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Quantifying Drought Using Machine Learning Models with SPEI indices and Weather Data

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ABSTRACT

Drought prediction is crucial for effective water resource management, particularly in regions prone to frequent droughts, such as Rajshahi, Bangladesh. This study presents a novel approach to quantifying and predicting drought conditions in Rajshahi, Bangladesh, utilizing machine learning models with the Standardized Precipitation Evapotranspiration Index (SPEI) as drought indices. We utilized monthly meteorological data (temperature, precipitation, humidity, wind speed, number of sunshine hours, cloud cover, potential evapotranspiration, and the climatic water balance) from 1965 to 2022. To train machine learning models, SPEI drought indicators were numerically encoded and classified into categorical drought situations. To forecast drought conditions in the Rajshahi region, we tested a variety of individual classification and regression algorithms, including Gradient Boosting, XGBoost, Multi-Layer Perceptron (MLP), Random Forest, Logistic Regression, Support Vector Machines, CatBoostClassifier, and Decision Trees. These models performed differently, with accuracy rates ranging from 85% to 88% for classification tests and R^2 scores from 0.25 to 0.71 for regression tasks. To increase forecast accuracy, we created two hybrid models: the Multi-Model Drought Forecaster and the Drought Anticipation Super Model. The "Multi-Model Drought Forecaster," which combines MLP, Random Forest, Gradient Boosting Classifier, and Decision Tree Classifier, obtained 92% accuracy. The "Drought Anticipation Super Model," incorporating Random Forest, Gradient Boosting, Decision Trees, Support Vector Regression, and CatBoost Classifier, increased the accuracy to 96%. The hybrid model's improved performance demonstrates that it can give more accurate and reliable drought forecasts in the Rajshahi region. These findings improve drought management strategies in Bangladesh and other climate-vulnerable areas. This study also created advanced hybrid machine learning models for drought forecasting in Rajshahi, Bangladesh, with the help of 58 years of meteorological data from 1965 to 2022 and SPEI indices. The "Multi-Model Drought Forecaster" is 92% accurate by utilizing MLP, Random Forest, Gradient Boosting, and Decision Trees. The "Drought Anticipation Super Model" is 96% accurate by adding Support Vector Regression and CatBoost Classifier to provide a better drought forecast to manage water resources effectively.

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1. INTRODUCTION

Climate change has affected mankind and is still doing so in the present. Heat waves, drought, cyclones, and heavy rains are known to cause displacement, hunger, and starvation [1]. Drought is a rather generic and widespread meteorological event that has adverse effects on the ecosystems, water supply, and agriculture all around the globe. Heat, dryness, velocity, and the absence of rain in the arriving months are attributes of drought conditions and can have an extreme impact on biophysical and social systems [2]. Drought is a climatic condition that is experienced in all parts of the world and has an impact on approximately 55 million people annually [3]. Data on drought characteristics are essential for sustainable development and management of resources in Bangladesh because of its sensitivity to climate change. Bangladesh is now being ranked as one of the most vulnerable countries in the world because of several social, economic, geographical, and meteorological factors that put the country in a very precarious situation to tackle disasters[4].The National Drought Mitigation Center has pointed out that Bangladesh has experienced more droughts in the last several decades. Severe droughts occurred in Bangladesh in 1973, 1978, 1979, 1981, 1982, 1992, 1994, 1995, 2000, 2006, and 2009 according to Bangladesh droughts[1]. Thus, drought can have drastic and severe effects. For people living in rural areas, it becomes difficult to get jobs, there will be less food available, and the prices will be high. It can create food crises, animal deaths, crop failure, and loss of biodiversity, perhaps followed by migration in the affected regions [5].

Drought is closely related to agriculture, meteorology, hydrology, and sociological concepts due to its complexity, intensity, and repercussions. Meteorological droughts are also categorized by the reduction in precipitation from the long-term mean [6]. Based on its location and meteorological features, the Rajshahi region of northwest Bangladesh is prone to drought conditions. Meteorological droughts are often defined with the help of atmospheric dryness indicators[7].Over the recent past, different measures have been developed for drought at regional and global levels[8], [9], [10], [11], [12], [13]. This has made the Standardized Precipitation-Evapotranspiration indicator (SPEI) widely used as a drought indicator because it can include the temperature and precipitation data, giving a deeper view of the drought situation. However, due to the complex relations between several meteorological factors, the correct forecasting of SPEI levels and the corresponding drought situations is possible. To the best of the authors' knowledge, there has been virtually no machine learning research carried out in Bangladesh, particularly in the Rajshahi division. To the authors' knowledge, no machine-learning models have been built for drought forecasting at a more regional level of disaggregation, and earlier work has been conducted on one or two areas only. The researchers did not compare the importance of the different meteorological parameters in assessing drought.

Over the last few decades, machine learning techniques have demonstrated that it is indeed possible to increase the accuracy of the drought forecast. The key data-driven methods enable the establishment of different exact relationships and even nonlinear dependencies in climatic data that could be hidden using traditional statistical methods. The integration of climatic parameters may be possible in ML models, and their usage can improve the predictability of droughts in climate research. The objective of this research is to develop and implement an innovative blend of machine learning algorithms to evaluate and predict drought status in Rajshahi. Bangladesh, based on the drought indices of SPEI. Even though Rajshahi and other regions in the northwest of Bangladesh have not been targeted by many scientific studies based on drought research using machine learning methodologies or the SPEI index to analyze the trends in drought. Moreover, there's no study on cross-comparison to assess if and how well SPEI could forecast future drought variability in this region. This research identifies and predicts drought occurrence in the Northern part of the Rajshahi division of Bangladesh. The study's particular aims are listed below: The specific objectives of the study are as follows:

a. To evaluate Rajshahi's drought duration trends from 1965 to 2022 using the Standardized Precipitation Evapotranspiration Index (SPEI).
b. To assess how well various machine learning algorithms anticipate the onset of droughts.
c. To create and evaluate hybrid multi-method models that combine many techniques to increase the precision of drought forecasts.
d. To determine the best technique for drought forecasting by comparing the performance of the produced models within the research area.

This work contributes to the literature on machine learning for climatology and weather forecasting. It suggests arriving at more accurate drought predictions in areas with such climatic conditions.

