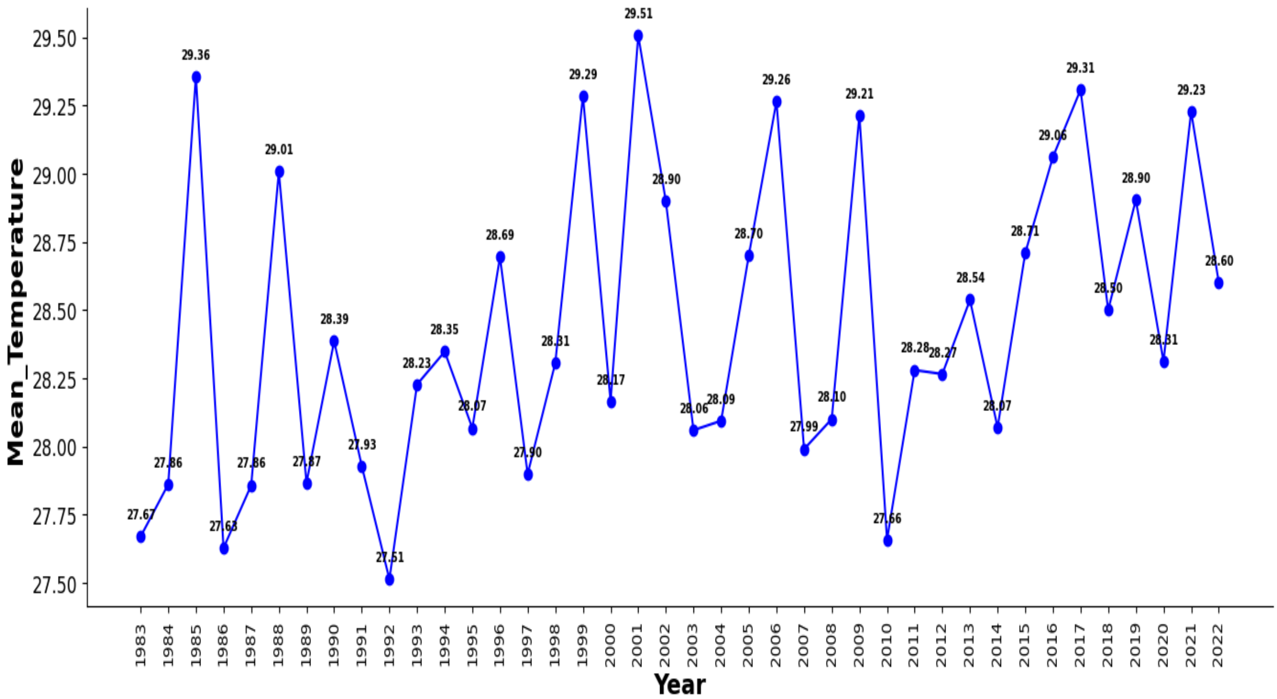

Figure 4.2.15: The flowchart of mean temperature from 1983 to 2022 in Winter Season

Analysing the temperature data spanning the last four decades Figure 4.2.15 reveals fluctuations in the average temperature during the winter season in Bangladesh. Unlike the consistent upward trend observed in summer temperatures, the winter temperatures exhibit a more variable pattern, characterized by both rises and falls over the years.

The data shows that during the early 1980s, the mean winter temperature was around 27.7°C, followed by slight fluctuations in the subsequent years. Notably, there are periods of both temperature increases and decreases throughout the dataset. For instance, there are noticeable rises in the mid-1980s, early 1990s, and early 2000s, with temperatures reaching peaks around 29.3°C in 2017. Conversely, there are also periods of temperature decreases, such as in the late 1980s, mid-1990s, and late 2000s.

Table 4.2.17: Temperature raising for 5 years gap in Summer

Year	Mean Temperature	Temperature Raising
1983 - 1987	32.27556	NULL
1988 - 1992	32.00559	-0.26997
1993 - 1997	31.89453	-0.11106
1998 - 2002	32.16472	0.27019
2003 - 2007	32.38197	0.21725
2008 - 2012	32.73038	0.34841
2013 - 2017	32.67322	-0.05716
2018 - 2022	32.99979	0.32657

Table 4.2.17 shows us the temperature rising of last 40 in 5 years gap. Between 1983 and 1987, the mean temperature was recorded at 32.27556°C, indicating a relatively stable period. However, from 1988 to 1992, there was a slight decrease in temperature, with the mean temperature dropping to 32.00559°C, reflecting a decrease of approximately -0.27°C. This trend continued into the subsequent years from 1993 to 1997, where temperatures further decreased to 31.89453°C, albeit at a slower rate (-0.11°C).

Conversely, from 1998 to 2002, there was a notable increase in temperature, with the mean temperature rising to 32.16472°C, marking a rise of approximately 0.27°C. This upward trend persisted from 2003 to 2007, showing a further increase to 32.38197°C, indicating a rise of approximately 0.22°C. The subsequent interval from 2008 to 2012 also experienced a significant temperature increase, with the mean temperature climbing to 32.73038°C, representing a rise of approximately 0.35°C.

However, from 2013 to 2017, there was a slight decline in temperature, with the mean temperature decreasing to 32.67322°C, albeit by a marginal -0.06°C. Despite this minor decrease, the most recent interval from 2018 to 2022 witnessed another temperature increase, with the mean temperature reaching 32.99979°C, reflecting a rise of approximately 0.33°C.

Table 4.2.18: Average Temperature for 5 years gap in Winter

Year	Mean Temperature
1983 - 1987	28.074974
1988 - 1992	28.140622
1993 - 1997	28.247408
1998 - 2002	28.632608
2003 - 2007	28.422072
2008 - 2012	28.303792
2013 - 2017	28.736916
2018 - 2022	28.709012

We can take an idea of mean temperature rising in the winter season from the Table 4.2.18. The mean temperature trends in Bangladesh during five-year intervals in the winter season. Over the years, there appears to be a fluctuating but generally increasing pattern in temperatures. From 1983 to 2022, the mean temperature gradually rises from 28.07°C to 28.71°C, with some variations observed in between. While there are slight fluctuations in certain periods, such as the slight increase from 1998 to 2002 followed by a slight decrease from 2003 to 2007, the overall trend suggests a gradual warming in winter temperatures over the decades. This data underscores the importance of monitoring and understanding climate patterns to better prepare for and adapt to the impacts of global climate change.

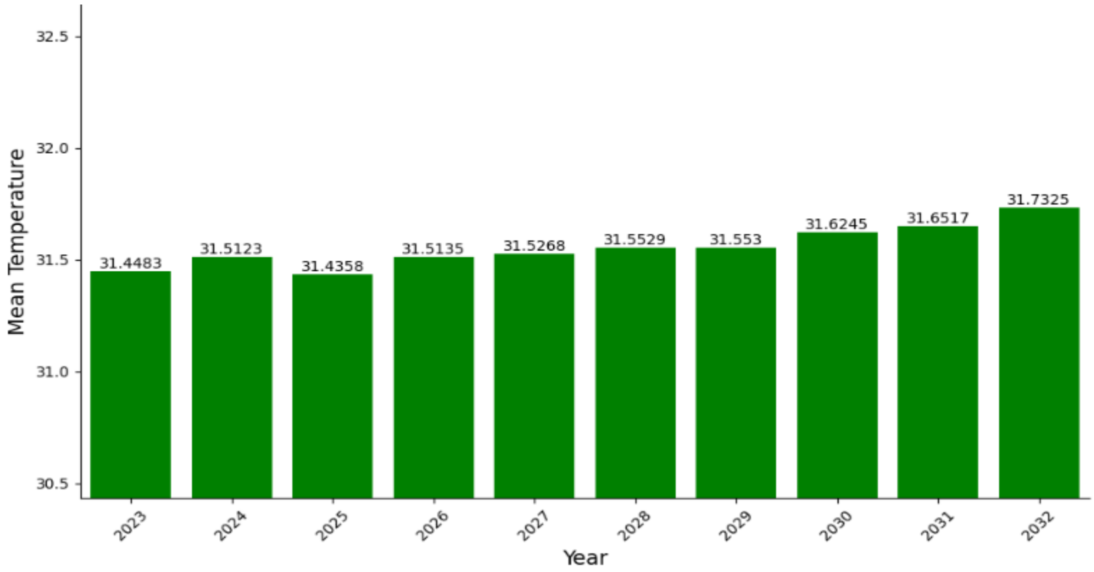

Figure 4.2.16: Yearly mean temperature of next 10 years (2023 – 2033)

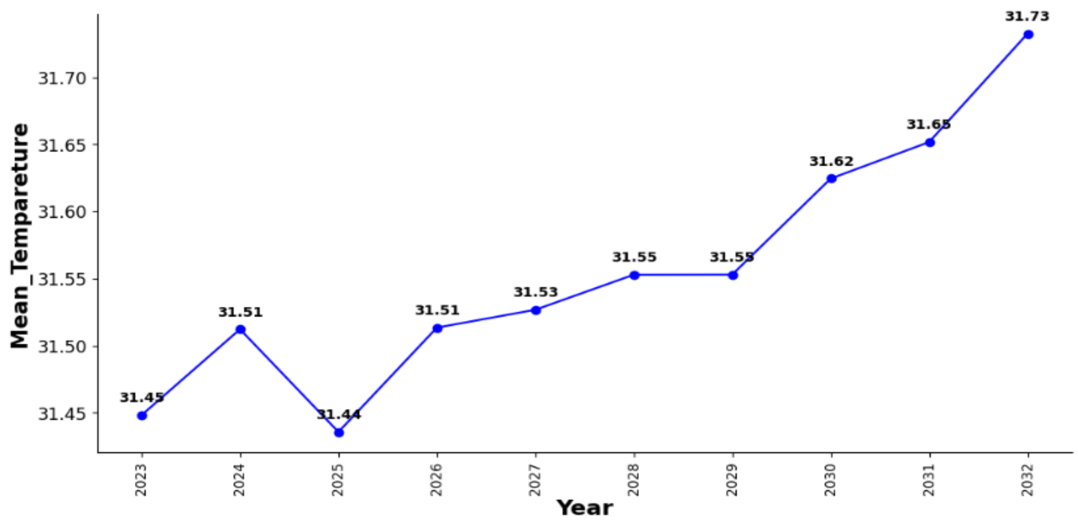

Figure 4.2.17: Flowchart of Yearly mean temperature of next 10 years (2023 – 2033)

This Figure 4.2.16 and 4.2.17 illustrates the average annual temperature in Bangladesh for the next 10 years (2023 – 2032). It's evident from this chart that Bangladesh's annual temperature is increasing every year. Although there's a slight decrease in temperature in 2023 and 2025, the temperature has been on the rise in the remaining years. The year 2032 is projected to have the highest temperature.

The increase in temperature in Bangladesh can be clearly understood from this Figure 4.2.18. It shows the Temperature growth every 10 years in Bangladesh. We can see from this Figure 4.2.18 the mean temperature is rising in every 10 years gap.

The increase in temperature in Bangladesh can be clearly understood from this Figure 4.2.19. It shows the Temperature growth every 5 years in Bangladesh. We can see from this Figure 4.2.19 the mean temperature is rising in every 5 years gap.

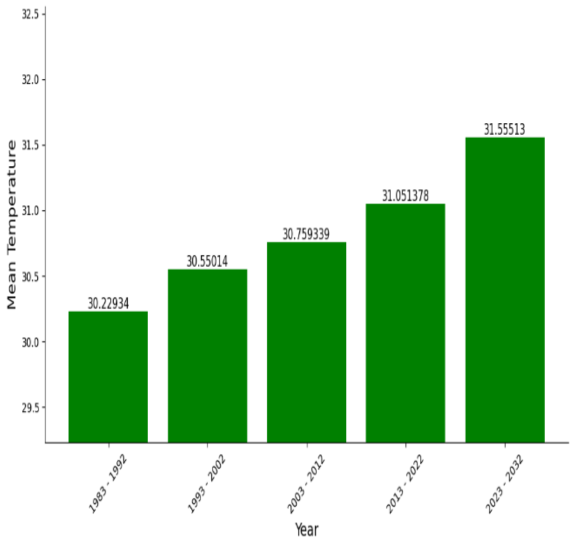

Figure 4.2.18: Mean Temperature rising in 10 years gap

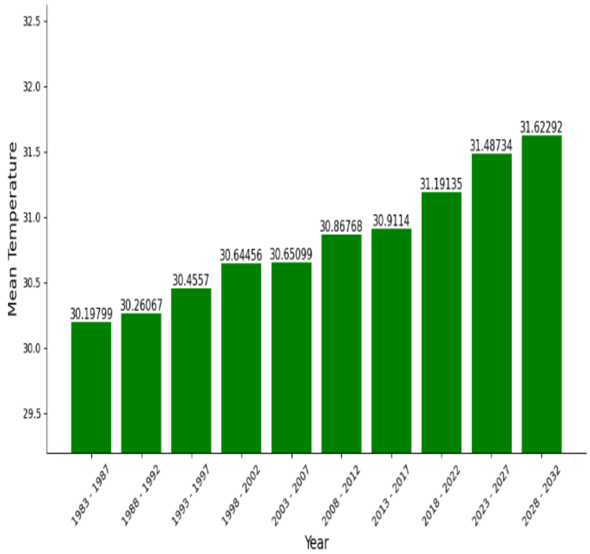

Figure 4.2.19: Mean Temperature rising in 5 years gap

Table 4.2.19: Temperature raising for 10 years gap

Year	**Mean Temperature**	**Temperature Raising**
1983 - 1992	30.2293361	NULL
1993 - 2002	30.5501369	0.3208008
2003 - 2012	30.759339	0.2092021
2013 - 2022	31.051378	0.292039
2023 - 2032	31.55513	0.503752

It is evident from this Table 4.2.19 that between 1983-1992, the temperature in the country was 30.2293361 degrees Celsius. However, in the following 10 years, from 1993-2002, the temperature increased by 0.3208008 degrees Celsius. Subsequently, in the next 10 years, the temperature rose to 30.759339 degrees Celsius. In the period of 2013-2022, compared to the previous decade, there has been an increase in temperature by 0.292039 degrees Celsius. And in the upcoming 10 years, the rate of temperature increase is projected to be even higher. In the period of 2023-2032, the temperature in the country could increase by 0.503752 degrees Celsius.

Table 4.2.20: Temperature raising for 5 years gap

Year	Mean Temperature	Temperature Raising
1983 - 1987	30.19799	NULL
1988 - 1992	30.26067	0.06268
1993 - 1997	30.4557	0.19503
1998 - 2002	30.64456	0.18886
2003 - 2007	30.65099	0.00643
2008 - 2012	30.86768	0.21669
2013 - 2017	30.9114	0.04372
2018 - 2022	31.19135	0.27995
2023 - 2027	31.48734	0.29599
2028 - 2032	31.62292	0.13557

In this Table 4.2.20, an amount of temperature increases every five years has been shown. And from this Table 10, it can also be seen that Bangladesh has experienced an increase in temperature even within every five-year interval. The data of temperature from 1983 to 2022 has been calculated here, and the amount of temperature increase in the next 10 years has been shown as well. The average temperature between 1983 and 1987 was 30.19799 degrees Celsius. After five years, between 1988 and 1992, the average temperature became 30.26067. This means the average temperature has increased by 0.06268 degrees Celsius. Following that, the increase in average temperature in every five-year interval was as follows: between 1993-1997, 0.19503; between 1998-2002, 30.64456; in the years 2003-2007, 0.00643 degrees Celsius. Then, in the period 2008-2012, the rate of temperature increase was much higher compared to previous years, almost 0.21669 degrees Celsius. In the five years between 2013 and 2017, although the rate of temperature increase decreased slightly, in the following five years, meaning from 2018 to 2022, within the past 40 years, the rate of temperature increase was the highest, namely 0.27995 degrees Celsius. And from our research, it is evident that in the next ten years, the amount of temperature increase will be 0.29599 between 2023 and 2027, and in the five years between 2028 and 2032, the temperature increase will be 0.13557 degrees Celsius.

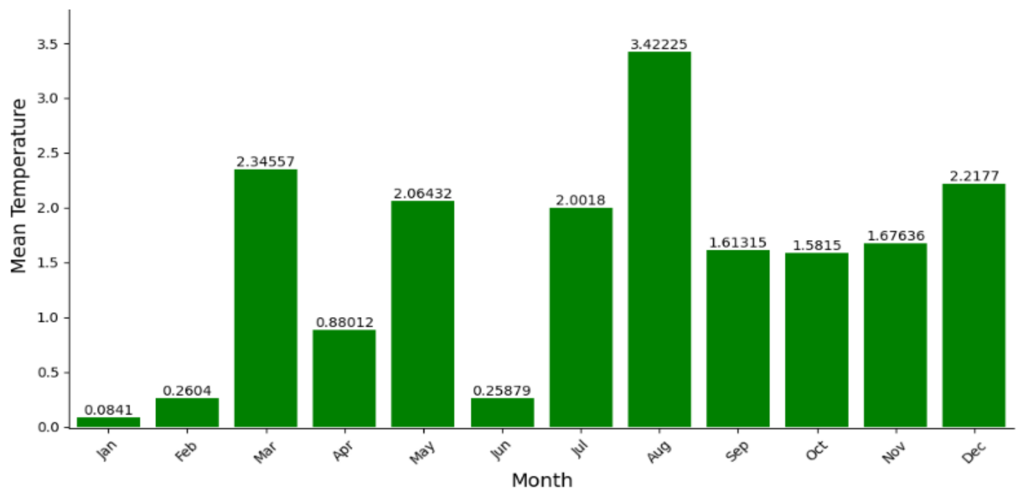

Figure 4.2.20: Monthly mean temperature rise between 1983 - 2022

Here Figure 4.2.20, a depiction of the monthly temperature changes over the past 40 years in Bangladesh is presented. The temperature variation from 1983 to 2022 is showcased. In this representation, it is evident that the rate of temperature increase was relatively lower in January and February. However, in March, the rate of temperature rise was significantly higher, almost 2.3457 degrees Celsius. This means that before the onset of summer, there is a substantial temperature surge. Consequently, the summer season is extending. On the other hand, in August, the temperature rise was the highest, approximately 3.4225 degrees Celsius. Bangladesh experiences its winter season from December to February. However, in December, there has been an increase in temperature, around 2.2177 degrees Celsius. Winter is becoming warmer each year, and the duration of the cold season is reducing, with temperatures rising annually. In recent years, this increase has been the most pronounced.

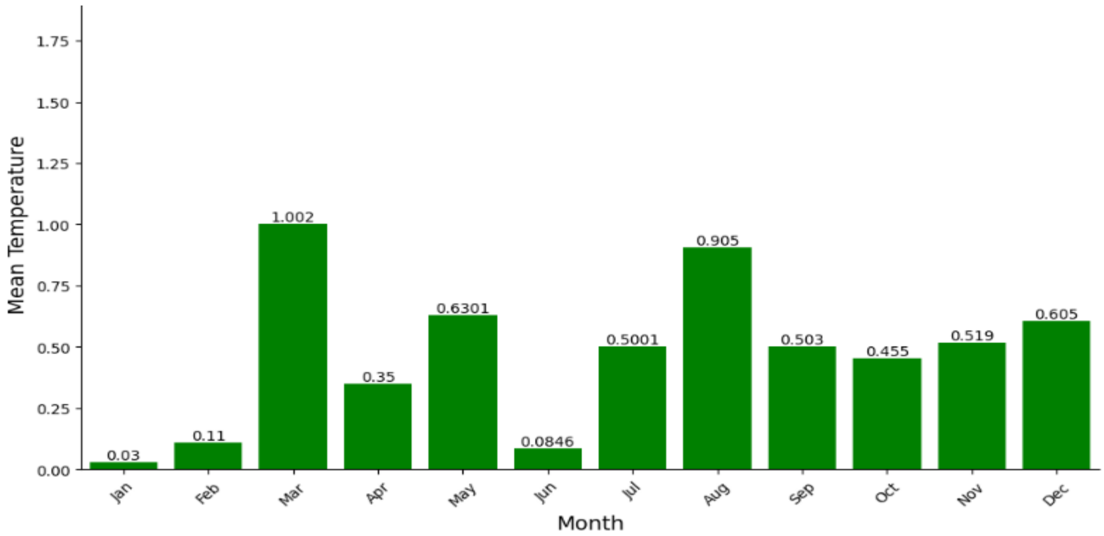

Figure 4.2.21: Future monthly temperature rising between 2023 – 2032

Winter in Bangladesh is gradually becoming warmer. This trend of temperature increase will persist in the upcoming years. From our research, the calculation we have obtained for the temperature rise in the following years indicates that monthly temperatures will continue to rise. The future monthly temperature rising trends we can see from the Figure 4.2.21. Moreover, in the upcoming years, the temperature increase in February will be even higher, and the summer season will extend until February**.**

4.3: Rainfall Prediction Using Distinct Algorithms:

we delve into the comparative analysis of five machine learning algorithms—Support Vector Regression (SVR), Decision Tree, Random Forest, K-Nearest Neighbors (KNN), and Multilayer Perceptron Neural Network (MLPNN)—for predicting rainfall trends over the next decade (2023-2032). By evaluating and comparing the performance of these algorithms, we found that Random Forest give best result.

4.3.1: Using Random Forest (RF): We have performed rainfall prediction using Random Forest both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, Random Forest is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and

RMSE. Following this assessment, we compare these results with those obtained from Random Forest with optimization algorithms.

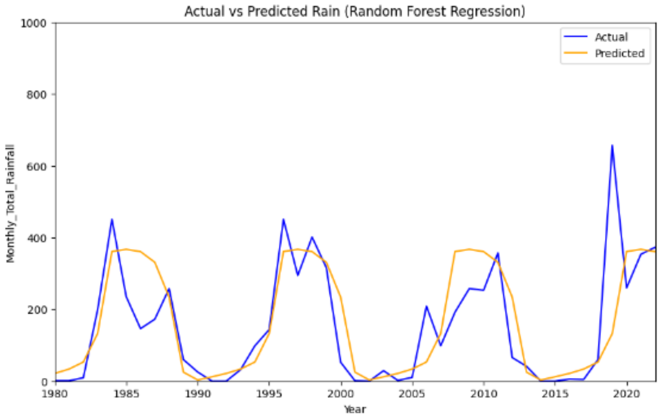

Figure 4.3.1: Actual Vs Predicted rainfall without optimization [RF]

Table 4.3.1: Training & Testing MSE & RMSE Vales for RF Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Random Forest	0.009081	0.011015	0.001934	0.095297	0.104955	0.009658

The table 4.3.1 showcases The Random Forest algorithm trained without optimization exhibits a training MSE of 0.009081 and a testing MSE of 0.011015. The difference between training and testing MSE is 0.001934. Additionally, the training RMSE is 0.095297, the testing RMSE is 0.104955, and the difference between training and testing RMSE is 0.009658.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with Random Forest to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

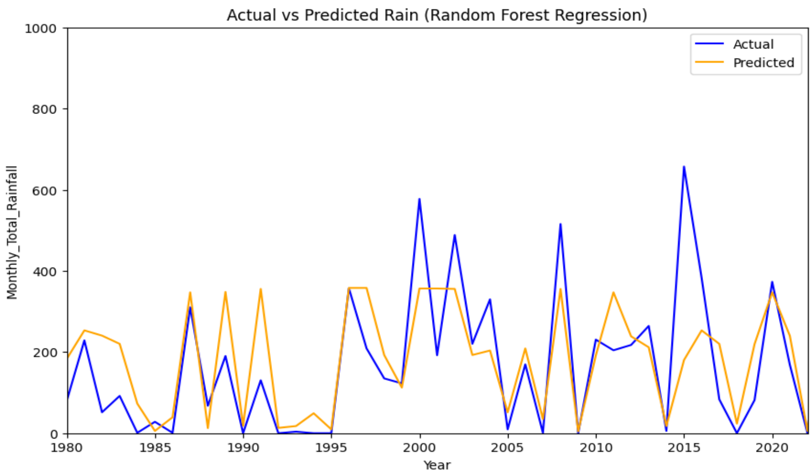

Figure 4.3.2: Actual Vs Predicted rainfall with optimization [RF]

Table 4.3.2: Training & Testing MSE & RMSE Vales for RF Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Random Forest	0.008727	0.014281	0.005554	0.093420	0.119506	0.026086

With optimization the table 4.3.2 showcases, the Random Forest algorithm achieves a training MSE of 0.008727and a testing MSE of 0.014281. The difference between training and testing MSE decreases to 0.005554, indicating improved generalization. Similarly, the training RMSE is 0.093420, the testing RMSE is 0.119506, with a reduced disparity of 0.026086 between training and testing RMSE, showcasing better balance and performance.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.3.3: Comparison of Training & Testing MSE & RMSE Vales for RF

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.009081	0.011015	0.001934	0.095297	0.104955	0.009658
With Optimization Algorithms	0.008727	0.014281	0.005554	0.093420	0.119506	0.026086

We can see from the Table 4.3.3 The model with optimization exhibits a smaller difference between training and testing MSE (0.005554) compared to without optimization (0.001934), indicating better balance and potentially less overfitting. Additionally, the training RMSE is slightly lower with optimization (0.008727) compared to without optimization (0.095298), suggesting better performance on the training data. However, the testing RMSE is higher with optimization (0.119506) compared to without optimization (0.104956), indicating poorer generalization to new data. Optimization may prioritize balance and performance on the training data.

4.3.2: Using Decision Tree: We have performed rainfall prediction using Decision Tree both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, Decision Tree is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and

RMSE. Following this assessment, we compare these results with those obtained from Decision Tree with optimization algorithms.

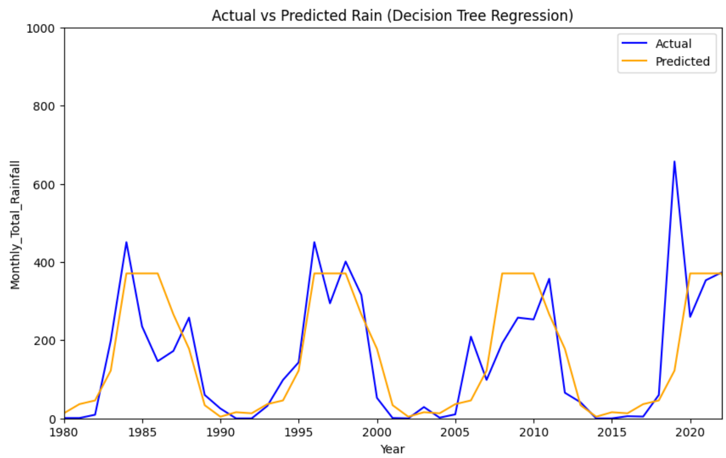

Figure 4.3.3: Actual Vs Predicted rainfall without optimization [DT]

Table 4.3.4: Training & Testing MSE & RMSE Vales for DT Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Decision Tree	0.009621	0.010717	0.001096	0.098087	0.103523	0.005436

The Table 4.3.4 presents the performance metrics of a Decision Tree algorithm on a dataset. It shows that the model achieved a training MSE of 0.009621 and a testing MSE of 0.010717, with a difference of 0.001096 between them. The corresponding training and testing RMSE values are 0.098087 and 0.103523, respectively, with a difference of 0.005436. Overall, the model demonstrates reasonably good performance with a relatively small difference between training and testing errors.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with Decision Tree to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

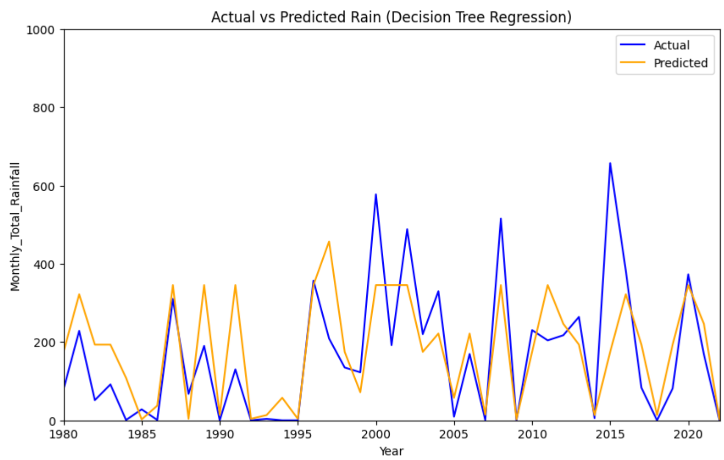

Figure 4.3.4: Actual Vs Predicted rainfall with optimization [DT]

Table 4.3.5: Training & Testing MSE & RMSE Vales for DT Predicted with Optimization

Algorithm's Name	**Training MSE**	**Testing MSE**	**Training MSE – Testing MSE**	**Training RMSE**	**Testing RMSE**	**Training RMSE – Testing RMSE**
Decision Tree	0.007831	0.014985	0.007154	0.088494	0.122414	0.033920

The Table 4.3.5 illustrates the performance metrics of a Decision Tree algorithm with optimization on a dataset. It reveals a training MSE of 0.007831 and a testing MSE of 0.014985, with a difference of 0.007154 between them. The corresponding training and testing RMSE values are 0.088494 and 0.122414, respectively, with a difference of 0.033920. The optimization appears to have improved the model's performance, as indicated by the reduction in MSE and RMSE values compared to the non-optimized version.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.3.6: Comparison between MSE & RMSE Vales for DT

Algorithm's Name	**Training MSE**	**Testing MSE**	**Training MSE – Testing MSE**	**Training RMSE**	**Testing RMSE**	**Training RMSE – Testing RMSE**
Without Optimization Algorithms	0.009621	0.010717	0.001096	0.098087	0.103523	0.005436

With Optimization Algorithms	0.007831	0.014985	0.007154	0.088494	0.122414	0.033920

We can see from Table 4.3.6 The decision tree model with optimization performs better than the one without optimization. The optimized model has lower training MSE (0.007831) and testing MSE (0.014985) compared to the non-optimized model (training MSE: 0.009621, testing MSE: 0.010717). Additionally, the difference in MSE between training and testing sets is smaller in the optimized model (0.007154) compared to the non-optimized one (0.001096). Similarly, the optimized model exhibits lower training and testing RMSE values, indicating improved overall performance in terms of accuracy and generalization.

4.3.3: Using K-Nearest Neighbors: We have performed rainfall prediction using KNN both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, KNN is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from KNN with optimization algorithms.

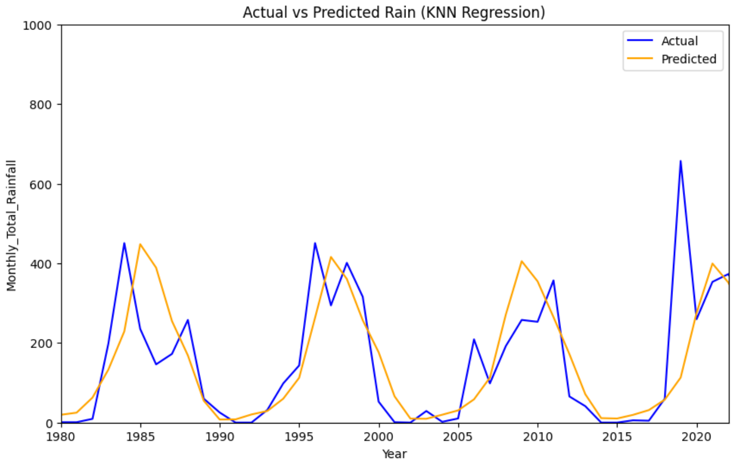

Figure 4.3.5: Actual Vs Predicted rainfall without optimization [KNN]

Table 4.3.7: Training & Testing MSE & RMSE Vales for KNN Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
KNN	0.0	0.011406	0.011406	0.0	0.106800	0.106800

The Table 4.3.7 shows , The KNN model without optimization achieves perfect training MSE (0.0) but relatively higher testing MSE (0.011406). The training and testing RMSE values are both 0.0, indicating perfect fit to the training data but limited generalization ability to unseen data, likely due to overfitting.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with KNN to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

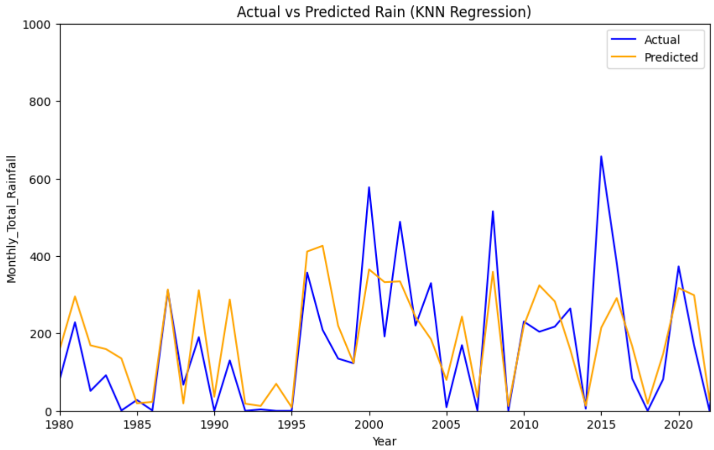

Figure 4.3.6: Actual Vs Predicted rainfall with optimization [KNN]

Table 4.3.8: Training & Testing MSE & RMSE Vales for KNN Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
KNN	0.008863	0.014538	0.005674	0.094146	0.120575	0.026429

The Table 4.3.8 illustrates With optimization, the KNN model achieves a reduced training MSE of 0.008863 and a testing MSE of 0.014538. The training MSE - testing MSE difference decreases to 0.005674, indicating improved generalization. Additionally, the training and testing RMSE values decrease to 0.094146 and 0.120575, respectively, resulting in a narrower gap between training and testing performance, suggesting better model generalization.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.3.9: Comparison between Training & Testing MSE & RMSE Vales of KNN

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.0	0.011406	0.011406	0.0	0.106800	0.106800

With Optimization Algorithms	0.008863	0.014538	0.005674	0.094146	0.120575	0.026429

The Table 4.3.9 shows that , The KNN model with optimization performs better compared to without optimization. With optimization, both the training and testing MSE values are lower, indicating improved model performance in capturing the underlying patterns in the data. Additionally, the optimization results in a smaller difference between training and testing MSE and RMSE, suggesting better generalization of the model to unseen data. Therefore, the KNN model with optimization is preferable as it achieves lower errors and demonstrates better generalization ability.

4.3.4: Using Support Vector Machine: We have performed rainfall prediction using SVM both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, SVM is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from SVM with optimization algorithms.

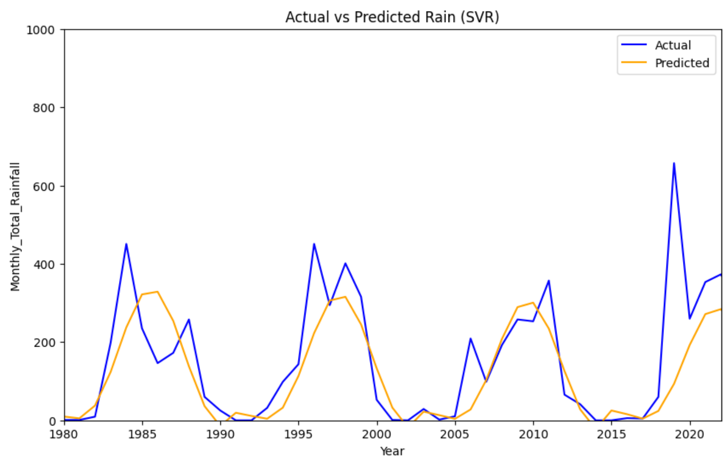

Figure 4.3.7: Actual Vs Predicted rainfall with optimization [SVM]

Table 4.3.10: Training & Testing MSE & RMSE Vales for SVM Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
SVM	0.011480	0.011537	5.708628	0.107145	0.107411	0.000266

The Table 4.3.10 shows that , Without optimization, the SVM model exhibits moderately high MSE values for both training and testing datasets, with minimal difference between them. However, the RMSE values are relatively low, indicating better performance in terms of error magnitude. Despite this, the model's ability to generalize to unseen data is limited, as evidenced by the small difference between training and testing RMSE.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with SVM to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

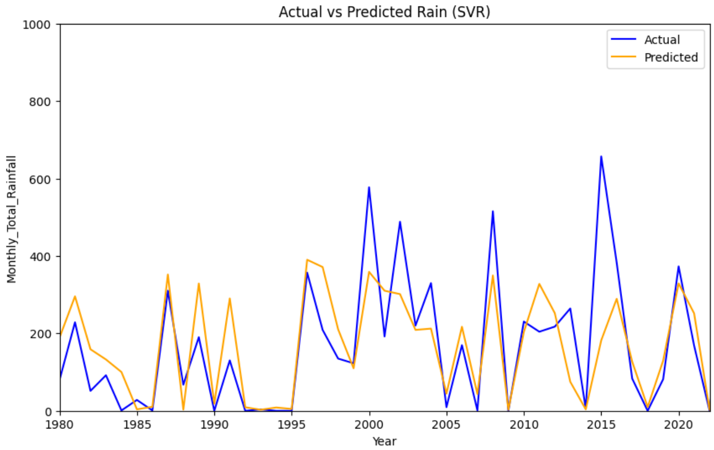

Figure 4.3.8: Actual Vs Predicted rainfall with optimization [SVM]

Table 4.3.11: Training & Testing MSE & RMSE Vales for SVM Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
SVM	0.008195	0.015018	0.006823	0.090527	0.122550	0.032023

We see from Table 4.3.11, With optimization, the SVM model achieves a lower MSE for training data compared to without optimization, indicating improved fit. However, the testing MSE is higher, suggesting potential overfitting. Despite this, the difference between training and testing MSE is smaller with optimization, indicating better generalization performance. Additionally, both training and testing RMSE values decrease slightly with optimization, indicating improved model accuracy.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.3.12: Comparison between Training & Testing MSE & RMSE Vales for SVM

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.011480	0.011537	5.708628	0.107145	0.107411	0.000266

With Optimization Algorithms	0.008195	0.015018	0.006823	0.090527	0.122550	0.032023

The Table 4.3.12 showcases that, With optimization, the SVM model achieves a lower MSE for both training and testing data compared to without optimization. Additionally, the difference between training and testing MSE is smaller with optimization, indicating better generalization performance and reduced overfitting. Moreover, the RMSE values also decrease with optimization, indicating improved model accuracy. Therefore, the SVM model with optimization is better as it provides improved performance metrics and generalization ability.