2. RELATED WORK

Drought forecasting and analysis have grown in popularity over the last decade due to the massive effects that such events have on the future of farming, water supply, and sustainability. Other studies have used ML approaches on drought indices such as the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). In order to assess drought, researchers are comparing SPI and SPEI. To enhance the chances of predicting the occurrence of drought in the future, various researchers have adopted machine learning models, and while developing models, the use of actual evapotranspiration data called SPEI has been deemed central to the entire process of modeling and estimating drought. In regions with large temperature variations, the research established that using SPEI is more appropriate than using SPI. The work's limitation lies in its focus on one area, which prevents it from being applied to others, thereby not utilizing these techniques in other areas with different climates [14].

The researchers also explored the use of advanced ensemble models for drought predictions. Hybrid techniques involving different ML algorithms provide enhanced predicted accuracy, which supports the ensemble learning approach. However, the study highlighted relatively few on short-term drought forecasting, while a gap was left in long-term forecasting methodologies, which are relevant to strategic planning for regions likely to be adversely affected by droughts [6]. This research explores the application of machine learning techniques for estimating SPEI values, featuring a detailed discussion on regression-based models. The findings indicated that models like Random Forest and Gradient Boosting outperformed traditional statistical methods. Although the study effectively predicted drought intensity, the authors did not explore temporal drought trends or integrate multi-model ensembles to enhance accuracy, highlighting a research gap for future investigations[12]. The authors introduced a machine learning approach aimed at predicting drought indices. Their results highlighted the effectiveness of Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) in forecasting drought conditions. But the study did not consider the variability of the forecast of the models or look at the coincidence of several drought indices, which could prove more effective[15].

Hossain [2023] used the FB Prophet time-series model and the Standardized Precipitation Index(SPI) to study drought prediction in Bangladesh. Using rainfall data from 1981 to 2017, the study sought to predict both short- and long-term drought situations in Dinajpur. SPI served as a forecasting input and was computed over a variety of time scales. Prior studies conducted in Bangladesh mostly examined the effects of drought without using predictive modeling in order to bridge the gap. This study combined machine learning-based forecasting for dynamic drought prediction with a traditional drought index [16].

Using historical climate data (1991-2020) and coupled model intercomparison project 6 data for the three seasons-pre-monsoon, monsoon, and this study sought to forecast Bangladesh's current and future drought susceptibility. In order to forecast regions that are susceptible to drought, they have used a sophisticated machine-learning approach that combines an artificial neural network (ANN) with a genetic algorithm (GA) optimizer. Drought susceptibility maps were created using nine hydrological parameters: rainfall, temperature, humidity, cloud cover, wind speed, sunlight, potential evapotranspiration, and solar radiation [17]. Using data from seven meteorological stations, the study aims to assess how well machine learning (ML) algorithms predict meteorological droughts in Bangladesh's central area between 1990 and 2022. In order to evaluate drought risks and pinpoint important social and physical susceptibility variables, SPI and SPEI were plotted inside a GIS context. According to the study, combining ARIMA with ML algorithms increased forecasting accuracy, predicting SPI and SPEI with over 92.0% accuracy, greatly boosting drought prediction skills [18].

3. STUDY AREA

The Rajshahi region in northwest Bangladesh was chosen as the research area due to its unusual weather patterns and high level of agricultural activity. The district's overall size is estimated to be around 2,407. 01 square kilometers. Rajshahi region has four distinct seasons: pre-monsoon from March to May, monsoon from June to September, post-monsoon from October to November, and winter from December to February, as is usual in Bangladesh. With isotherms exhibiting significant seasonal changes in both temperature and precipitation, the region's climate is mostly hot and dry. According to Bangladesh Meteorological Department (BMD) statistics, Rajshahi Division receives an average annual rainfall of 1542. 1 to 2235. 8 mm. The Bangladesh Meteorological Department (BMD) reported that Rajshahi's average yearly temperature was 25.1 °C. The midsummer high is 40°C, while the wintertime low is 6°C, particularly in January. Rajshahi is well-known for being hot and dry compared to the rest of Bangladesh, owing to higher temperatures and lower humidity. The weather varies greatly throughout the year, with a dry season with minimal rainfall and a wet season with a lot of it. The Bangladesh Meteorological Department (BMD) reports that the average annual rainfall in Rajshahi Division is between 1542 and 2235. The region's annual precipitation is predicted to be 8 mm. The Bangladesh Meteorological Department indicates that Rajshahi has an average yearly temperature of 25 degrees Celsius. One degree Celsius. Summer temperatures average around 40°C, while winter temperatures average around 6°C in January. The weather of Rajshahi is severally defined to be warmer and drier than the rest of Bangladesh due to it being hotter and having less humidity.

4. MATERIAL AND METHODS
4.1. Dataset Description
In our research, we have collected data from two major sources. Bangladesh Agricultural Research Council (BARC) and 2. Bangladesh Meteorological Department (BMD). Due to these organizations, it has become possible to gather comprehensive climate records in the Rajshahi division of Bangladesh from 1965 to 2022[19]. These statistics are helpful for the assessment of drought conditions and the prognosis of their further development, as the data given is precise and accurate in the description of the climate of the region for the past 60 years. Some of the collected climate variables include maximum and minimum temperatures in oC, sunshine hours in oC, monthly rainfall in mm, humidity in, wind speed in m/s, cloud coverage, and PET. The data collected were monthly, making them appropriate for evaluating long-term changes in climate and variations. In addition, Climatic Data was used to estimate the Climatic Water Balance (CWB), 6 Month Standardized Precipitation Evapotranspiration Index (SPEI), and 12 Month Standardized Precipitation Evapotranspiration Index (SPEI), providing an extensive evaluation of the region's water availability.

Table 1. Data Split for drought category with 70% Training, 15% Validation, and 15% Testing Sets

Drought Category	Class	Total Entries	Training Set (70%)	Validation Set (15%)	Test Set (15%)
Normal	0	456	319	68	69
Extremely Dry	1	435	304	65	66
Extremely Wet	2	350	244	52	54
Severely Wet	3	325	227	48	50
Moderately Wet	4	392	274	58	60

To enrich the dataset to support a more thorough analysis of drought conditions, additional attributes were derived from the available set and included Monthly Average Temperature, Average Rainfall for the previous 12 months, Standard Rainfall for the last 12 months, Average Temperature for the previous 12 months, Average Humidity for the previous 12 months, Average Wind Speed over the previous 12 months and Average CWB for the previous 12 months. These derived properties, in addition to the fundamental variables, were critical in developing a huge dataset that could be used efficiently by artificial neural networks to approximate the interaction of multiple climatic components necessary for exact drought prediction.