4.3.5: Using Multilayer Perceptron: We have performed rainfall prediction using MLP both with optimization and without optimization.

A. Without Optimization Algorithms: Initially, MLP is applied without optimization. Subsequently, we evaluate the performance of this algorithm using MSE and RMSE. Following this assessment, we compare these results with those obtained from MLP with optimization algorithms.

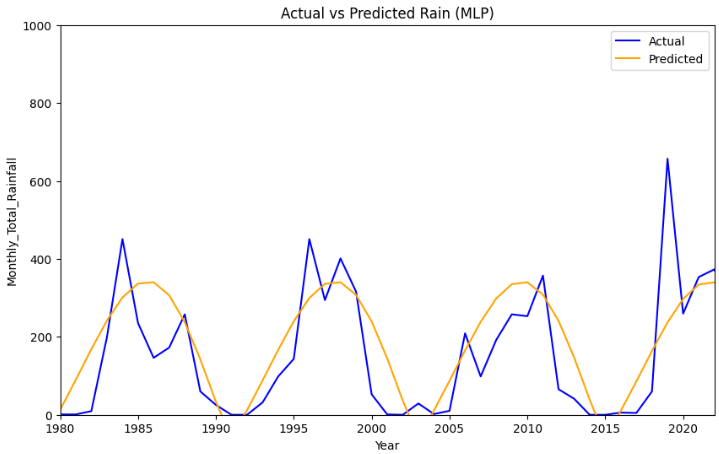

Figure 4.3.9: Actual Vs Predicted rainfall without optimization [MLP]

Table 4.3.13: Training & Testing MSE & RMSE Vales for MLP Predicted without Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
MLP	0.011993	0.012917	0.000924	0.109515	0.113657	0.004141

Table 4.3.13 shows that, without optimization, the MLP model shows a relatively low difference between training and testing MSE, indicating balanced performance. However, the MSE values for both training and testing are relatively high compared to other optimized models, suggesting suboptimal performance in minimizing prediction errors. Similarly, the RMSE values indicate moderate accuracy but not as precise as optimized models, potentially indicating underfitting or insufficient model complexity.

B. With Optimization Algorithms: We apply sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO) algorithms with MLP to obtain improved results. Subsequently, we compare these optimized results with those obtained without optimization.

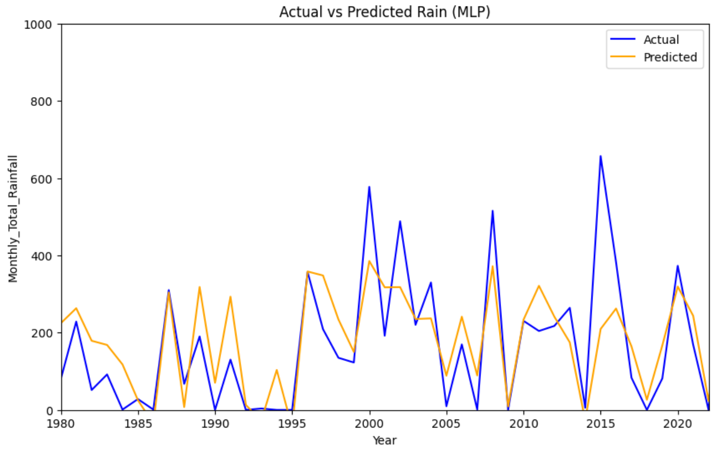

Figure 4.3.10: Actual Vs Predicted rainfall with optimization [MLP]

Table 4.3.14: Training & Testing MSE & RMSE Vales for MLP Predicted with Optimization

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
MLP	0.009640	0.014749	0.005108	0.098186	0.121447	0.023260

With optimization see from Table 4.3.14, the MLP model demonstrates a notable improvement in performance, as indicated by lower MSE values for both training and testing datasets compared to the unoptimized version. The reduced difference between training and testing MSE suggests improved generalization capability, indicating that the optimized model achieves better balance and avoids overfitting. Furthermore, the decrease in RMSE values signifies enhanced accuracy in predictions, reflecting a more refined fit to the data.

C. Comparison Between with and without Optimization Algorithms: The MSE and RMSE values obtained with and without optimization algorithms are compared. It is observed that the MSE and RMSE values with optimization are lower than those without optimization. Lower MSE and RMSE values indicate better performance.

Table 4.3.15: Comparison between Training & Testing MSE & RMSE Vales for MLP

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Without Optimization Algorithms	0.011993	0.012917	0.000924	0.109515	0.113657	0.004141

With Optimization Algorithms	0.009640	0.014749	0.005108	0.098186	0.121447	0.023260

In this case the Table 4.3.15 shows, the model without optimization performs better. It has lower testing MSE and RMSE compared to the optimized one, indicating better generalization to unseen data. The optimized model shows higher testing error metrics, suggesting potential overfitting to the training data. Therefore, the non-optimized model is preferred as it demonstrates better performance on unseen data, which is crucial for real-world applications.

4.3.6: Comparative Analysis of the Algorithms for Rainfall

In this study, we initially apply the algorithms to the rainfall dataset without optimization, followed by applying them with sequential optimization using genetic algorithm (GA) and particle swarm optimization (PSO). It is consistently observed that applying the algorithms with optimization yields better results compared to without optimization. Therefore, we consistently prefer using these algorithms with optimization. Subsequently, we calculate the MSE and RMSE values for all algorithms with optimization to determine which algorithm provides the best output for our dataset.

Table 4.3.16: Training & Testing MSE & RMSE Vales for Rainfall of the Algorithms

Algorithm's Name	Training MSE	Testing MSE	Training MSE – Testing MSE	Training RMSE	Testing RMSE	Training RMSE – Testing RMSE
Random Forest	0.008727	0.014281	0.005554	0.093420	0.119506	0.026086
Decision Tree	0.007831	0.014985	0.007154	0.088494	0.122414	0.033920
SVM	0.008195	0.015018	0.006823	0.090527	0.122550	0.032023
KNN	0.008863	0.014538	0.005674	0.094146	0.120575	0.026429
MLP	0.009640	0.014749	0.005108	0.098186	0.121447	0.023260

Based on the provided performance metrics written in Table 4.3.16, several algorithms show promising results for future rainfall prediction:

Random Forest: With a Testing MSE of 0.014281 and Testing RMSE of 0.119506, Random Forest demonstrates competitive predictive accuracy. It also exhibits a relatively small difference between Training and Testing MSE (0.005554) and RMSE (0.026086), indicating effective generalization and consistency in predictive performance across datasets. Moreover, Random Forest displays a minimal difference between Testing and Training errors, suggesting robustness against overfitting.

Decision Tree: Although Decision Tree performs reasonably well with a Testing MSE of 0.014985 and Testing RMSE of 0.122414, it shows slightly higher Testing MSE and RMSE compared to Random Forest, implying slightly weaker generalization. Additionally, Decision Tree exhibits a higher Training RMSE – Testing RMSE difference (0.033920), which may indicate potential issues with overfitting.

SVM: SVM displays a Testing MSE of 0.015018 and Testing RMSE of 0.122550. While it demonstrates competitive performance, SVM shows a slightly higher Training MSE – Testing MSE difference (0.006823) and Training RMSE – Testing RMSE difference (0.032023) compared to Random Forest, suggesting slightly weaker generalization.

KNN: Despite having a relatively low Training MSE (0.008863), KNN exhibits higher Testing MSE (0.014538) and RMSE (0.120575), indicating potential issues with generalization. Additionally, KNN shows a higher Training RMSE – Testing RMSE difference (0.026429), which may imply overfitting.

MLP: While MLP performs reasonably well with a Testing MSE of 0.014749 and Testing RMSE of 0.121447, it displays a higher Training RMSE – Testing RMSE difference (0.023260) compared to Random Forest, suggesting potential issues with overfitting.

Considering the balance between training and testing performance, Random Forest emerges as the most suitable algorithm for future rainfall prediction. It demonstrates superior generalization, lower testing error, and robustness against overfitting compared to the other models.

4.3.7: Analyzing the Overall Rainfall Conditions of Bangladesh

Rainfall is an extremely crucial matter for Bangladesh. The country's environment is intricately tied to rainfall. Many crops in Bangladesh require rainfall for their growth. Due to the influence of the monsoon climate, Bangladesh experiences abundant rainfall during the rainy season. Therefore, the annual rainfall in this country is quite high. However, due to climate change, the amount of rainfall in Bangladesh has been decreasing gradually over recent years.

We have conducted research to predict a probable amount of rainfall in Bangladesh for the next ten years, from 2023 to 2033, using rainfall data from 1980 to 2022. We used Random Forest Algorithm for forecasting next 10 years rainfall of Bangladesh. By analysing the monthly rainfall of 34 stations in the country and calculating their average, we have estimated a probable amount of rainfall for the upcoming ten years. This estimation suggests that Bangladesh's average rainfall in the coming years will decrease compared to previous years. The projected average rainfall for Bangladesh in the next ten years is 187.066 mm, which is 15.542 mm less than the rainfall between 2012 and 2022. This indicates a potential decrease in rainfall in Bangladesh in the upcoming years.

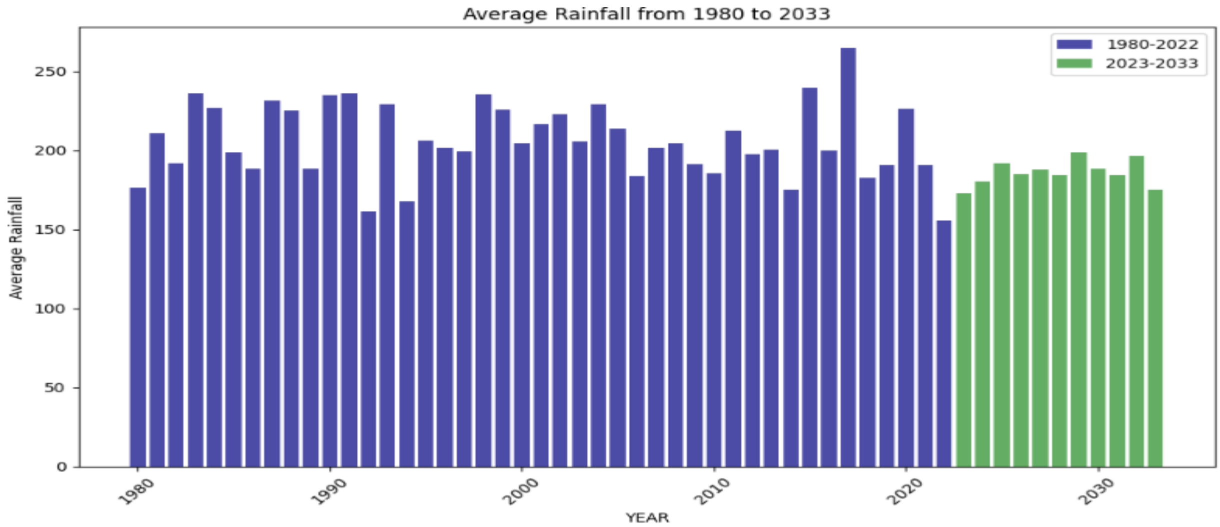

Figure 4.3.11: Average Rainfall from 1980 to 2033

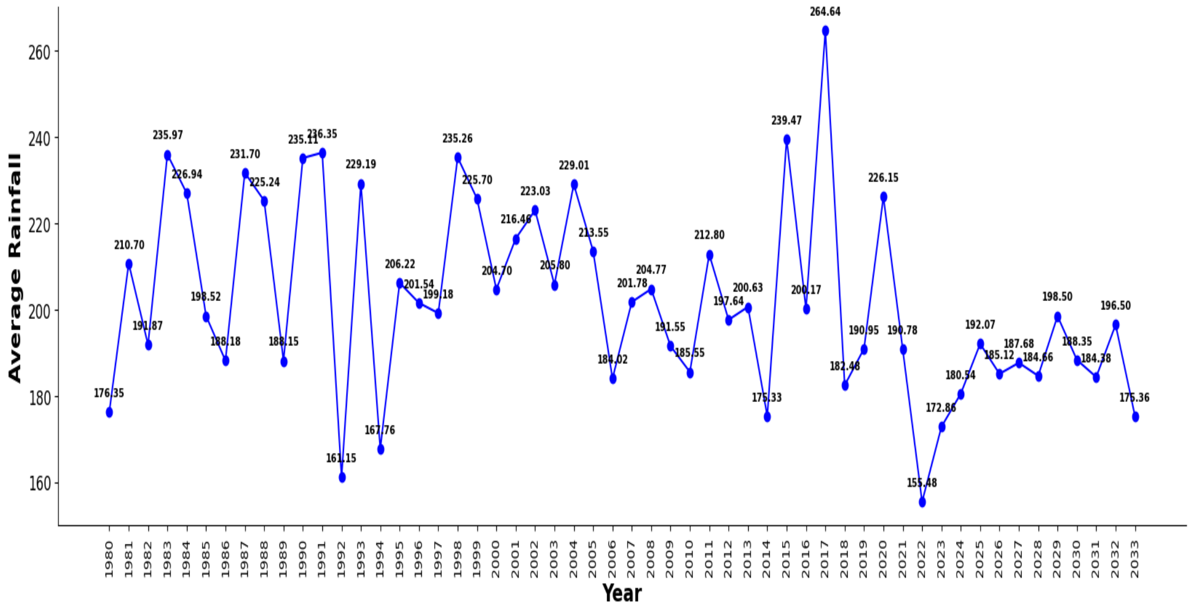

Figure 4.3.12: The flowchart of Average Rainfall from 1980 to 2033

The Figure 4.3.11 and 4.3.12 visually represents the average rainfall patterns in Bangladesh over several decades, providing valuable insights into the country's precipitation trends. Observing the graph, it becomes evident that Bangladesh experiences considerable variability in rainfall from year to year, as depicted by the fluctuating data points. However, a concerning trend emerges in the more recent years, notably from around 2022 onwards. Here, a discernible decline in rainfall is illustrated, highlighting a troubling trajectory of decreasing precipitation levels.

The forthcoming years from 2023 to 2033 paint a sobering picture for Bangladesh's rainfall patterns, as indicated by the projections displayed in the graph. With a continued downward trend in precipitation levels, the nation faces an escalating challenge that could profoundly impact its socio-economic fabric and environmental equilibrium.

From our research, we have found that even though in the upcoming years, the annual average rainfall in Bangladesh will come close to around 200 millimeters, it will not surpass the 200-millimeter mark. This calculation shows in the Figure 33 and 34. However, in previous years, for the most part, the annual average rainfall was above 200 millimeters. Due to the changes in climate, the quantity of annual rainfall will decrease year by year in the upcoming years as well.

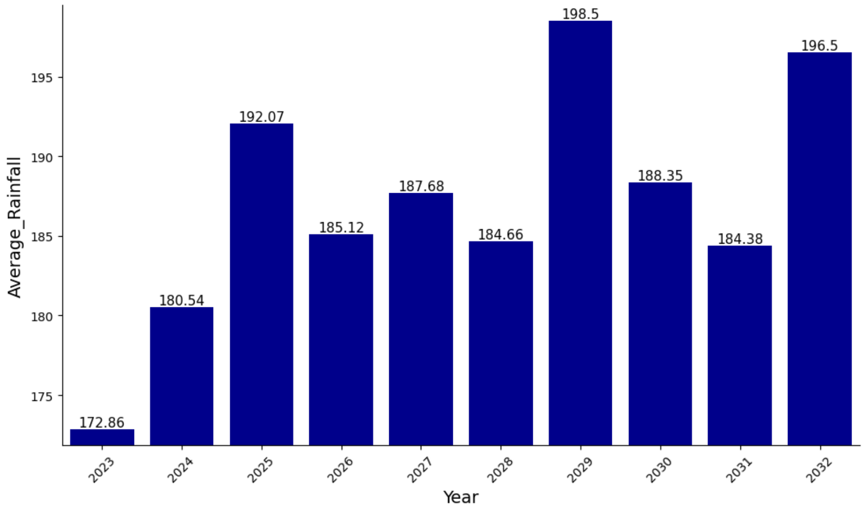

Figure 4.3.13: Average Rainfall for next 10 years (2023 – 2032)

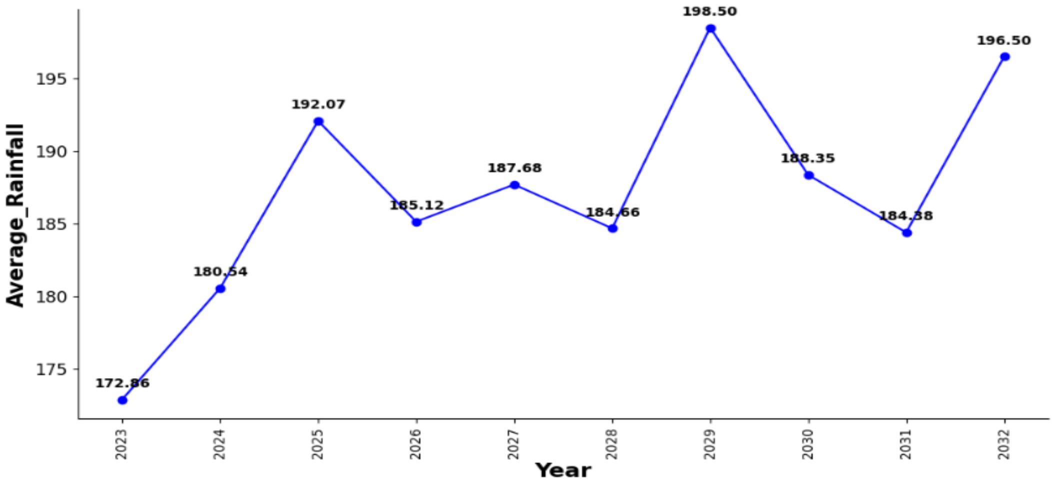

Figure 4.3.14: The flow of the Average Rainfall for next 10 years (2023 – 2032)

In this Figure 4.3.13 and 4.3.14, we can see the average annual rainfall in Bangladesh for the next 10 years, from 2023 to 2032. We have derived the monthly rainfall from 34 stations and then calculated the average annual rainfall from those. And from this graph, we observe that in the future, the average annual rainfall will decrease slightly each year.

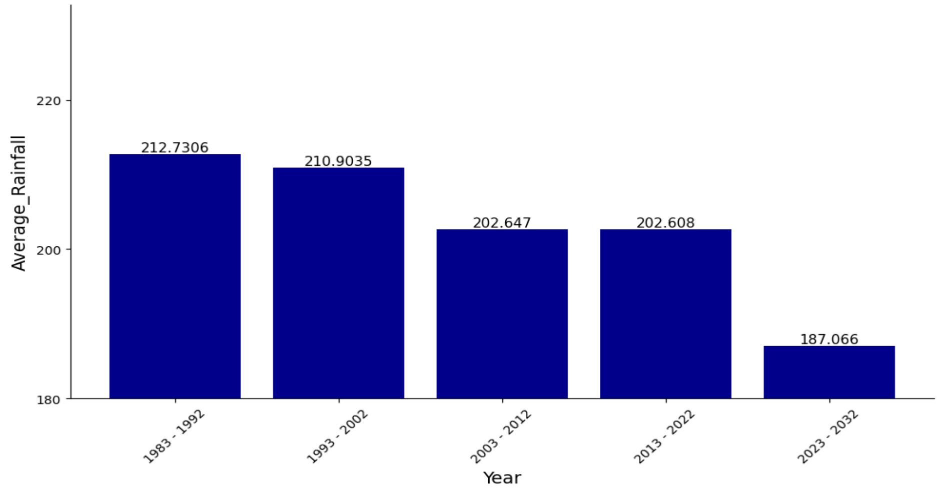

Figure 4.3.15: Average Rainfall for 10 years gap

In the past decades, the average rainfall has decreased noticeably. From Figure 4.3.15 we see that, the average rainfall was 212.7306 from 1983 to 1992, decreased to 210.9035 from 1993 to 2002, further decreased to 202.6475 from 2003 to 2012, and remained around 202.608 from 2013 to 2022. These statistics indicate a consistent decline in Bangladesh's annual rainfall due to climate change.

Table 4.3.17: Average Rainfall and Rainfall decreasing for 10 years gap

YEAR	Average Rainfall(mm)	Rainfall decreases(mm)
1983 - 1992	212.7306	NULL
1993 - 2002	210.9035	1.8271
2003 - 2012	202.6475	8.256
2013 - 2022	202.608	0.0395
2023 - 2032	187.066	15.542

From Table 4.3.17, we can see that, the rainfall decreased by 1.8271mm from the decade between 1983-1992 to the decade between 1993-2002. On the other hand, it decreased by 8.256mm in the subsequent decade of 2003-2012. From 2013 to 2022, the rainfall decreased by 0.0395mm. Moreover, from our research, we have found that in the upcoming decade, from 2023 to 2033, the rainfall will further decrease significantly by 15.542mm.

Although in recent years the amount of rainfall in Bangladesh is decreasing, and our research indicates that in the coming years, the average annual rainfall will also decrease, it doesn't mean there will be a significant change in the average annual rainfall amount in Bangladesh.

However, despite the decrease in rainfall, another issue is emerging from the pattern of recent years' rainfall in Bangladesh. That is, the average rainfall during the monsoon season is decreasing.

In Bangladesh, the monsoon primarily occurs during the months of June, July, and August. Due to the monsoonal influence, these three months experience the highest rainfall in Bangladesh. However, recent years have shown a decrease in rainfall during the monsoon season compared to previous years. From our research in Figure 4.3.16 and 4.3.17, we infer that based on the weather patterns of upcoming years, the trend indicates that the average rainfall during Bangladesh's monsoon season will further decrease in the subsequent years.

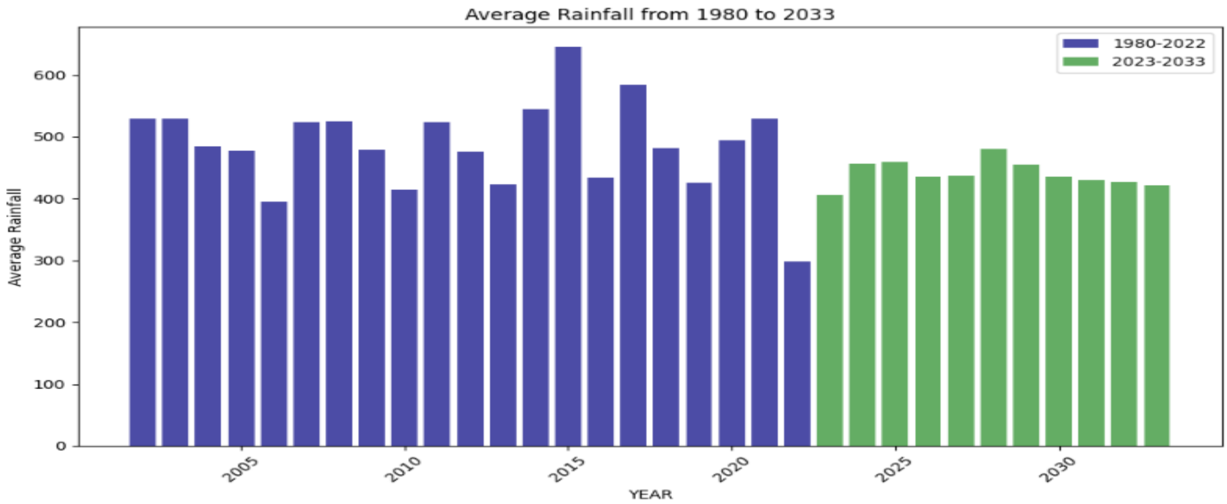

Figure 4.3.16: Average Rainfall in the Rainy Season in Bangladesh

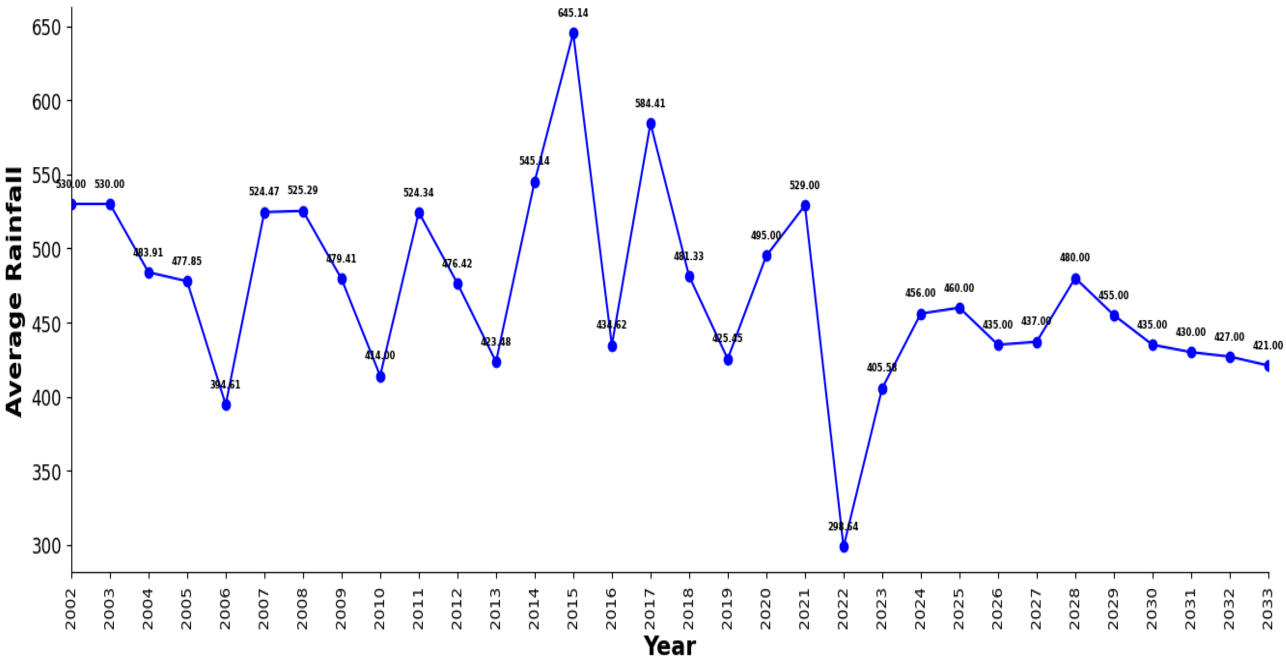

Figure 4.3.17: Average Rainfall in the Rainy Season in Bangladesh

Here in Figure 4.3.18, we have shown the average amount of rainfall during Bangladesh's monsoon season every 5 years from this table. It can be observed that in the period of 2003-2007, the amount of rainfall decreased compared to the subsequent 5 years. Then, during 2013-2017, although there was an increase in rainfall, in the following 5 years, namely 2018-2022, there has been a significant decline in rainfall during the monsoon season in Bangladesh.

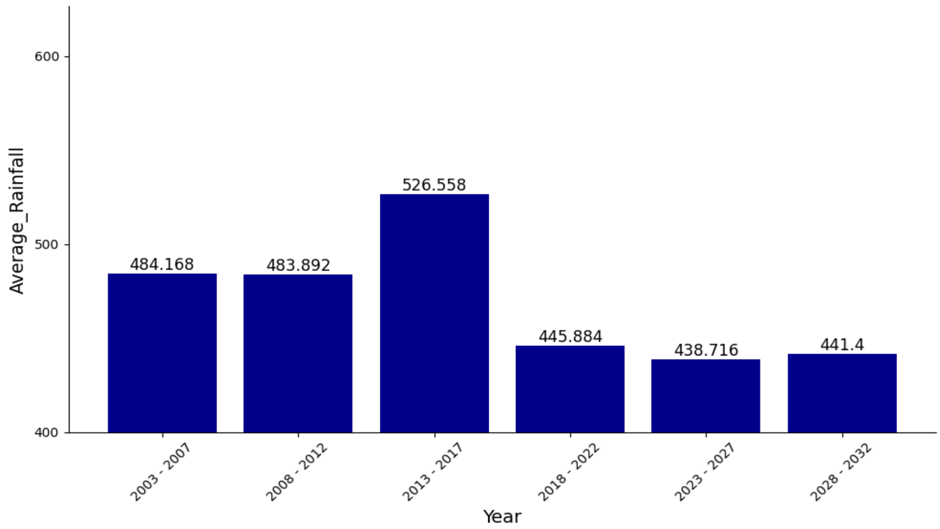

Figure 4.3.18: Average Rainfall for 5 years gap in the Rainy Season in Bangladesh

From our research, we have calculated the average rainfall for June, July, and August, which are the months of the monsoon, based on 34 stations. And from this data, we infer that the trend of decreasing rainfall during the monsoon season in Bangladesh will likely continue in the coming years.

Table 4.3.18: Average Rainfall in Rainy Season for 5 years gap

Year	Average Rainfall in Rainy Season
2003 - 2007	484.168
2008 - 2012	483.892
2013 - 2017	526.558
2018 - 2022	445.884
2023 - 2027	438.716
2028 - 2032	441.4

From the Table 4.3.18, we can see that the rainfall during the monsoon season of Bangladesh over the span of 5 years from 2008 to 2012 decreased by 1 millimeter than the years 2003 to 2007. On the other hand, within the subsequent 5 years from 2013 to 2017, there was an increase in rainfall by 43 millimeters. However, in the immediate next period, from 2018 to 2022, there was a significant decrease in rainfall by 445 millimeters. This signifies that in comparison to the 5-year period of 2013-2017, there was nearly an 81-millimeter decrease and around a 38-millimeter decrease compared to the 5-year period of 2008-2012. According to our research, we've found that from 2023 to 2027, within the upcoming 5 years, rainfall will decrease by approximately 7 millimeters compared to the period of 2018-2022. Moreover, there's a possibility of further reduction in rainfall by a few more millimeters in the subsequent 5 years.

In recent years in Bangladesh, it's been observed that the average rainfall in September and October is increasing annually. Our research suggests that this trend of increased rainfall during these two months will continue in the upcoming years as well.

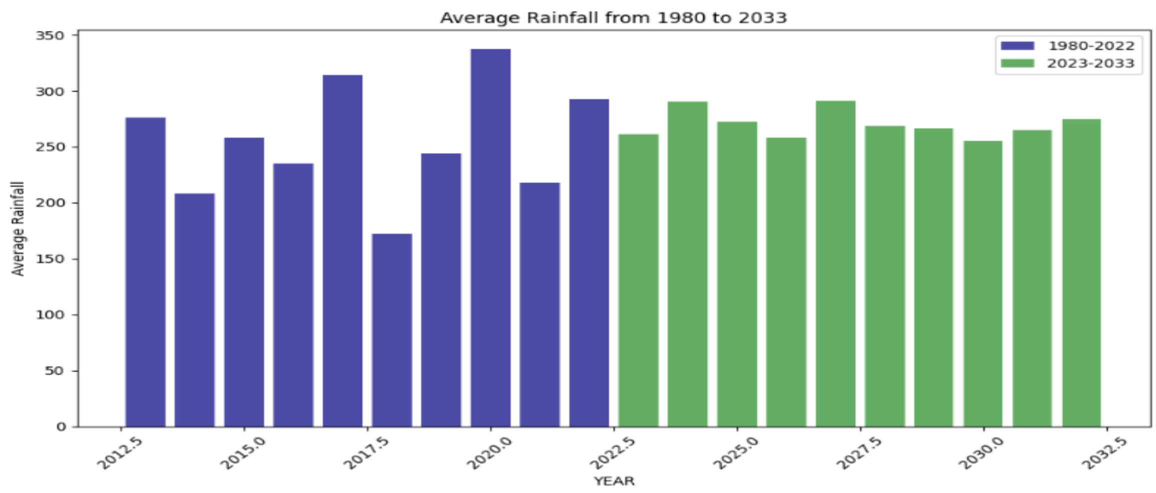

Figure 4.3.19: Average Rainfall in the post Rainy Season in Bangladesh

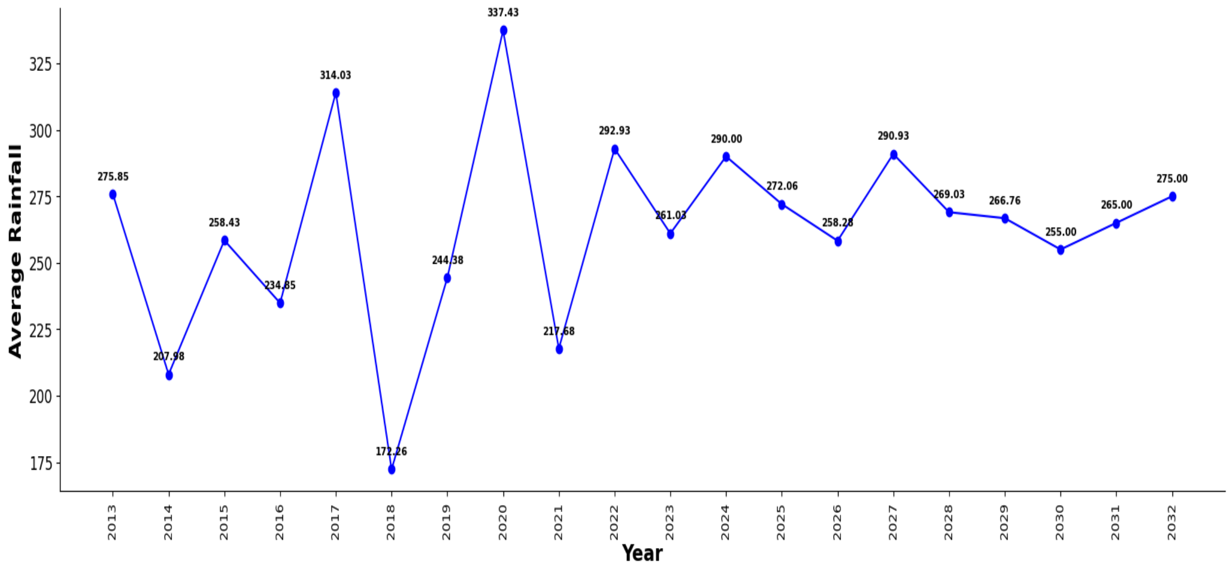

Figure 4.3.20: Average Rainfall in the post Rainy Season in Bangladesh

Here, in this Figure 4.3.19 and 4.3.20, we've shown the average rainfall for September and October from 2012 to 2033. It's evident from this graph that the rainfall during these two months has been gradually increasing from 2012 to 2022. Moreover, based on our research, the average rainfall during these two months from 2023 to 2033 shows a certain increase compared to previous years' rainfall for the same period.

Here in the Figure 4.3.21, we have observed the average rainfall for September and October in Bangladesh at intervals of every 5 years from 2008 to 2032. From this Table 4.3.19, it's evident that from 2008 to 2012, the average rainfall was 255.228 millimeters. It increased to 258.228 from 2013 to 2017. On the other hand, from 2018 to 2022, it decreased to 252.936. One reason for this slight decrease is that in some years within these 5 years, the average rainfall was significantly lower, resulting in decreased rainfall during these two months as well. On the contrary, our research indicates that in the upcoming years, the average rainfall during these two months will increase. For instance, from 2023 to 2027, the average rainfall might increase to 262.46, and from 2028 to 2032, it might further increase to 264.158.

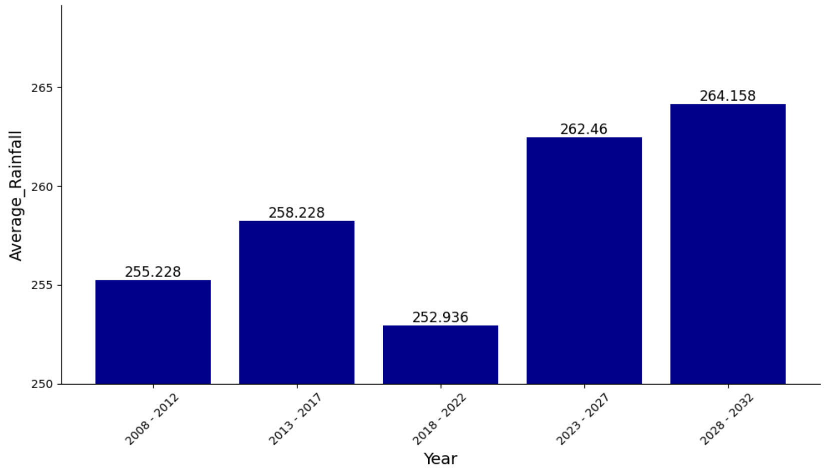

Figure 4.3.21: Average Rainfall in the post Rainy Season in Bangladesh for 5 years gap

Table 4.3.19: Average Rainfall in the post Rainy Season for 5 years gap

Year	Average Rainfall(mm)	Rainfall Change(mm)
2008 - 2012	255.228	NULL
2013 - 2017	258.228	3
2018 - 2022	252.936	-5.292
2023 - 2027	262.46	9.524
2028 - 2032	264.158	1.698

In this Figure 4.3.22, we've looked at the average rainfall for September and October over a span of 10 years. From here, we can see that from 2013 to 2022, the average rainfall for these two months in Bangladesh was 255.582 millimeters. And from 2023 to 2032, in this 10-year span, the average rainfall could reach 263.309.