The SPEI readings were classified into the following drought categories using typical SPEI classification tables: Extra Low, Low, Moderate Low, Average, Moderate High, High, Extra High (Table 1). To facilitate the development of machine learning models, the following mapping was applied to these categorical data: The ‘Normal’ was assigned to scale value of 0, the ‘Extremely Dry’ to scale value of 1, the ‘Extremely Wet’ to scale value 2, the ‘Severely Wet’ to scale value of 3, the ‘Moderate Wet’ to scale value of 4 while the ‘Moderate Dry’ to scale value of 5 and other classification to scale value of 6 (Table 2).

4.2. SPEI Value Calculation
The SPEI incorporates both precipitation and temperature, in contrast to the SPI, which only looks at rainfall. SPEI is normally applied in sequences with 1 to 24 months length of stay. The Thornthwaite method requires the following stages for calculation:

A. Thornthwaite Heat Index (I)

Calculate the monthly temperature index W_i for each month[12]:

$$Wi = \{100 \times (5Ti)\ 1.5140 \quad if\ Ti > 0 \quad if\ Ti \leq 0 \tag{1}$$

where T_i the monthly average temperature in °C.

B. Thornthwaite Exponent (a)

Calculate the Thornthwaite Exponent[12]:

$$a = 6.75 \times 10 - 7I3 - 7.71 \times 10 - 5I2 + 0.01792I + 0.49239 \tag{2}$$

This exponent adjusts the impact of temperature on PET (Potential Evapotranspiration).

C. Potential Evapotranspiration (PET)
Calculate the monthly PET[12]:

$$PET = 16 \times ((10 \times Ti)/I)^{a} \tag{3}$$

D. Monthly Water Balance (P - PET):
The monthly water balance is calculated as the difference between total monthly precipitation ((P)) and PET:

$$\text{Water Balance} = \text{P} - \text{PET} \tag{4}$$

This represents the variance in water availability for the month.
E. Standardization to Obtain SPEI
Standardize the water balance values to obtain SPEI using the z-score formula[12]:

$$SPEI = \frac{(P-PET)-\mu}{\sigma} \tag{5}$$

Where, μ= Mean of (P−PET), σ = Standard deviation of (P−PET)

This process allows SPEI to reflect drought conditions by comparing current water availability to historical data across different locations and timescales

Table 2. SPEI drought index categories and mapped the categories[12]

SPEI Value Range	Drought Category	Mapped Numerical Value
2.0 and above	Extremely Wet	2
1.5 to 1.99	Severely Wet	3
1.0 to 1.49	Moderately Wet	4
-0.99 to 0.99	Normal	0
-1.0 to -1.49	Moderately Dry	5
-1.5 to -1.99	Severely Dry	6
-2.0 and below	Extremely Dry	1

4.3. Data Engineering

In these stages, before building a model, raw data were cleaned and transformed into an analysis-ready format. This includes issues of handling missing values, scaling of values, and the general approach to the consistency of the variables. In order to enhance the dataset's capability to make predictions, feature engineering was applied. However, one crucial process in this procedure was the categorization of the SPEI values into classes of drought, where SPEI values were grouped into classes of severity (for instance, mild, moderate, severe). Moreover, the categorical classes were encoded numerically in order to use the results in the training of the model. These features were: minimum temperature (T.Min), monthly average temperature, 12-month average temperature, monthly rainfall (mm), 12-month average rainfall, and 12-month standard deviation of rainfall. Others, like humidity, cloud, the average wind speed over the next twelve months, and

CWB were added to reflect changes in atmospheric and environmental conditions. By selecting the features, we ensured the models captured the essential factors driving drought events.

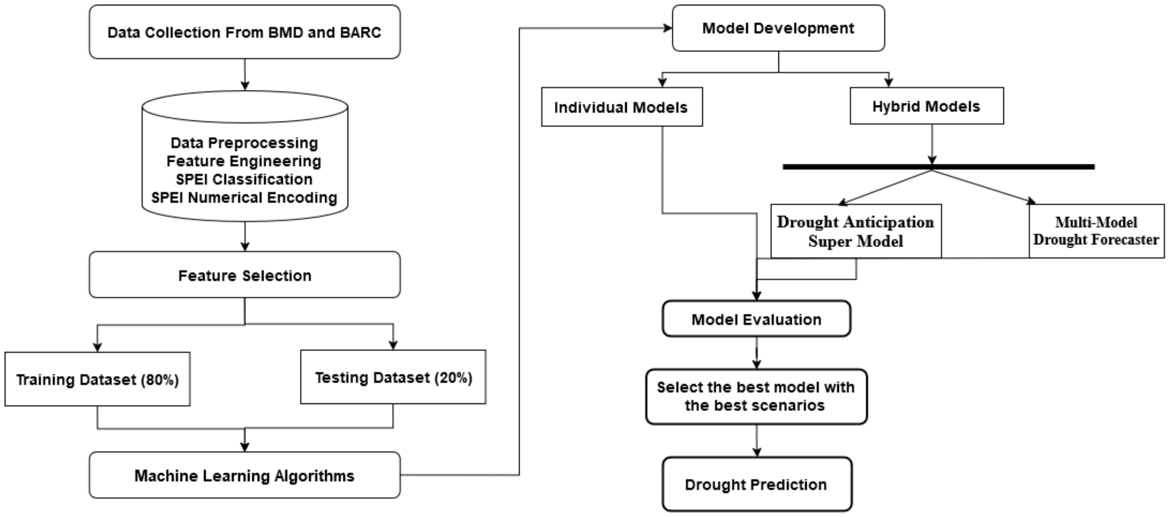

Figure 1. Overview of the Research Methodology

From Figure 1, the methodology for developing a drought prediction system begins with data collection from the Bangladesh Meteorological Department (BMD) and Bangladesh Agricultural Research Council (BARC). The collected data undergoes preprocessing, which includes tasks like SPEI (Standardized PrecipitationEvapotranspiration Index) classification and numerical encoding to prepare the data for analysis. Feature selection is applied to identify the most relevant attributes, ensuring efficient model training. The dataset is then divided into training (80%) and testing (20%) subsets for model development and evaluation. The process proceeds with the application of machine learning algorithms, which are used to build both individual and hybrid models. Among these, two hybrid models are emphasized: the Drought Anticipation Super Model and the Multi-Model Drought Forecaster. These models are subjected to rigorous evaluation to determine the most accurate and reliable model for drought prediction. The selected model is optimized for predicting various drought scenarios, enabling proactive measures for effective drought management and mitigation strategies.