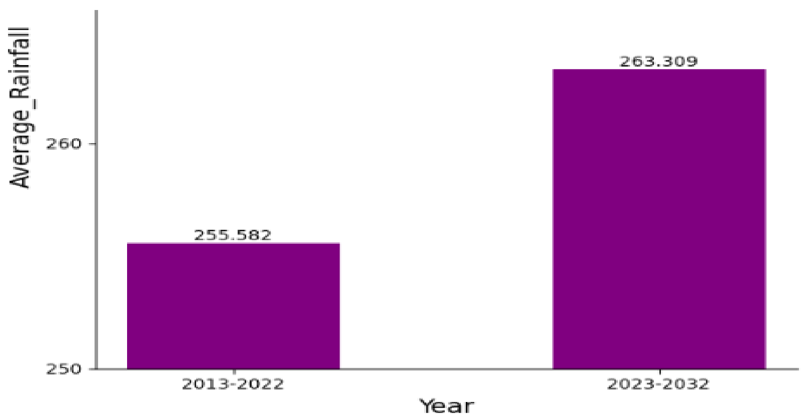

Figure 4.3.22: Average Rainfall difference between 2013 – 2022 and 2023 - 2032

This means that in the next 10 years, the average rainfall during these two months could increase by up to 8 millimeters. These statistics indicate that Bangladesh's monsoon season is gradually lengthening. The average rainfall during the monsoon season is decreasing year by year, only to increase after the monsoon, hinting at a fundamental shift. This change is expected to become more extensive in the coming years, leading to a longer monsoon season.

This prolonged monsoon season and reduced rainfall will create an adverse impact on agriculture in our country. The environment needed for crop production will no longer be available. Consequently, crop yields will decrease day by day. Even in recent years, due to inadequate rainfall, rice production has significantly declined, which could persist as a problem in the future, as indicated by this research's findings.

4.4. Flood Prediction Using Distinct Algorithms

Bangladesh faces yearly floods mainly because of its location, heavy monsoon rains, and the large rivers like the Ganges, Brahmaputra, and Meghna. These floods usually happen from June to September when the intense monsoon rains cause widespread flooding in the lower regions.

Bangladesh has been suffering to floods for many years. Excessive rainfall during the monsoon season and the overflow of water from the Himalayas elevate the water levels of rivers, leading to the creation of floods in this country. Floods cause devastating losses to the economy of Bangladesh. Consequently, significant assets are lost every year. Floods also claim many lives annually. Therefore, understanding and being prepared for floods are extremely crucial for the people of Bangladesh.

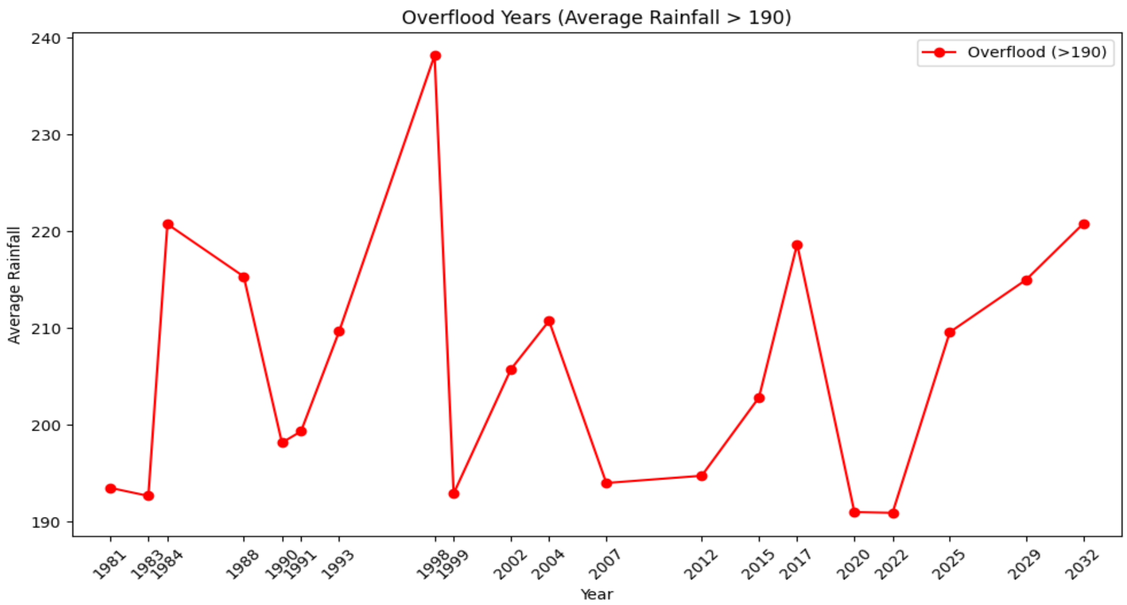

Figure 4.4.1: The major floods of Bangladesh from 1981 to 2032

Generally, four types of floods happen in Bangladesh. They are flash floods, riverine floods, rainfall induced floods and storm surges floods [52]. Flash flood - Flash floods primarily affect the northern and eastern regions of Bangladesh. These events are characterized by a sudden and significant rise in river water levels, leading to overflow with high velocity onto nearby banks. Additionally, flash floods are notable for the rapid withdrawal of water from floodplains. In Bangladesh, they typically occur following intense rainfall in the adjacent hills and mountains. Riverine flood - Riverine floods typically exhibit a gradual rise and fall of water levels over a period of 10 to 20 days or longer. The overflow from major rivers and their branches can result in widespread destruction of lives and property. The severity of flood damage is heightened when the three main rivers reach their peak stages simultaneously. It is believed that snow melting in the Himalayas significantly contributes to river flooding in Bangladesh. Rainfall induced flood - Floods triggered by rainfall result from intense and prolonged local precipitation during the monsoon season. In Bangladesh, these floods predominantly affect embanked areas. Storm surges floods - Storm surge floods impact the coastal regions of Bangladesh, characterized by vast estuaries, extensive tidal flats, and low-lying islands. These surges, often induced by tropical cyclones, inflict widespread damage on the lives and property of coastal residents.

The nation has a lengthy past of devastating floods that greatly affected people's lives and possessions. In the 1800s, six significant floods were documented: in 1842, 1858, 1871, 1875, 1885, and 1892. Throughout the 1900s, there were eighteen major floods. The ones in 1951, 1987, 1988, and 1998 had catastrophic outcomes.

The 1988 flood, also highly destructive, happened between August and September. It submerged around 82,000 square kilometers (32,000 sq. mi) of land. Heavy rainfall combined with the simultaneous surges in flow from the country's three main rivers worsened the flood in just three days.

In 1998, more than 75% of the entire country, including half of Dhaka, was submerged. It resembled the catastrophic 1988 flood in the scale of inundation. The flood resulted from intense rainfall inside and outside the country, along with the convergence of peak river flows.

The floods of 1999, while not as severe as those in 1998, still posed significant risks and incurred substantial expenses. Similarly, the 2004 flood mirrored the 1988 and 1998 floods, submerging two-thirds of the country. In 2007, floods impacted 252 villages across 40 districts, leaving countless people without homes. Bangladesh also experienced floods in 2015 and 2017, with the 2017 flood being particularly hazardous. [53][54].

In addition to floods in Bangladesh in 1981, 1983, 1990, and 1991, organized floods occurred. However, these floods were not as devastating as the floods of 1988, 1998, 2004, or 2017. Nevertheless, these floods were of moderate scale and caused extensive damage. Furthermore, in recent times, floods occurred in Bangladesh in 2020 and 2022. The 2020 flood was of a moderate scale. On the other hand, in 2022, there was widespread flooding in the Sylhet region of Bangladesh. This was also a significant flood, but it caused more damage in the Sylhet region.

Due to climate change, extensive changes are observed in Bangladesh's weather patterns. There has been a gradual decrease in rainfall each year. The monsoon season has lengthened. Bangladesh experiences heavy rainfall mainly due to the influence of seasonal winds. This rainfall continues throughout the entire year. However, as a result of climate change, the annual rainfall has decreased overall, but during certain times of the year, there are sudden periods of abundant rainfall. Within this short time, excessive rainfall significantly amplifies the impact of floods. Therefore, it appears that despite an overall reduction in total rainfall in recent times, the quantity of flooding has increased.

Bangladesh typically encounters four main categories of floods: flash floods, riverine floods, floods triggered by rainfall, and storm surge floods. In Bangladesh, riverine floods and floods triggered by rainfall mainly occur together. During the rainy season, there is extensive rainfall due to the monsoon winds, causing the water levels in rivers to rise. On the other hand, as most of our rivers originate from the Himalayan Mountain ranges. When in the rainy season there heavy rainfall occurs, the water levels in these rivers also tend to be higher. The combination of these two factors primarily leads to the creation of floods during the monsoon season. The major floods in our country are the result of the combination of these two reasons. Here in our research, we have predicted floods triggered by rainfall. For this we have took our own predicted rainfall from 2023 to 2032 and using this rainfall we have predicted upcoming years flood. We have not predicted flood using Machine Learning, we have predicted rainfall using ML and this rainfall is used for flood prediction.

We have worked on Bangladesh's past occurrences of overflooding in our research. Almost every region in Bangladesh faces some flooding during the monsoon season each year. However, in our research, we've focused on predicting when overflooding might happen in the future. Many of the major floods in Bangladesh have occurred due to excessive rainfall. Hence, we've investigated the likelihood of flooding resulting from rainfall. To achieve this, we've gathered the annual rainfall data from the years when overflooding occurred in Bangladesh's history. We've utilized this data to train our models. By incorporating this historical rainfall data into our models, we've attempted to predict when such floods might recur. Typically, if the average rainfall exceeds 190 millimeters, it results in moderate flooding. However, when the rainfall surpasses 210 millimeters, it leads to overflooding.

From our research, we've found that in the next 10 years, Bangladesh might face three major floods. Figure 4.4.1 illustrates the major flood occurrences in Bangladesh from 1981 to 2032. It depicts both past major floods and potential future flood events within a single frame. These floods primarily result from heavy rainfall. Among these, two could be moderate floods, and one might lead to overflooding. Bangladesh could experience floods in 2025, 2029, and 2032. Among these, floods in 2025 and 2029 might be moderate floods similar to those in the years 1999, 2007, or 2022. However, in 2032, there's a possibility of an overflood situation in Bangladesh, akin to the floods experienced primarily in 1988 or 1998.

4.5 Drought Prediction Using Distinct Algorithms: Drought, a calamity impacting water availability, crop growth, environmental balance, and food yield, surpasses other weather-related disasters in its widespread impact on communities and their sustenance across vast regions. Its severity amplifies significantly, posing a greater threat due to global warming and climate change, consequently elevating the risk of more intense drought occurrences. Monitoring and predicting droughts involve employing specific indices for mitigation purposes. Since 1970, the global landscape has witnessed a noticeable escalation in drought severity, duration, and affected regions, particularly in tropical and subtropical areas, attributed to escalated temperatures and reduced precipitation.

In recent years, there has been widespread utilization of drought indices to effectively monitor and describe drought occurrences. Drought and climate experts have developed several indices tailored for this purpose. These indices have distinct data input requirements and are designed to characterize various forms of drought. To pinpoint meteorological droughts, commonly employed indices include the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), China Z Index (CZI), and Effective Drought Index (EDI).

Due to climate change, there have been significant alterations in Bangladesh's weather. Currently, harsher conditions are observed compared to previous years. Particularly, in the northern districts of the country, the severity of drought has escalated in recent years. As a result of climate change in Bangladesh, temperatures are rising, and precipitation patterns are undergoing distinct changes, leading to an increasing trend in drought occurrences. Primarily, meteorological and hydrological droughts occur in Bangladesh. To predict these meteorological and hydrological droughts, two types of indices are used: the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). Among these, the most effective is the Standardized Precipitation Evapotranspiration Index (SPEI) since it incorporates both temperature and precipitation data. In contrast, SPI relies solely on temperature data. Therefore, in our research, we utilize the Standardized Precipitation Evapotranspiration Index (SPEI) to predict drought.

In our research, we have focused on the three stations in the northern region of Bangladesh: Bogra, Rajshahi, and Rangpur. SPEI is a value which calculate from the temperature and rainfall of a particular area. It can calculate using SPEI equation or nowadays there some apps which can calculate SPEI values automatically after giving them mean temperature and monthly average rainfall. We've analysed the monthly average temperatures and rainfall data from these regions for calculating SPEI for the past 43 years, from 1980 to 2022 for finding the drought conditions of these years. Then we have taken rainfall and temperature data that we have predicted in these regions for the next 10 years. Using this data we have calculated SPEI for the next 10 years and have tried to find out the future drought conditions of these regions. We have used Machine Learning algorithms for predicting rainfall and temperature for next 10 years. Using those values, we calculate SPEI for drought prediction.

The Standardized Precipitation Evapotranspiration Index (SPEI) stands as a multi-dimensional drought indicator relying on climatic data. It was formulated by Vicente-Serrano et al. (2010) at the Institute Pirenaico de Ecologia in Zaragoza, Spain. Unlike its predecessor, SPI, SPEI is a more recent index that integrates a temperature factor, enabling it to incorporate temperature's influence on drought progression through a fundamental water balance computation. SPEI adopts a scale measuring both positive and negative values, effectively identifying periods of wetness and dryness. Its flexibility allows computation for varying time intervals, ranging from as short as 1 month to as long as 48 months or beyond.

The SPEI is determined across various time scales: 1, 3, 6, 9, 12, 18, and 48 months. Within this index, positive values signify wet conditions, while negative values indicate dryness. These values are derived using either the SPEI equation or specialized SPEI tools. In our case, we employed SPEI tools by providing mean temperature and monthly rainfall data as input, generating SPEI values as output. Varied SPEI values correspond to different categories or intensities of drought.

Table 4.5.1: Drought Classes Based on SPEI value

SPEI Value	Class
More than 2.00	Extremely Wet
1.50 to 1.99	Severely Wet
1.00 to 1.49	Moderately Wet
0.50 to 0.99	Slightly Wet
-0.49 to 0.49	Near Normal
-0.99 to -0.50	Mild Dry
-1.49 to – 1.00	Moderately Dry
-1.99 to -1.50	Severely Dry
Less than -2.00	Extremely Dry

In our research, we have calculated the SPEI for three stations in Bangladesh—Rangpur, Bogura, and Rajshahi—across 3, 6, 12, and 18-month periods.

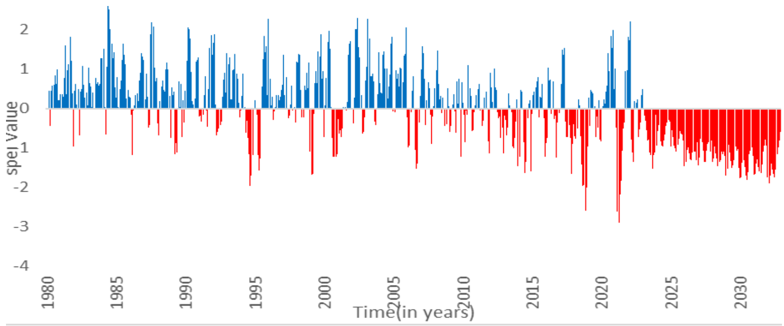

Figure 4.5.1: spei_3 values for Rangpur

This the Figure 4.5.1 show the SPEI-3 result for the Rangpur station from 1980 to 2032. The 3-month SPEI demonstrates fluctuating outcomes, depicting both wet and dry conditions within a single year. Here, from the figure we can see that Rangpur suffer from drought in all the times. It Suffer long term drought in the year 1994 – 1995. It Also Suffer drought in 2000 – 2001. But after 2010 the number of droughts of 3 months was increased. After 2015 3 months drought is increased every year and 2021 – 2022 Rangpur suffer severe drought. From our research, we have found that in the upcoming years, there will be a decrease in rainfall and an increase in temperature. As a result, the level of drought in this region will also escalate. Starting from the year 2025, within a 3-month interval, the amount of drought present in the Rangpur region will significantly rise. Moreover, a majority of the area will experience moderate drought, with instances of mild and severe drought observed as well.

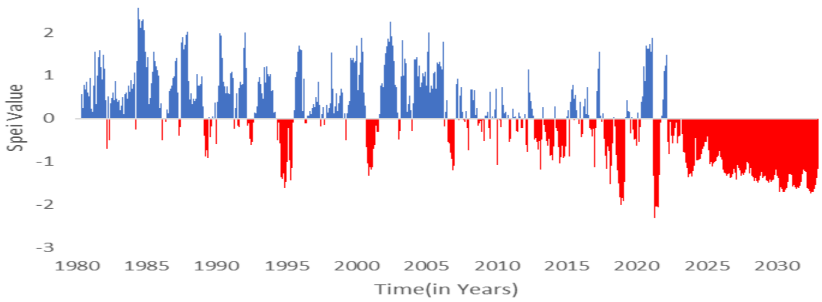

Figure 4.5.2: spei_6 values for Rangpur

In The Figure 4.5.2 These are 6-month scale SPEI values. Here, it can be observed that these drought occurrences are somewhat distinct from those seen in the 3-month scale. It is noticeable that droughts occurred in Rangpur in 1995 and during 2002-2003. Additionally, after 2010, there has been an increase in drought at the 6-month scale in this region. Post-2018, there has been a consistent annual occurrence of drought in this area, and the amount of drought has further increased in 2021-2022. Our research indicates that in the future, the level of drought in this region will escalate further. Beyond 2025, this area will become drier, experiencing continuous and prolonged drought conditions.

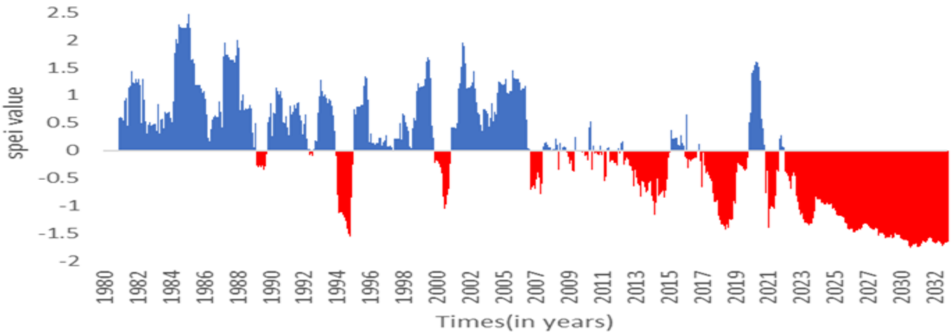

Figure 4.5.3: spei_12 values for Rangpur

In the Figure 4.5.3 Here, 12-month scale SPEI values are depicted. The SPEI values for 3 and 6 months primarily signify short-term drought, while the 12-month scale SPEI values indicate long-term drought conditions. In this context as well, it is evident that in the future, Bangladesh will experience an increase in long-term droughts. The region of Rangpur in Bangladesh is heading towards a perilous drought situation, which will profoundly impact agriculture in the area, significantly reducing agricultural productivity.