4.4. Machine Learning Algorithms

Gradient Boosting Classifier: The Gradient Boosting Classifier builds multiple weak learners (typically decision trees) sequentially, with each tree correcting the errors of the previous ones. It minimizes a loss function, such as log loss or exponential loss, by updating predictions iteratively[11]:

$$Fm(x) = Fm - 1(x) + \eta \cdot i = 1\sum n\gamma ihi(x) \tag{6}$$

The learning rate η controls the impact of each tree, helping prevent overfitting. This method works well for both binary and multiclass classification.

MLP Classifier: A Multilayer Perceptron (MLP) is a fully connected neural network where each node in layer n connects to every node in layer n+1n+1n+1. It addresses regression and classification problems using the function[20]:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{7}$$

MLP updates weights via backpropagation with gradient descent, leveraging activation functions like sigmoid and ReLU to capture complex patterns.

Random Forest Classifier: A Random Forest Classifier is an ensemble method that generates multiple decision trees using bootstrap samples and a random subset of features at each split. The final prediction is the class with the most votes[12]:

$$y = mode\big(T1(x), T2(x), \dots, Tn(x)\big) \quad (8)$$

This approach enhances generalization and reduces overfitting, performing well in binary and multiclass classification tasks, and is tolerant of missing data and noise.

Decision Tree Classifier:A Decision Tree Classifier is a supervised learning algorithm that splits the dataset based on feature values to form a tree structure. Each internal node represents a feature test, each branch an outcome, and each leaf a class label. It aims to reduce impurity (e.g., using Gini Index or Entropy) at each split.

y=T(x)=leaf node output after traversing based on x

This model is easy to interpret, handles both numerical and categorical features, but can overfit, which can be mitigated with pruning or limiting tree depth.

CatBoost Classifier: CatBoost is a gradient boosting algorithm that handles categorical features natively and minimizes target leakage with ordered boosting. It builds trees sequentially, where each tree corrects the previous one's errors to optimize the loss function [12].

$$y = \sum_{i=0}^{n} \gamma i T i(x) \quad (9)$$

It is robust to overfitting, works well with missing data, and requires minimal preprocessing.

Support Vector Regression (SVR): SVR is also a technique of supervised learning that aims at predicting third type values by finding a hyperplane, in high dimensions. It is great for capturing interaction which exists between variables like temperature and precipitation data in the study of drought because it uses kernel functions to model nonlinearity.

Random Forest Regression: Random Forest Regression is an improved form of model building as it generates more decision trees from bootstrap samples and random features. The final forecast is the average of all the tree outputs, which makes the result less likely to be over-fitted. High-dimensional characteristics and data-intensive, and will have better generalization capabilities compared to individual decision trees.

Gradient Boosting Regression: Gradient Boosting Regression is an ensemble technique that builds trees sequentially, each tree minimizing the errors of the preceding trees. It employs gradient descent to minimize residuals and overall loss (e.g., mean squared error). This method improves accuracy from the fact that prediction is done repetitively in the process.

Decision Tree Regression: Decision tree regression is a method of supervised learning. It achieves so by segmenting data based on major attributes, resulting in a tree-like structure. This applies to all terminal nodes that incorporate a forecast of the target variable. Decision trees are simple to understand and can be used to model a variety of relationships. They are also simple to make; nevertheless, they tend to overfit as one gets deep into the tree.

4.5. Model Development

A. Multi-Model Drought Forecaster

The proposed multi-model drought forecasting method aims at achieving higher accuracy in drought conditions by using sophisticated computational tools of machine learning. The approach starts with data pre-processing, where missing values are handled, new features are derived, and normalization is done on the data to enhance the reliability of the information. Once the data is pre-processed, it is fed into a number of classifiers, like the MLP, random forest, gradient boosting, and the decision tree classifiers. All of these models were selected based on their properties, which include the ability to handle complex patterns, non-linear relations, and feature importance assessment. The models are then trained on the processed dataset shown below, which captures the temporal and spatial variability of drought conditions. Depending on the model, several metrics are used to evaluate performance. For category drought severity estimations, classification accuracy serves as the major performance metric. In regression-based settings, MSE and R^2 are used to measure the accuracy of continuous data, such as drought indices. Figure 2 explains the architecture.

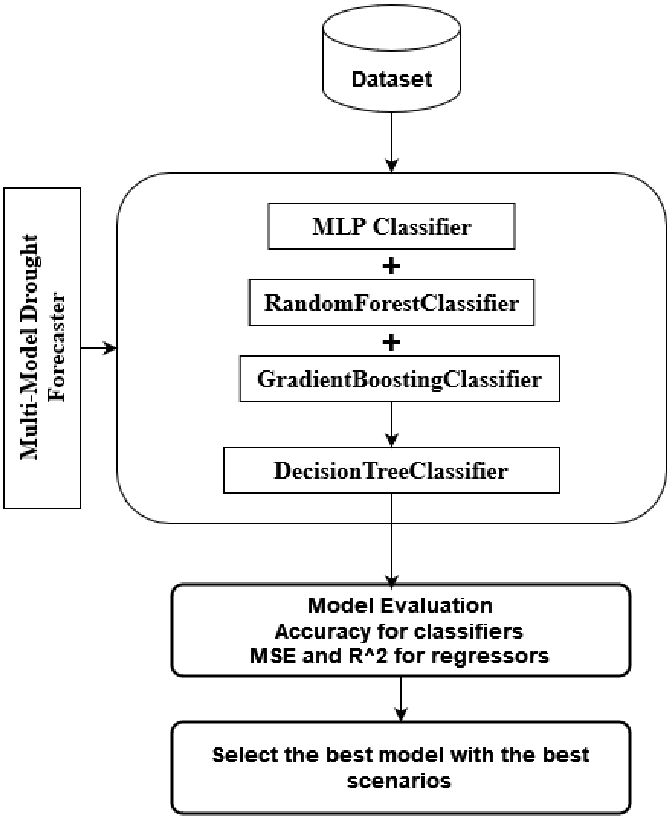

Figure 2. Architecture of Multi-Model Drought Forecaster Hybrid Model

Finally, during the evaluation and after training, the performance of all models is evaluated under different scenarios based on the two models' features and parameters. In this case, the model with the best predicted precision or the lowest error level is determined to be the most efficient. This procedure assures that the structure can accommodate variations in environmental and climatic circumstances, yielding trustworthy and precise outcomes. By integrating various machine learning techniques, the framework addresses the shortcomings of single models and improves overall predictive accuracy. This combined approach increases the system's reliability, allowing it to effectively manage the complexities and uncertainties associated with drought forecasting. In the end, the chosen model, along with its best configuration, is implemented to provide accurate and actionable insights for decision-makers, supporting proactive drought management and resource planning.