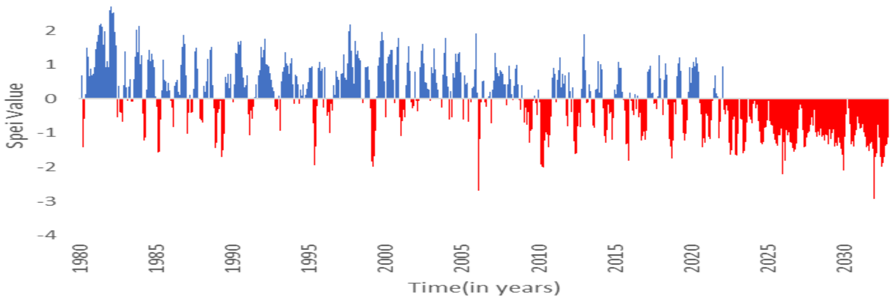

Figure 4.5.4: spei_3 values for Rajshahi

Here, Figure 4.5.4 3-month scale SPEI values are displayed. It can be observed from the graph that drought has been prevalent in this region since 1980. However, the intensity of drought increased from 2007-2008, and since 2010, there has been a consistent annual occurrence of drought in this area, with its severity escalating notably in 2018-2019. From 2020, the region has been experiencing ongoing drought conditions, persisting till the present. Our research indicates that this unavoidable drought situation will continue in the upcoming years, and beyond 2025, the drought is expected to intensify further.

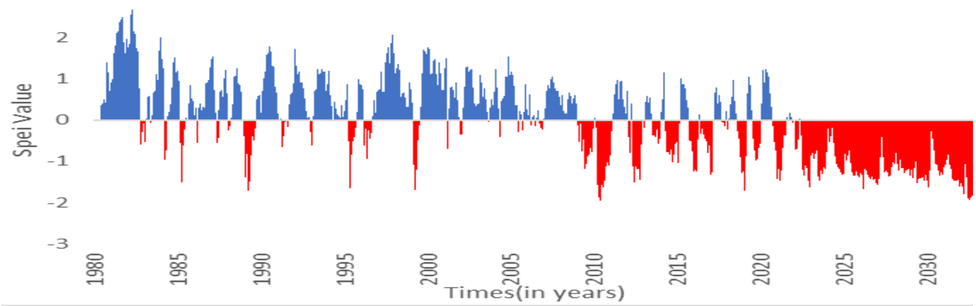

Figure 4.5.5: spei_6 values for Rajshahi

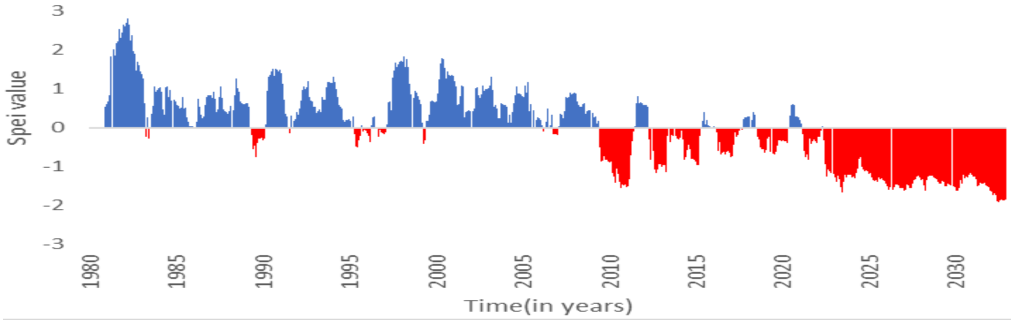

Figure 4.5.6: spei_12 values for Rajshahi

From these two figures 4.5.5 and 4.5.6, the 6-month scale SPEI values and 12-month scale SPEI values are evident. It can be inferred that after 2010, the amount of drought increased at the Rajshahi station, but from 2018, a more severe form of drought has been observed. Moreover, in the years 2021-2022, the area was significantly affected by drought. We have projected the drought situation from 2023 to 2032, and it is apparent that drought will persist in this region in the future, with its severity increasing day by day.

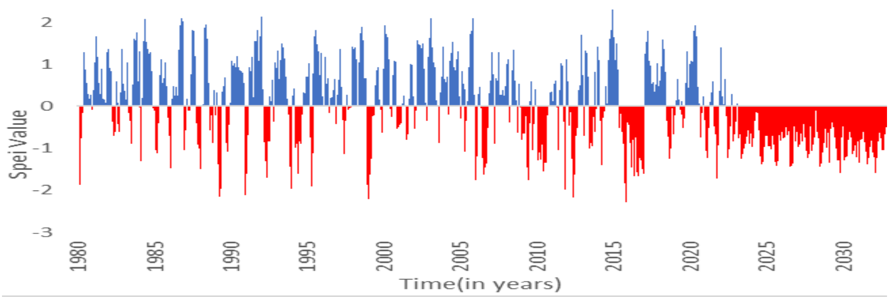

Figure 4.5.7: spei_3 values for Bogra

Here in the Figure 4.5.7 , 3-month scale SPEI values are depicted. From the chart, it can be seen that drought has been prevalent in this region since 1980. There was an increase in drought in Bogra during 2010 and 2016-2017. However, unlike the other two stations, there wasn't notably increased drought observed in this station towards 2018. Yet, again, there is a presence of drought in the period of 2021-2022. Drought is projected to persist in this station from 2023 to 2032. However, the majority of the drought occurrences in this area will be classified as mild drought.

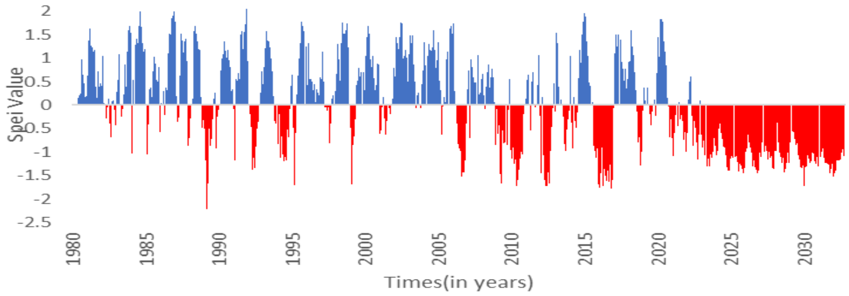

Figure 4.5.8: spei_6 values for Bogra

Here in Figure 4.5.8 , 6-month scale SPEI values are presented. It can be observed that from 2020, drought has been evident in this area, persisting from 2020 to 2022 and expected to continue in the future.

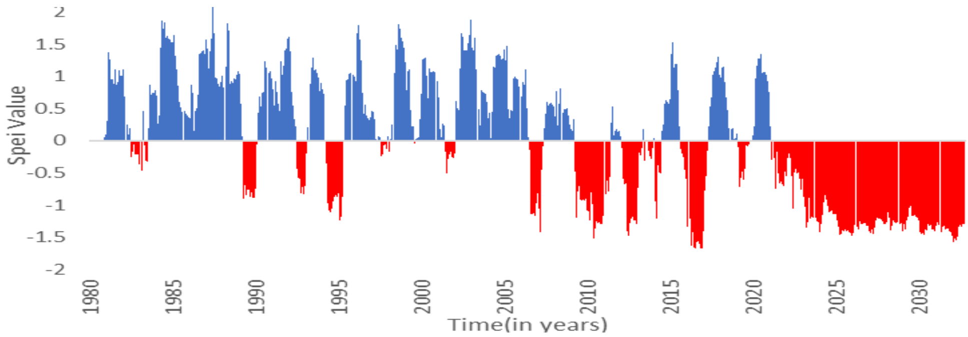

Figure 4.5.9: spei_12 values for Bogra

This Figure 4.5.9 illustrates the 12-month scale SPEI values for the Bogura station. From these values, it can be understood that there will be an increase in long-term drought in this station in the future.

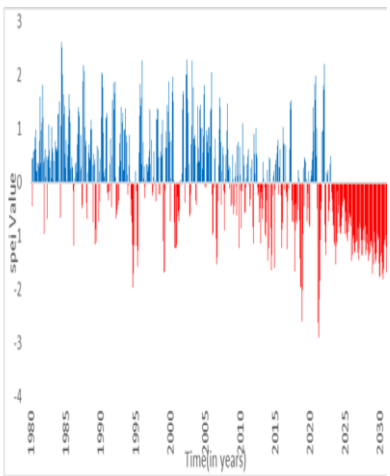

Figure 4.5.1: spei_3 values for Rangpur

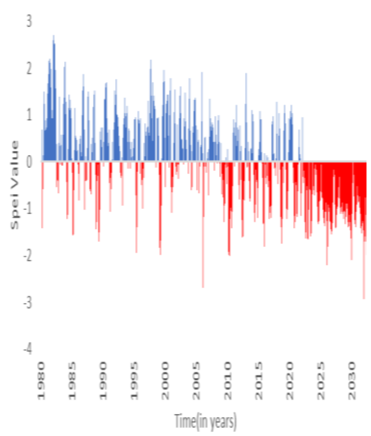

Figure 4.5.4: spei_3 values for Rajshahi

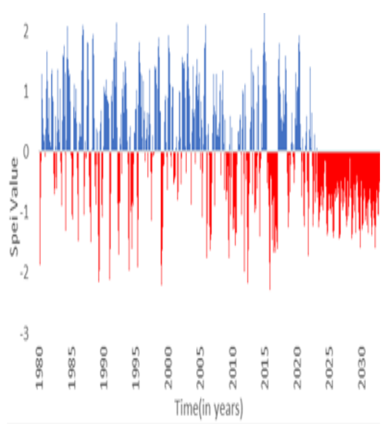

Figure 4.5.7: spei_3 values for Bogra

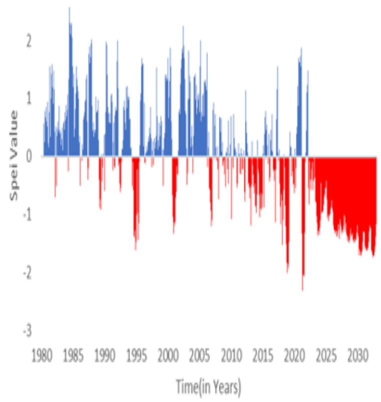

Figure 4.5.2: spei_6 values for Rangpur

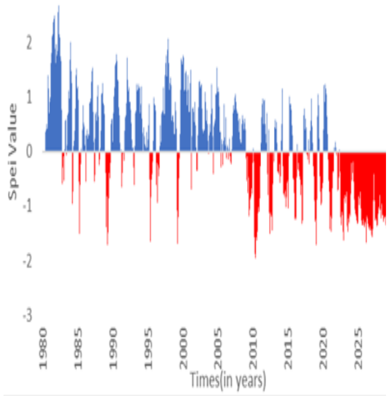

Figure 4.5.5: spei_6 values for Rajshahi

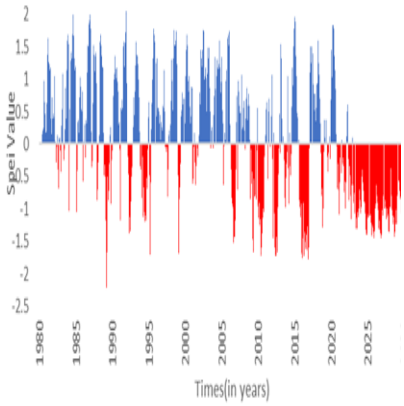

Figure 4.5.8: spei_6 values for Bogra

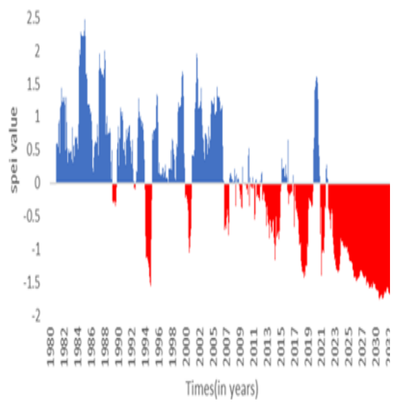

Figure 4.5.3: spei_12 values for Rangpur

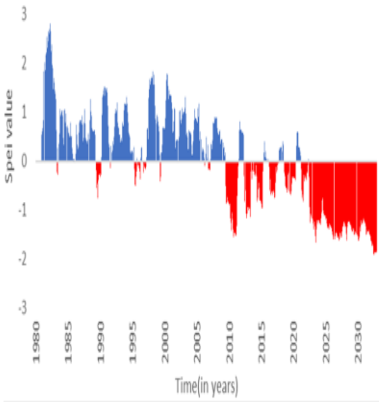

Figure 4.5.6: spei_12 values for Rajshahi

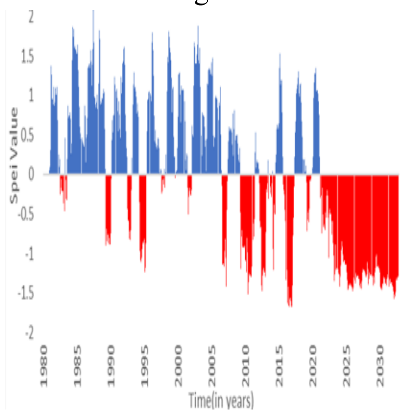

Figure 4.5.9: spei_12 values for Bogra

Although we have calculated SPEI values at three different time scales, below we have gathered some statistics on drought occurrences in Bangladesh at various times. To derive these statistics, we have utilized the SPEI 6 values.

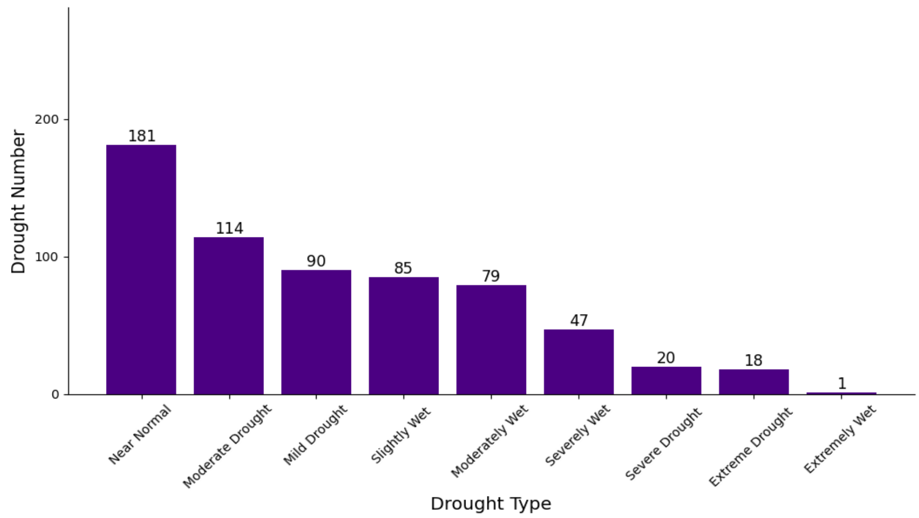

Figure 4.5.10: Different Types of Droughts conditions in Bogra

This Figure 4.5.10 displays various levels of drought at the Bogra station. From the chart, it is evident that in our country, there is a higher occurrence of Moderate Drought and Mild Drought. The levels of Severe Drought and Extreme Drought are relatively lower.

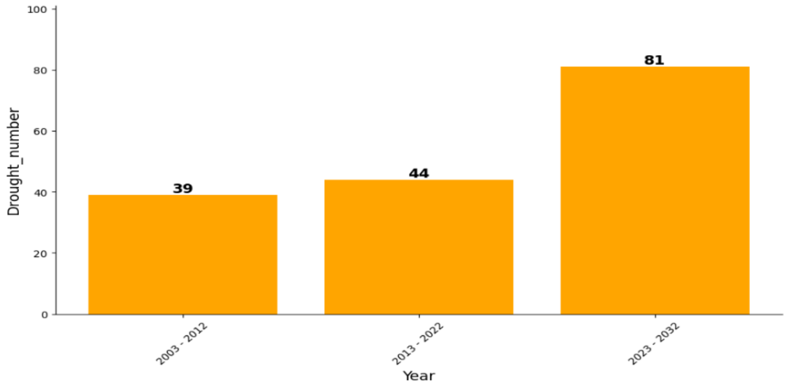

Figure 4.5.11: Droughts conditions in Bogra for 10 years gap

Here, figure 4.5.11 the amount of drought in the Bogra region is depicted over three time periods. Within the ten years from 2003 to 2012, there were 39 occurrences of drought. Again, within the following ten years from 2013 to 2022, the number of drought instances slightly increased to 44. Consequently, our research indicates an estimated 81 drought instances in the upcoming ten years. This suggests a significant rise in drought occurrences in the upcoming years, potentially posing severe threats to agriculture in this station.

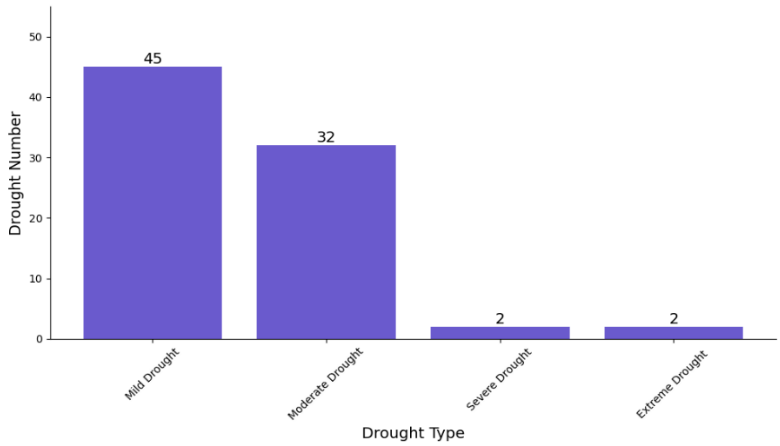

Figure 4.5.12: Future Droughts conditions in Bogra

However, in Figure 4.5.12 what is shown here regarding the amount of drought primarily includes the collective count of Moderate Drought, Mild Drought, Severe Drought, and Extreme Drought. Among these, the count of Moderate Drought and Mild Drought is relatively higher. Nevertheless, in the upcoming years, there will likely be an increase in the instances of Severe Drought and Extreme Drought compared to the previous years.

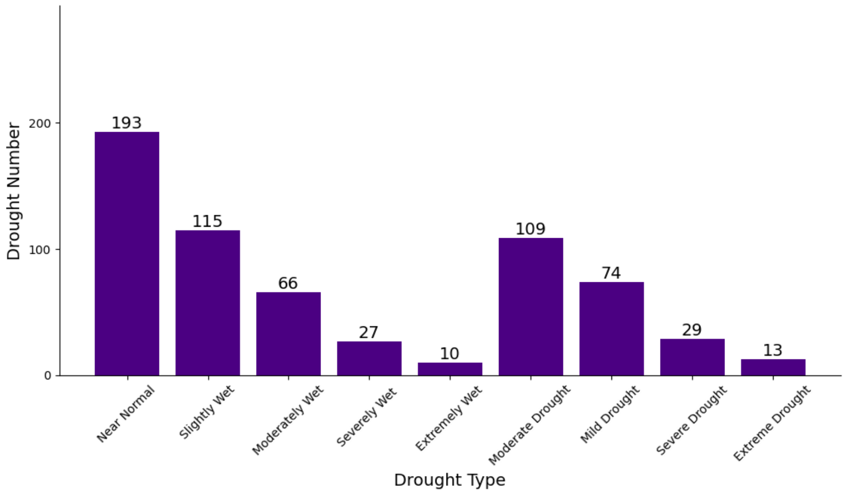

Figure 4.5.13: Different Types of Droughts conditions in Rajshahi

This Figure 4.5.13 displays various levels of drought at the Rajshahi station. From the chart, it is evident that in our country, there is a higher occurrence of Moderate Drought and Mild Drought. The levels of Severe Drought and Extreme Drought are relatively lower.