B. Drought Anticipation Super Model

The proposed Drought Anticipation Super Model combines different machine learning algorithms to anticipate drought conditions in an effective and flexible manner as shown in Figure 3. The pre-processed data set is used to initialize the system with meteorological, hydrological, and environmental characteristics. This dataset is used to train a variety of regression and classification models; each chosen for its ability to discover and model the desired data patterns.

The model ensemble includes Random Forest Regression, Gradient Boosting Regression, Decision Tree Regression, Support Vector Regression, and the Catboost Classifier. While regression methods forecast flood intensity measures as such as deficits of rainfall and drought indices, the severity of drought is classified by the CatBoost Classifier. Each algorithm possesses distinct strengths: Random Forest and Gradient Boosting model handle non-linearity and feature interactions well; Decision Tree Regression is simple and easy to interpret; Support Vector Regression is good for high-dimensional data; and CatBoost handles categorical variables and imbalanced data well. Finally, the system uses approach-specific evaluation measures to determine the model's performance. For the CatBoost Classifier, the classification accuracy is used, while for regression, the Mean Squared Error (MSE) is used for the coefficient of determination (R^2).

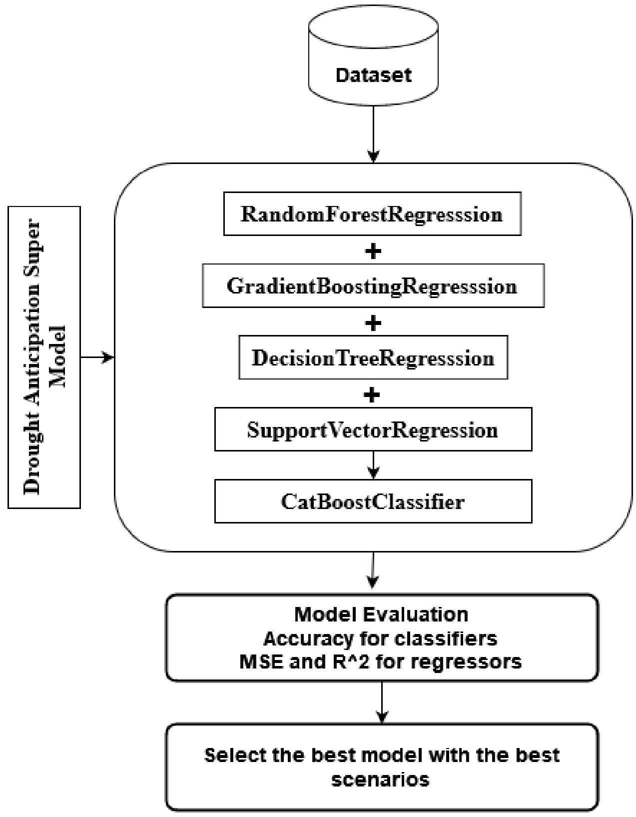

Figure 3. Architecture of Drought Anticipation Super Model Hybrid Model

This makes the evaluation procedure reliable in both the classification and regression issues of the framework. After analyzing performance, the system evaluates all models across many scenarios, taking into account various feature combinations and parameter changes. The best model for predicting droughts is chosen based on its accuracy, error rates, and robustness. This strategy ensures adaptation to changing climatic circumstances and improves the system's ability to predict drought occurrence. The 'Drought Anticipation Super Model', which combines many regressions and classification models, offers a more comprehensive and efficient method of drought prediction. It is an important instrument in drought management because of its many and varied uses, especially for proactive planning aimed at reducing the severe consequences of drought.

4.6. PerformanceEvaluation

A confusion matrix is a performance evaluation tool used in classification tasks to summarize the predictions made by a model against the actual labels. It provides detailed insight into how well a classification model performs by showing the number of correct and incorrect predictions for each class. The confusion matrix highlights true positives (correct predictions for a class), false positives (incorrectly predicted as a class), false negatives (missed predictions for a class), and true negatives (correct rejections of other classes). This allows for the assessment of key performance metrics such as accuracy, precision, recall, and F1-score, making it particularly useful in multi-class classification problems like drought severity prediction.

In this study, confusion matrices were used to evaluate the performance of the Multi-Model Drought Forecaster and the Drought Anticipation Super Model across different drought severity levels. This approach allows us to analyze how effectively the models classify normal, extremely dry, extremely wet, severely wet, and moderate wet conditions.

Multi-Model Drought Forecaster:

The Multi-Model Drought Forecaster demonstrated effective classification capabilities by leveraging an ensemble approach that combines multiple classification algorithms. The confusion matrix in Figure 4 provides insights into the model's performance across different drought categories.