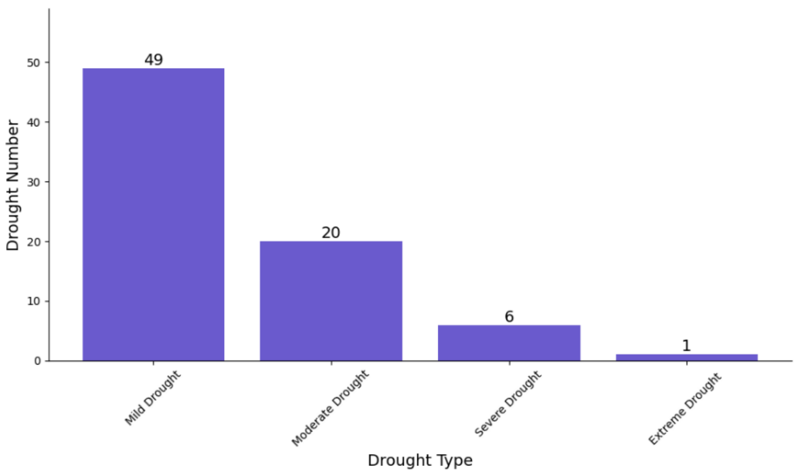

Figure 4.5.14: Future Droughts conditions in Rajshahi

However, what is shown here in Figure 4.5.14 regarding the amount of drought primarily includes the collective count of Moderate Drought, Mild Drought, Severe Drought, and Extreme Drought. Among these, the count of Moderate Drought and Mild Drought is relatively higher. Nevertheless, in the upcoming years, there will likely be an increase in the instances of Severe Drought and Extreme Drought compared to the previous years.

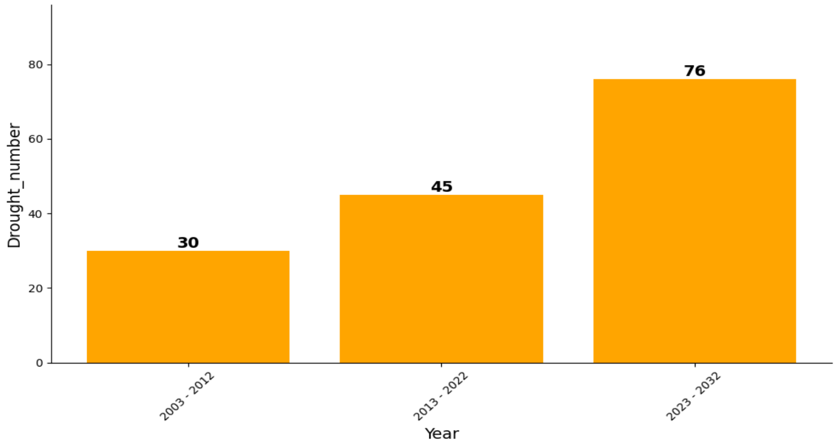

Figure 4.5.15: Droughts conditions in Rajshahi for 10 years gap

Here, in Figure 4.5.15 the amount of drought in the Rajshahi region is depicted over three time periods. Within the ten years from 2003 to 2012, there were 30 occurrences of drought. Again, within the following ten years from 2013 to 2022, the number of drought instances slightly increased to 45. Consequently, our research indicates an estimated 76 drought instances in the upcoming ten years. This suggests a significant rise in drought occurrences in the upcoming years, potentially posing severe threats to agriculture in this station.

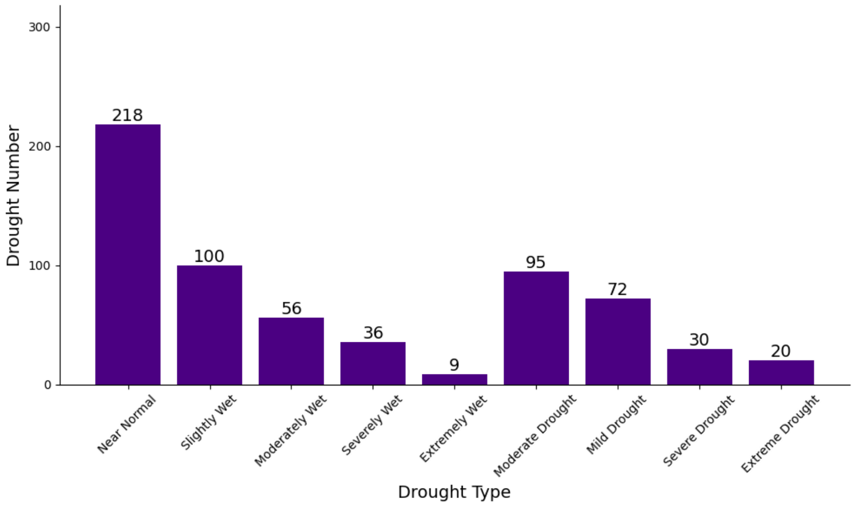

Figure 4.5.16: Different Types of Droughts conditions in Rangpur

This Figure 4.5.16 displays various levels of drought at the Rangpur station. From the chart, it is evident that in our country, there is a higher occurrence of Moderate Drought and Mild Drought. The levels of Severe Drought and Extreme Drought are relatively lower.

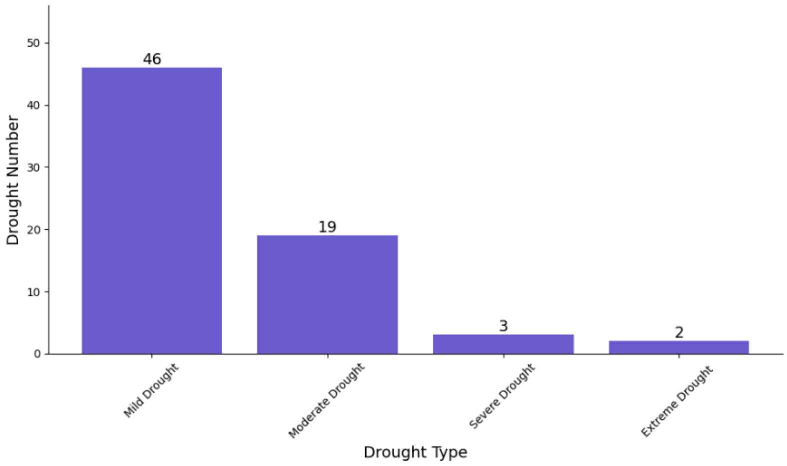

Figure 4.5.17: Future Droughts conditions in Rangpur

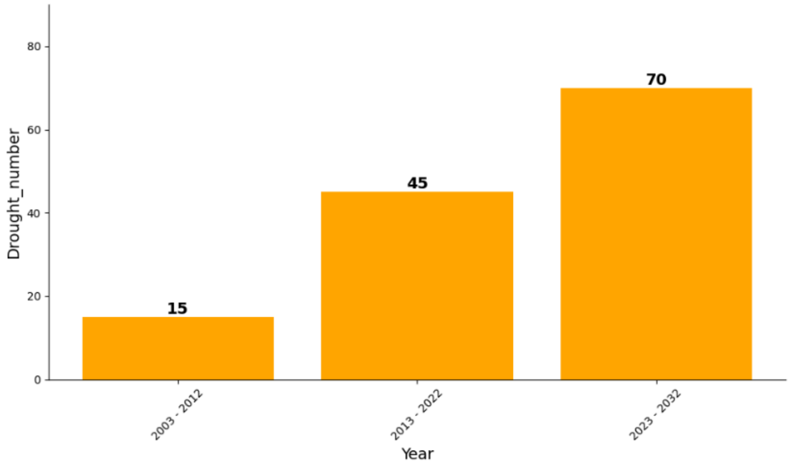

Figure 4.5.18: Droughts conditions in Rangpur for 10 years gap

However, what is shown here in Figure 4.5.17 regarding the amount of drought primarily includes the collective count of Moderate Drought, Mild Drought, Severe Drought, and Extreme Drought. Among these, the count of Moderate Drought and Mild Drought is relatively higher. Nevertheless, in the upcoming years, there will likely be an increase in the instances of Severe Drought and Extreme Drought compared to the previous years.

Here, in the Figure 4.5.18 shows that, the amount of drought in the Rangpur region is depicted over three time periods. Within the ten years from 2003 to 2012, there were 15 occurrences of drought. Again, within the following ten years from 2013 to 2022, the number of drought instances slightly increased to 45. Consequently, our research indicates an estimated 76 drought instances in the upcoming ten years. This suggests a significant rise in drought occurrences in the upcoming years, potentially posing severe threats to agriculture in this station.

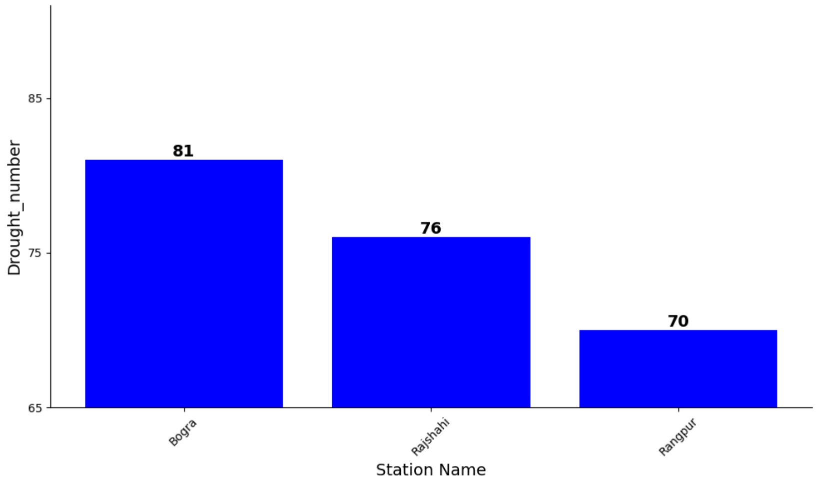

Figure 4.5.19: Three station future drought no

Here, the Figure 4.5.19 showcases that, the drought amount over a span of 10 years from 2023 to 2033 in Bangladesh is presented. It indicates that in the Rajshahi region, there might be 76 instances of drought, 70 in Rangpur, and possibly 81 in Bogura. This suggests that in the upcoming years, the Rajshahi region will experience a higher incidence of severe drought. Among these three stations, they represent the highest occurrence of drought in Bangladesh. It's anticipated that in the coming years, the instances of drought will be nearly doubled.

4.6 Interrelation Among the Weather Attributes

In our research, we have predicted the future weather conditions of Bangladesh. Our findings indicate that the temperature in Bangladesh will rise steadily each year. As a result of this temperature increase, the overall rainfall is expected to decrease gradually. However, due to the impact of global warming, the climate is changing rapidly, leading to significant shifts in rainfall patterns.

Although the general trend shows declining rainfall, certain periods within the seasons may experience excessive rainfall. This excessive rainfall, occurring within a short span of time, can lead to sudden and devastating floods. In this way, while the total amount of rainfall decreases, the frequency and severity of floods will increase over time.

On the other hand, droughts are closely linked to both temperature and rainfall. Higher temperatures combined with reduced rainfall will increase the likelihood of droughts. As the temperature continues to rise and rainfall decreases, the occurrence of droughts is projected to nearly double in the coming years, posing serious challenges to Bangladesh's agriculture.

The weather attributes—temperature, rainfall, flood occurrences, and droughts—are interrelated. A change in one attribute inevitably influences changes in the others. This interconnectedness underscores the importance of understanding how weather patterns evolve and how they may affect various sectors, particularly agriculture, in Bangladesh's future.

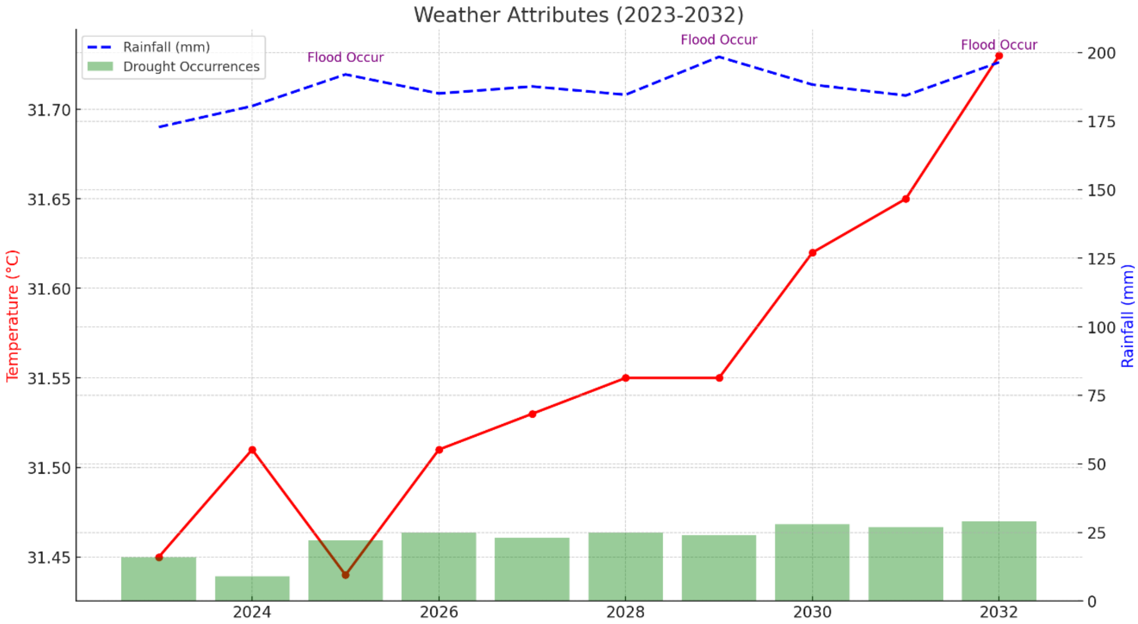

Figure 4.6.1: Interrelation Among the Weather Attributes

Here's the combined graph showing the interrelationships among temperature, rainfall, flood occurrences, and drought occurrences from 2023 to 2032.Temperature (red line) shows a gradual increase over the years. Rainfall (blue dashed line) fluctuates but has notable peaks during flood years, indicated by labels. Flood Occurrences are marked on the graph at specific points where the rainfall exceeds 190 mm. Drought Occurrences (green bars) show a rising trend, correlating with the overall increase in temperature and variable rainfall patterns.

4.7 Discussion

Bangladesh is a tropical country in South Asia. Although it is often called a land of six seasons, primarily it has three seasons. From November to February, Bangladesh experiences the winter season. From March to May, it's the summer season. Monsoon, the rainy season in this country, occurs from June to October. During the summer season, the temperature in Bangladesh remains relatively high. Conversely, the monsoon brings substantial rainfall crucial for the country's agriculture. However, due to climate change, significant changes in the country's weather patterns have been observed over the past few years. The temperature has increased by approximately 1-1.5 degrees Celsius during the summer. On the other hand, the typical winter experiences have been diminishing, with temperatures not reaching the same lows as before. The duration of the winter season has reduced considerably. Conversely, the summer has become hotter and more prolonged. Our research, based on previous data and predictions for the next ten years from 2023 to 2032, suggests that Bangladesh's temperature is likely to increase by nearly 0.5 degrees Celsius compared to the previous ten years from 2013 to 2022. Specifically, in winter months like November and December, the temperature is expected to rise by around 0.5 to 0.6 degrees Celsius. Consequently, even during these months, the typical cold experience might not be felt as distinctly as before. The duration of the winter season will reduce further in the coming days.

Analysing precipitation in Bangladesh, we've found that the country's annual rainfall is decreasing each year. Through our research on future precipitation, it indicates that in the upcoming years, Bangladesh might experience slightly lower rainfall amounts annually. The most significant finding we've encountered is that precipitation patterns are changing significantly and are likely to undergo further changes in the future. Notably, the characteristic of rainfall is altering, and it will continue to evolve in the future. Although the overall annual precipitation might decrease slightly, there will be a substantial reduction in total rainfall during the monsoon season. The seasonal distribution of rainfall will change as well, with reduced precipitation during the monsoon's onset and an increase in rainfall towards its end. This change primarily affects the specificity of rainfall patterns and signifies an elongated monsoon season.

From ancient times, the people of Bangladesh have been grappling with natural calamities. Almost every year, our country witnesses some form of natural disaster. Monsoonal weather and the cascading water from the Himalayas during the rainy season are the primary causes of these calamities. However, in some years, Bangladesh has experienced severe flooding, such as in 1988, 1998, and others. We have analysed the data of past years' floods in Bangladesh and predicted the possibility of future floods. In the next 10 years, Bangladesh might face three major floods: in 2025, 2029, and 2032. Among these, the flood in 2032 could be particularly devastating.

Although Bangladesh is not prone to severe droughts, the quantity of drought in this country has increased significantly in recent years. Due to low rainfall and higher temperatures, the soil is losing its moisture. As a result, the soil is becoming drier day by day. Additionally, the decrease in rainfall is causing the water table of the soil to decline steadily. These factors are exacerbating the prevalence of drought. Our research has identified three stations in Bangladesh with the highest likelihood of facing future drought conditions. From our research, we have concluded that in the coming years, the areas around these stations may experience a nearly twofold increase in the quantity of drought. Moreover, there is a continuous risk of persistent drought, leading to further drying of the soil. This situation could have a significantly adverse impact on agriculture in these regions, potentially causing a considerable reduction in agricultural production.

4.8 Impacts of Climate Change on Bangladesh

Over the past four decades (1980-2022), there's a discernible upward trend in temperature across seasons. Particularly noteworthy is the consistent increase in mean temperatures over five-year intervals, with a gradual rise observed in both summer and winter. Projections for the next decade (2023-2033) indicate a continuation of this trend, with temperatures expected to rise steadily. By 2032, temperatures could potentially exceed 31.7 degrees Celsius, indicating a significant warming trend. Rising temperatures can lead to heat stress, affecting public health, agriculture, and energy demand across the country. While there's some variability in rainfall patterns over the years, an overall decrease in average rainfall is observed, particularly during the rainy season. Over the next decade, a notable decrease in rainfall is predicted, with a reduction of around 15.5 millimeters in average rainfall from 2023 to 2032.Additionally, changes in rainfall distribution between rainy and post-rainy seasons might impact agricultural cycles and water availability. Bangladesh faces a heightened risk of flooding in the coming years, with projections indicating three major flood events in the next decade. Drought conditions are projected to worsen in several districts, including Rangpur, Bogura, and Rajshahi. The frequency and severity of droughts are expected to increase, with the number of drought events rising notably over the next decade.

The combination of rising temperatures, decreasing rainfall, increased flood frequency, and worsening drought conditions poses significant challenges for Bangladesh's development and resilience. These climate-related impacts can have cascading effects on various sectors, including agriculture, water management, infrastructure, public health, and socio-economic well-being. The impacts of climate change of Bangladesh are given below:

1. Rising temperatures increase heat-related illnesses, raising hospitalizations and mortality during heatwaves. They worsen existing health conditions like heart and lung diseases and boost heat-related illnesses. High temperatures also worsen air quality, making respiratory issues worse.

2. Rising temperatures increase the likelihood of prolonged periods of extreme heat, leading to heat stress among individuals. Vulnerable populations, including the elderly, children, outdoor workers, and those with pre-existing health conditions, are particularly at risk of heat-related illnesses.

3. Rising temperatures increase the demand for cooling systems, such as air conditioners and fans, to mitigate heat stress and maintain indoor comfort. Increased energy demand for cooling during heatwaves can strain electricity grids, leading to power outages and increased energy costs. Higher energy consumption for cooling contributes to increased greenhouse gas emissions, exacerbating climate change and further perpetuating the cycle of warming temperatures.

4. High temperatures and heatwaves stunt crop growth and diminish yields, while altering rainfall patterns disrupt planting and growth stages, leading to crop failures and reduced productivity. These changes also impact pest and disease distribution, further complicating crop production. Erratic rainfall, like droughts and floods, exacerbates the situation by damaging crops, causing soil erosion, and depleting essential nutrients, posing significant threats to agricultural sustainability.

5. Changes in rainfall patterns disrupt ecosystems and biodiversity, altering habitats and species distributions. Reduced rainfall leads to habitat loss, less vegetation, and increased wildfire risk. Rising temperatures exacerbate these impacts, further stressing ecosystems and jeopardizing vital services like water purification and flood control.

6. Altered rainfall patterns can affect surface water and groundwater recharge rates, leading to fluctuations in water levels in rivers, lakes, and aquifers. Reduced rainfall may lower water tables and groundwater levels, exacerbating groundwater depletion and saltwater intrusion in coastal areas. Changes in precipitation patterns can also impact the timing and magnitude of river flows, affecting hydropower generation, navigation, and ecosystem health.

7.In future, drought number will increase. Drought hits farming hard, slashing crop yields and livestock feed. Less rain means dry soil, stunting crops and raising the chance of crop failure.

Farmers can't grow enough food, leading to shortages. This leaves people struggling to get enough healthy food, especially those in rural areas and small farms.

8. Drought makes water scarce by drying up rivers, lakes, and reservoirs. Less rain means rivers and groundwater levels drop, making it hard to get water for farming, drinking, and sanitation. Farming suffers as irrigation water runs low, making crop losses worse and food shortages more likely.

9.Bangladesh faces a heightened risk of flooding in the coming years, with projections indicating three major flood events in the next decade. While two floods are expected to be moderate in severity, one event in 2032 could lead to significant overflooding, reminiscent of historically catastrophic floods. These flood events pose substantial threats to infrastructure, agriculture, and the livelihoods of millions of people residing in low-lying areas.

Climate change poses multifaceted challenges to Bangladesh, including temperature rise, altered rainfall patterns, increased flood risk, and heightened drought vulnerability. These climatic shifts threaten the country's agricultural productivity, water resources, infrastructure resilience, and socio-economic stability. Urgent adaptation measures, including improved water management, resilient infrastructure, and climate-resilient agriculture, are imperative to mitigate the adverse impacts of climate change and safeguard the well-being of Bangladesh's population. This analysis underscores the pressing need for concerted efforts at local, national, and global levels to address the complex and interrelated challenges posed by climate change in Bangladesh.

4.9 Suggestions for Reducing Climate Change Impacts on Bangladesh

To tackle the impacts of climate change in Bangladesh, we've come up with some practical suggestions. From managing land and water sustainably to involving communities in adaptation efforts, these ideas cover a lot of ground. By combining nature-friendly solutions with smart tech and inclusive policies, Bangladesh can tackle climate challenges and keep its people and environment safe for the long haul.

1.Launch large-scale tree plantation campaigns to increase green cover and enhance carbon sequestration in urban and rural areas. Establish urban forests, community gardens, and green corridors to provide habitat for wildlife, improve air quality, and reduce heat island effects in cities.

2. Enhance urban planning and design to incorporate green spaces, parks, and tree cover to mitigate the urban heat island effect and lower ambient temperatures. Implement energy-efficient building codes and standards to reduce energy consumption for cooling and decrease heat emissions from buildings and infrastructure. Promote afforestation and reforestation efforts to increase vegetative cover, sequester carbon dioxide, and provide natural cooling through shade and transpiration.

3. Invest in water conservation and management strategies such as rainwater harvesting, water recycling, and efficient irrigation practices to optimize water use and minimize losses. Implement watershed management and soil conservation measures to enhance water retention in soils, reduce runoff, and improve groundwater recharge. Diversify agricultural practices and

crop varieties to adapt to changing precipitation patterns and optimize water utilization in rainfed and irrigated agriculture.

4. To adapt agriculture to climate change, farmers can diversify crops, use climate-resilient varieties, and improve water management with techniques like drip irrigation. Adapting crops to climate change involves diversifying crop varieties, selecting resilient breeds, and enhancing water management techniques like drip irrigation. Crop rotation and intercropping methods can also improve soil health and pest management, ensuring more stable yields in changing climates.

5. Enhance flood management with early warnings, floodplain zoning, and natural flood controls like wetland restoration. Strengthen infrastructure against floods, retrofitting existing buildings, and designing new ones to resist flooding. Build community resilience through education, training, and participatory planning to minimize flood impacts on people and livelihoods.

6. Establish drought early warning systems and plans for water rationing and drought-resistant crops. Invest in water-saving technologies for agriculture and industry to conserve water during droughts. Provide support to vulnerable populations, like small farmers, with social safety nets and livelihood assistance during drought-induced crises.

By following these things, we can reduce the impact of climate change of Bangladesh.

4.10 Summary

The temperature in Bangladesh is rising day by day, resulting in longer summers and shorter winters. Additionally, rainfall is decreasing steadily, and the rainy season is extending. Consequently, the soil is losing its moisture annually, leading to an increase in droughts. The impact of climate change on Bangladesh is significant, as the country gradually loses its familiar climate conditions and experiences hotter weather. This change has adverse effects on people's health, as they fall ill due to the changing weather patterns. Moreover, the loss of soil moisture and changing weather patterns are causing a decline in crop production, which negatively impacts the economy. In response to these challenges, the people of Bangladesh must remain vigilant and take necessary measures to mitigate the adverse effects of climate change.

CHAPTER -5

CONCLUSION

5.1 Conclusion:

Weather forecasting is of great significance in Bangladesh due to its vulnerability to weather-related risks and heavy reliance on agriculture. Bangladesh is prone to cyclones, floods, and heavy rainfall, which can cause significant damage to both lives and property. Accurate weather prediction allows for timely preparedness and response, assisting in mitigating the impact of these hazards.

I. The prediction of weather holds immense importance for the farmers of Bangladesh as it allows them to make informed decisions regarding their agricultural practices. By knowing the weather conditions in advance, farmers can take necessary steps to mitigate risks and ensure optimal crop growth. In our research, we focused on predicting rainfall, flood, temperature, and drought. We collected data pertaining to these weather parameters from the Bangladesh Meteorological Department (BMD). Applying machine learning algorithms to this data, we will forecast future weather conditions in Bangladesh.

II. In our research, we found that the Random Forest with sequential optimization of GA and PSO algorithm yields the best results compared to other algorithms for weather data. Hence, we utilized the Random Forest algorithm to forecast our future data. We forecasted the weather conditions—temperature, rainfall, flood, and drought—for the next 10 years (2023-2032). Our research indicates that the temperature in Bangladesh is increasing, with an estimated average yearly temperature rise of 0.5 degrees Celsius over the next decade. Summers are expected to prolong, and winters will become warmer.

III. The average rainfall is projected to decrease annually. Monsoon rainfall is anticipated to decrease, while post-monsoon rainfall will likely increase, altering the rainfall patterns and extending the rainy season. We anticipate three instances of flooding in Bangladesh within the next 10 years potentially occurring in 2025, 2029, and 2032.

IV. Droughts in Bangladesh are intensifying progressively. Our study focused on three stations: Bogura, Rajshahi, and Rangpur. Across these stations, the incidence of drought is expected to increase significantly in the coming years, possibly doubling in frequency. Bangladesh is likely to experience exceedingly hot and drier weather in the future, exacerbating the negative impacts of climate change throughout the country.

V. We analyzed both past and future data and identified a trend of rising temperatures and decreasing rainfall from 1980 to 2032. Our aim was to illustrate the changing climate of Bangladesh, depicting how it has worsened in recent years and how it is projected to evolve in the future. Overall, our research endeavors to provide a comprehensive overview of these trends.

VI. Regarding climate change, our objective is to assess its impact on Bangladesh and explore potential solutions to mitigate these effects.

5.2 Future Scope

In the future, we aim to predict cyclones and earthquakes in Bangladesh. Additionally, we plan to focus on predicting heat stress and related conditions, allowing people to anticipate and prepare for periods of high heat stress in advance. While this paper specifically addresses flood prediction related to rainfall, our future research will also explore riverine flood prediction.

REFERENCE

1. https://documents1.worldbank.org/curated/en/819691634012303755/pdf/Hotter-and-more-Humid-with-Erratic-Rainfall-Climate-Change-in-Bangladesh.pdf

2.https://www.worldbank.org/en/news/feature/2021/10/07/climate-change-in-bangladesh-impact-on-infectious-diseases-and-mental-health#:~:text=Changing%20and%20erratic%20weather%20pattern,with%20deteriorating%20mental%20health%20conditions.

3.https://www.germanwatch.org/sites/default/files/20-2-01e%20Global%20Climate%20Risk%20Index%202020_14.pdf

4. T.-w. Kim, H. Ahn, G. Chung and C. Yoo, Stochastic multi-site generation of daily rainfall occurrence in south Florida, Stochastic Environmental Research and Risk Assessment 22(6) (2008), 705–717.

5. R.F. Chevalier, G. Hoogenboom, R.W. McClendon and J.A. Paz, Support vector regression with reduced training sets for air temperature prediction: a comparison with artificial neural networks, Neural Computing and Applications 20(1) (2011), 151–159.

6. E.J. Gill, E.B. Singh and E.S. Singh, Training back propagation neural networks with genetic algorithm for weather forecasting, in: IEEE 8th International Symposium on Intelligent Systems and Informatics, IEEE, 2010, pp. 465–469.

7. F. Olaiya and A.B. Adeyemo, Application of data mining techniques in weather prediction and climate change studies, International Journal of Information Engineering and Electronic Business 4(1) (2012), 51.

8. D. Luminto, Weather analysis to predict rice cultivation time using multiple linear regression to escalate farmer's exchange rate, in: 2017 International Conference, Concepts, Theory, and Applications (ICAICTA), 2017.

9. N. Sharma, P. Sharma, D. Irwin and P. Shenoy, predicting solar generation from weather forecasts using machine learning, in: 2011 IEEE international conference on smart grid communications (SmartGridComm), IEEE, 2011, pp. 528–533.

10. S.A. Nishe, T.A. Tahrin, N. Kamal, M.S. Hoque and K.T. Hasan, Micro-level meteorological data sourcing for accurate weather prediction, in: 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), IEEE, 2017, pp. 353–356.

11. V.M. Krasnopolsky and M.S. Fox-Rabinovitz, Complex hybrid models combining deterministic and machine learning components for numerical climate modeling and weather prediction, Neural Networks 19(2) (2006), 122–134.

12. Luo X, Nadiga BT, Park JH, Ren Y, Xu W, Yoo S. A Bayesian Deep Learning Approach to Near-Term Climate Prediction. Journal of Advances in Modeling Earth Systems. 2022 Oct; 14(10):e2022MS003058.

13. Ramos MP, Tasinaffo PM, Cunha AM, Silva DA, Gonçalves GS, Dias LA. A canonical model for seasonal climate prediction using Big Data. Journal of Big Data. 2022 Dec; 9(1):1-25.

14. Abebe WT, Endalie D. Artificial intelligence models for prediction of monthly rainfall without climatic data for meteorological stations in Ethiopia. Journal of Big Data. 2023 Jan 3; 10(1):2.

15. D. N. Fente and D. Kumar Singh. Weather Forecasting Using Artificial Neural Network. 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 2018.

16. Belayneh A, Adamowski J. Drought forecasting using new machine learning methods. Journal of Water and Land Development. 2013; 18(9):3-12.

17. Kaur A, Sood SK. Artificial intelligence-based model for drought prediction and forecasting. The Computer Journal. 2020 Nov; 63(11):1704-12.

18. Ahmed F, Loc HH, Park E, Hassan M, Joyklad P. Comparison of Different Artificial Intelligence Techniques to Predict Floods in Jhelum River, Pakistan. Water. 2022 Nov 3; 14(21):3533.

19. Gauhar N, Das S, Moury KS. Prediction of flood in Bangladesh using K-nearest neighbors' algorithm. In2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) 2021 Jan 5 (pp. 357-361). IEEE.

20. Khan MM, Siddique MA, Sakib S, Aziz A, Tasawar IK, Hossain Z. Prediction of temperature and rainfall in Bangladesh using long short-term memory recurrent neural networks. In2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) 2020 Oct 22 (pp. 1-6). IEEE.

21. Bhaskar Rao DV, Tallapragada V. Tropical cyclone prediction over Bay of Bengal: a comparison of the performance of NCEP operational HWRF, NCAR ARW, and MM5 models. Natural hazards. 2012 Sep; 63:1393-411.

22. Syeed MM, Farzana M, Namir I, Ishrar I, Nushra MH, Rahman T. Flood Prediction Using Machine Learning Models. arXiv preprint arXiv:2208.01234. 2022 Aug 2.

23. Mahabub A, Habib AB. An Overview of Weather Forecasting for Bangladesh Using Machine Learning Techniques. Machine Learning. 2019:1-36.

24. Ahmed N, Hoque MA, Arabameri A, Pal SC, Chakrabortty R, Jui J. Flood susceptibility mapping in Brahmaputra floodplain of Bangladesh using deep boost, deep learning neural network, and artificial neural network. Geocarto International. 2021 Nov 16:1-22.

25. Rizvee MA, Arju AR, Al-Hasan M, Tareque SM, Hasan MZ. Weather forecasting for the North-Western region of bangladesh: A machine learning approach. In2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) 2020 Jul 1 (pp. 1-6). IEEE.

26. Y. Zaman, Machine Learning Model on Rainfall-A Predicted Approach for Bangladesh, PhD thesis, United International University, 2018.

27. N. Hasan, M.T. Uddin and N.K. Chowdhury, Automated weather event analysis with machine learning, in: 2016 International Conference on Innovations in Science, Engineering and Technology (ICISET), IEEE, 2016, pp. 1–5.

28. K. Mohammadi, S. Shamshirband, S. Motamedi, D. Petkovi´c, R. Hashim and M. Gocic, Extreme learning machine-based prediction of daily dew point temperature, Computers and Electronics in Agriculture 117 (2015), 214–225.

29. N. Hasan, N.C. Nath and R.I. Rasel, A support vector regression model for forecasting rainfall, in: 2015 2nd International Conference on Electrical Information and Communication Technologies (EICT), IEEE, 2015, pp. 554–559.

30. C. Rudin and K.L. Wagstaff, Machine learning for science and society, Springer, 2014.

31. L. Delle Monache, F.A. Eckel, D.L. Rife, B. Nagarajan and K. Searight, Probabilistic weather prediction with an analog ensemble, Monthly Weather Review 141(10) (2013), 3498 3516.

32. S. Johnson, F. Fielding, G. Hamilton and K. Mengersen, An integrated Bayesian network approach to Lyngbya majuscule bloom initiation, Marine Environmental Research 69(1) (2010), 27–37.

33. S.J. Moe, S. Haande and R.-M. Couture, Climate change, cyanobacteria blooms and ecological status of lakes: a Bayesian network approach, Ecological modelling 337 (2016), 330 347.

34. W.M. Dlamini, A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland, Environmental Modelling & Software 25(2) (2010), 199–208.

35. A.-Z.S.B. Habib, S. Mallick, A.S. Ahmed, S.S. Alam and A.S. Ahmad, Performance Appraisal of Spectrum Sensing in Cognitive Radio Network, in: 2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT), IEEE, 2018, pp. 162–167.

36. Uddin, M.J., Hu, J., Islam, A.R.M.T. et al. A comprehensive statistical assessment of drought indices to monitor drought status in Bangladesh. Arab J Geosci 13, 323 (2020).

37. Islam, S.M. Taohidul & Saha, Sajal & Evan, Ali & Halder, Nabonita & Dey, Shakti. (2016). Monthly Weather Forecasting through ANN Model: A Case Study in Barisal, Bangladesh. IJARCCE. 5. 1-6. 10.17148/IJARCCE.2016.5601.

38. Ali, MM & Kishtawal, Chandra & Jain, Sarika. (2007). Predicting cyclone tracks in the north Indian Ocean: An artificial neural network approach. Geophysical Research Letters - GEOPHYS RES LETT. 34. 10.1029/2006GL028353.

39. Abebe, Wondmagegn & Endalie, Demeke. (2023). Artificial intelligence models for prediction of monthly rainfall without climatic data for meteorological stations in Ethiopia. Journal of Big Data. 10. 10.1186/s40537-022-00683-3.

40. Yalavarthi, Radhika & Shashi, M. (2009). Atmospheric Temperature Prediction using Support Vector Machines. International Journal of Computer Theory and Engineering. 1. 55-58. 10.7763/IJCTE.2009.V1.9.

41. Kumar, Pankaj & Kashyap, P.S. & Ali, Javed. (2013). Temperature Forecasting using Artificial Neural Networks (ANN). Journal of Hill Agriculture. 4. 110-112. 10.5958/2230-7338.2014.

42. Nalluri, Sravani & Ramasubbareddy, Somula & Kannayaram, G. (2019). Weather Prediction Using Clustering Strategies in Machine Learning. Journal of Computational and Theoretical Nanoscience. 16. 1977-1981. 10.1166/jctn.2019.7835.

43. https://www.javatpoint.com/genetic-algorithm-in-machine-learning

44.https://learn.microsoft.com/en-us/archive/msdn-magazine/2011/august/artificial-intelligence-particle-swarm-optimization

45.https://www.analyticsvidhya.com/blog/2021/10/an-introduction-to-particle-swarm-optimization-algorithm/

46. https://365datascience.com/tutorials/machine-learning-tutorials/decision-trees/

47. https://discuss.boardinfinity.com/t/what-is-the-svm-algorithm/19000

48. https://www.kdnuggets.com/2020/11/most-popular-distance-metrics-knn.html

49. https://www.ejable.com/tech-corner/ai-machine-learning-and-deep-learning/random-forest-in-machine-learning/

50. https://en.wikipedia.org/wiki/Mean_squared_error

51. https://arize.com/blog-course/root-mean-square-error-rmse-what-you-need-to-know/

52. AM, Dewan, Makoto Nishigaki, and Mitsuru Komatsu. "Floods in Bangladesh: a comparative hydrological investigation on two catastrophic events." 岡山大学環境理工学部研究報告 8.1 (2003): 53-62.

53. https://en.wikipedia.org/wiki/Floods_in_Bangladesh

54. https://www.wsws.org/en/articles/1999/10/bang-o20.html