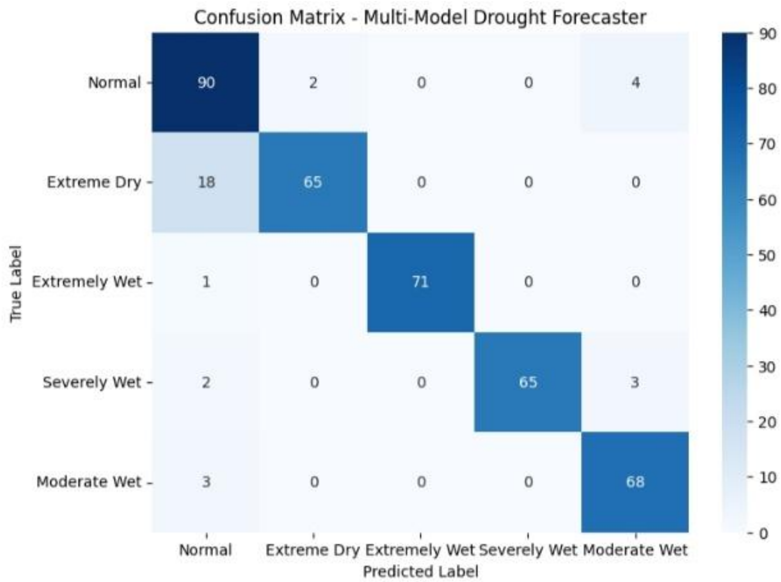

Figure 4. Multi-Model Drought Forecaster Confusion Matrix and Accuracy of each class

Class 0 (Normal): The model accurately classified 90 instances of normal conditions, with a small misclassification rate.
Class 1 (Extreme Dry): Out of the actual extreme dry instances, 65 were correctly predicted, although 18 were misclassified, indicating some challenges with this category due to its complexity or limited sample size.
Class 2 (Extremely Wet): This class had a strong performance with 71 instances correctly classified, showing high reliability for detecting extreme wet conditions.
Class 3 (Severely Wet): The model achieved 68 accurate predictions for severely wet conditions, with minimal misclassification.
Class 4 (Moderate Wet): Moderate wet conditions were effectively identified with 68 accurate predictions, showing balanced performance.

The confusion matrix underscores the forecaster's overall balanced performance, with slight weaknesses in extreme dry classification, which could be attributed to data imbalance or feature complexity.

Drought Anticipation Super Model:

The Drought Anticipation Super Model outperformed other models in this study, achieving the highest accuracy levels. The confusion matrix in Figure 5 highlights its superior ability to classify drought and wet conditions.

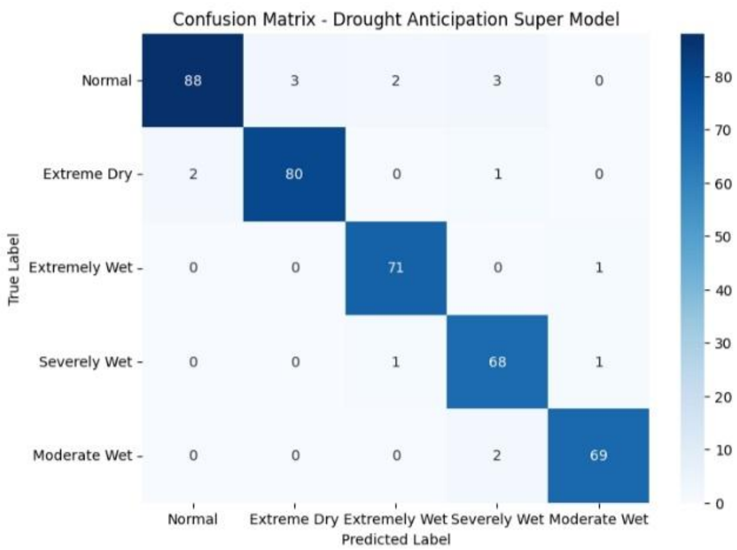

Figure 5. Drought Anticipation Super Model Confusion Matrix and Accuracy of each class

Class 0 (Normal): With 68 correct classifications, the model showed slightly lower accuracy for normal conditions compared to the Multi-Model Drought Forecaster.
Class 1 (Extreme Dry): This model significantly improved the classification of extreme dry instances, with 80 correct predictions, reducing misclassification compared to the previous model.
Class 2 (Extremely Wet): The supermodel achieved exceptional performance in detecting extremely wet conditions, correctly classifying all 71 instances.
Class 3 (Severely Wet): This class saw consistent and highly accurate classification, with 68 instances accurately identified.
Class 4 (Moderate Wet): The model maintained strong performance in identifying moderate wet conditions, with 69 correct classifications.

The Drought Anticipation Super Model displayed exceptional overall accuracy, addressing the limitations of individual models and previous ensemble methods. Its superior results in extreme conditions make it a robust and reliable system for drought anticipation and classification.

5. RESULTS AND DISCUSSION

5.1. Analysis Of The Drought Events And Characteristics During 1965-2022

Drought series and its characteristics from 1965-2022 were used for the analysis, and 12-month SPEI was used to deduce the drought condition. To study the history of droughts in the Rajshahi region, the length and frequency of droughts were analyzed. Figure 6 presents a trend of the percentage of droughts by year in the study period to underscore the severe drought and its occurrence with time. The analysis of drought history revealed that the region experienced a considerable number of droughts in the course of the studied period, including 1972, 1982, 1987, 1995, and 2006, among other years. Although both the duration and frequency of such periods vary, the data sheds light on the cyclicality of droughts in the region and calls for improving the models of their characterization. To do this, different machine learning algorithms were employed and trained on past drought data. During training, 80% of the data set was provided while the remaining 20% was used for testing and validation. The models' primary output variable was the 12-month SPEI drought index; the other climate variables included temperature, rainfall, humidity, cloud cover, and wind speed as input data.

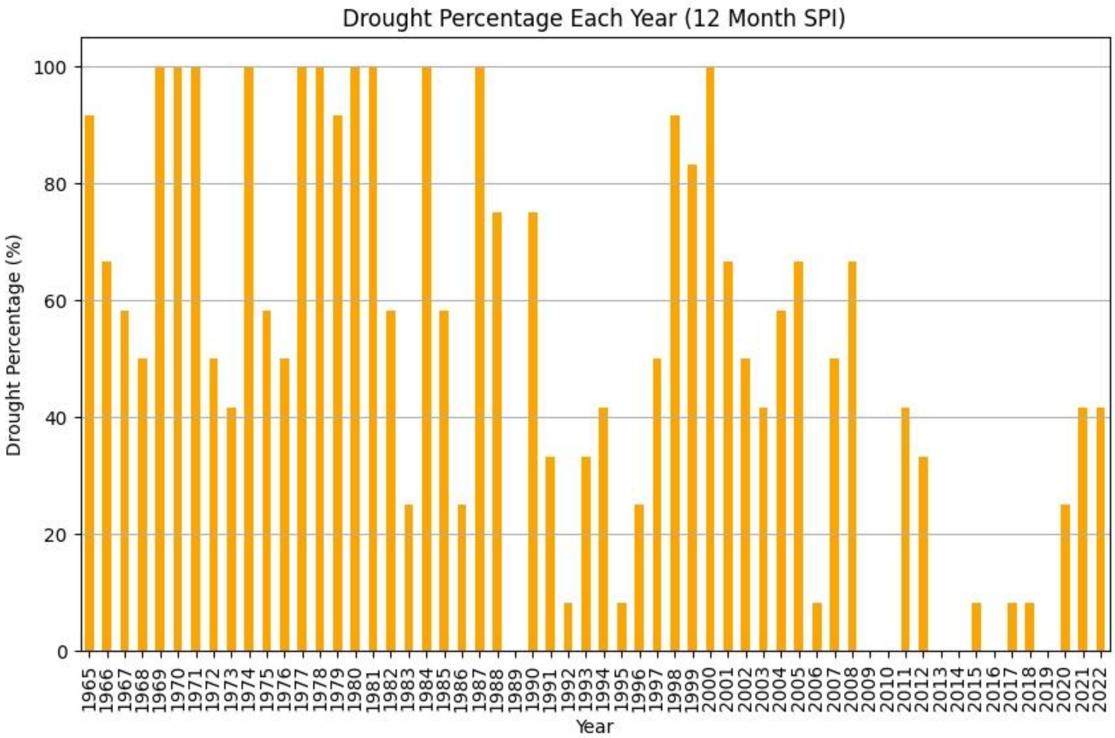

Figure 6. Drought Occurrence Percentage Each Year Based On SPEI

5.2. Evaluation of The Machine Learning Models

In this research, machine learning models are trained to help improve the accuracy of drought prediction in the Rajshahi region. The selected models work with historical meteorological data, and the 12-month Standardized Precipitation Evapotranspiration Index (SPEI) is chosen as the target variable. In this section, the performance of basic as well as hybrid ensemble models is compared. To determine their efficiency in predicting drought, a comparative analysis of all the approaches is made. The Method for computing the performance of classification algorithms is in the form of accuracy parameters, while that of regression algorithms is in the form of Mean Squared Error (MSE) and the coefficients of determination (R^2). The described multiple approach allows for better assessment of the advantages and drawbacks of each model, which in turn, fosters better understanding of the drought forecasting.

Multi-Model Drought Forecaster:

The Multi-Model Drought Forecaster was designed as an ensemble system that combined the results of multiple classification models to enhance the performance of the drought forecasting system. This ensemble model took the advantages of the individual classifiers to generate a better and accurate classification of drought categories in the Rajshahi region. This system yielded an average accuracy of 92 % which is way above the individual classifiers used in this study. The evaluation of this model was based on the percentage correctness of classifying the various drought severity levels using SPEI. The percentage accuracy of each of the class labels depicted in Figure 7 also shows how well the model performs in detecting drought and wet conditions at different severity levels.

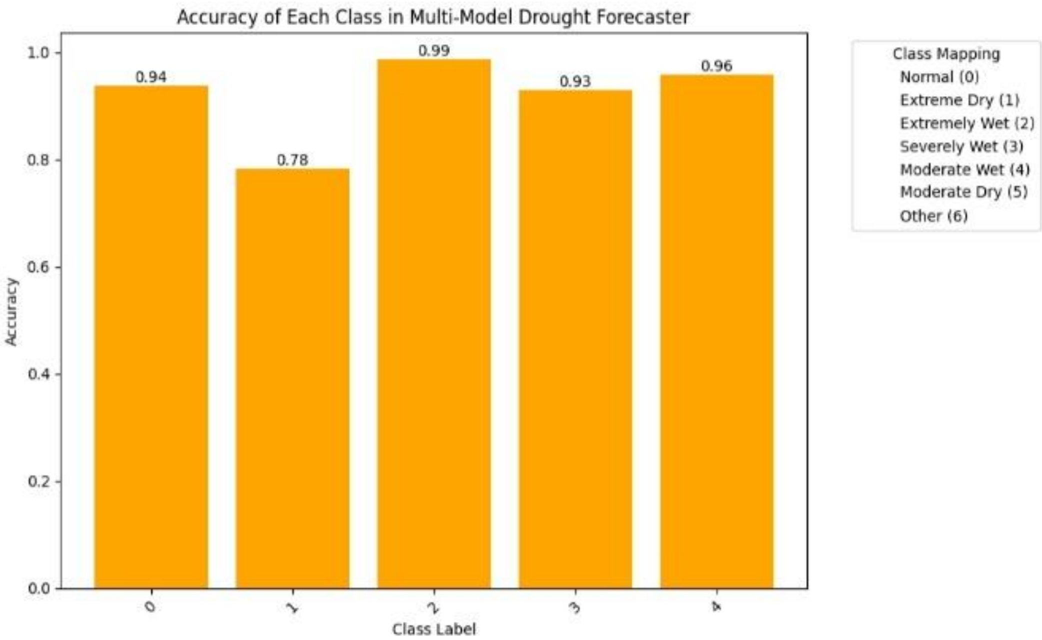

Figure 7. Multi-Model Drought Forecaster Accuracy of each class

The Multi-Model Drought Forecaster's performance across six classes is as follows:

Class 0: Normal (94%)

Able to correctly classify normal conditions at 94 percent, meaning most of the time, the model can recognize if there are no extreme drought or wet conditions.

Class 1: Extreme Dry (78%)

Lower accuracy of 78% because of the small number of extremely dry samples, which are hard to predict.

Class 2: Extremely Wet (99%)

The highest test accuracy of 99% in the validation data set suggests good ability to capture intense wet periods.

Class 3: Severely Wet (93%)

A high true positive rate of 93 % in detecting severely wet conditions.

Class 4: Moderate Wet (96%)

Moderate wet condition recognition accuracy of 96%, which can be considered highly accurate.

Drought Anticipation Super Model:

The Drought Anticipation Super Model was designed to be a nested system, consisting of several advanced regression and classification models that would enhance the efficiency and efficacy of drought prediction. This model for ensemble learning, which has capitalized on various categories of machine learning algorithms, namely, Random Forest Regression, Gradient Boosting Regression, Decision Tree Regression, Support Vector Regression, and the CatBoost Classifier. By implementing the above algorithms, the system can generate a hierarchical structure for classifying and predicting the severity levels of drought in the Rajshahi region. This model has an overall accuracy of 96% which is much higher than the accuracy of individual machine learning models and the previous Multi-Model Drought Forecaster. In the evaluation of this model, the concern was on the efficiency of classifying drought and the performance indices such as MSE and R^2 for regression-based methods. Similarly, the performance metrics of each class also revealed its great performance in identifying and predicting all drought and wet conditions, as presented in Figure 8.

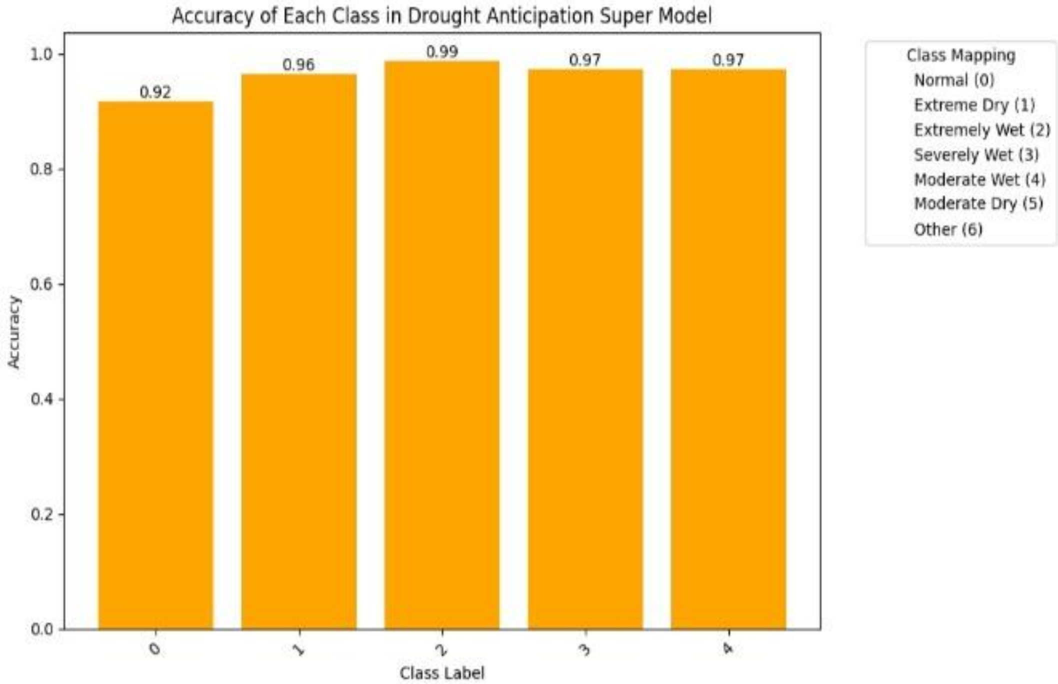

Figure 8. Drought Anticipation Super Model Accuracy of each class

Class 0 (Normal)

Obtained an accuracy of 92%, which demonstrates the model's effectiveness in distinguishing normal conditions without drastic drought or wet episodes.

Class 1 (Extreme Dry)

It had an accuracy of 96% to show that the current model had improved on the previous one in terms of extreme dry conditions prediction.

Class 2 (Extremely Wet)

The last of these was achieved with an astonishing 99% accuracy, which proves the model's high recognition capabilities in the extremely wet conditions.

Class 3 (Severely Wet)

Obtained an accuracy of 97% proving how efficient it is in detecting overly wet conditions.

Class 4 (Moderate Wet)

Achieved an accuracy of 97%, as it supports the findings that the system was accurate in identifying moderate wet conditions.

Table 3. Evaluation Report for Classifications

Model Name	Accuracy	Precision	Recall	F1- Score	Support
GBC	0.85	0.85	0.85	0.84	392
XGB	0.87	0.88	0.87	0.87	392
MLP	0.67	0.69	0.67	0.65	392
RF	0.88	0.89	0.88	0.87	392
LR	0.55	0.54	0.55	0.54	392
DT	0.57	0.62	0.57	0.58	392
CB	0.86	0.86	0.86	0.85	392
Multi-Model Drought Forecaster	0.92	0.93	0.92	0.92	392
Drought Anticipation Super Model	0.96	0.96	0.96	0.96	392

Precision measures the accuracy of positive predictions. It's the ratio of correctly predicted positive observations to the total predicted positive observations. We can calculate it,

$$\textbf{Precision} = TP / (TP + FP) \tag{10}$$

Recall measures the proportion of actual positive instances that were correctly predicted by the model. We can calculate it,

$$\textbf{Recall} = TP / (TP + FN) \tag{11}$$

The F1-score is the harmonic mean of precision and recall. It provides a balance between precision and recall. We can calculate it,

$$\textbf{F1-Score} = 2 * (Precision * Recall) / (Precision + Recall) \tag{13}$$

Support refers to the number of actual occurrences of the class in the dataset. It's the number of samples of the true response that lie in that class. Accuracy is another crucial metric that measures the overall correctness of the model's predictions. We can calculate it,

$$\textbf{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \tag{14}$$

Table 4. Evaluation Report for Regression

Model Name	MAE	MSE	RMSE	R^2
Random Forest Regression	0.45	0.61	0.78	0.71
Gradient Boosting Regression	0.70	0.92	0.96	0.55
Support Vector Regression	0.96	1.56	1.25	0.25
Decision Tree Regression	0.99	1.54	1.24	0.25

The evaluation report for regression is shown in Table 4. In this research used evaluation metrics for regression problem:

Mean Absolute Error

The average absolute difference between actual and predicted values. It measures the magnitude of errors without considering their direction[21].

$$\textbf{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{15}$$

Mean Squared Error

The average of the squared differences between actual and predicted values. It gives higher weight to larger errors, making it sensitive to outliers [21].

$$\textbf{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{16}$$

Root Mean Squared Error

The square root of MSE. It is in the same unit as the original data and provides a measure of how spread out the residuals is[21]

$$\textbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{17}$$

Measures how well the predicted values approximate the actual data. **R^2Score** of 1 indicates perfect prediction, while 0 means the model does no better than the mean of the target values[21].

$$\textbf{R2} = 1 - \frac{SSresidual}{SStotal} \tag{18}$$

6. CONCLUSION

The aim and scope of this research are to evaluate and forecast the drought conditions in the Rajshahi region of Bangladesh by employing effective machine learning techniques and considering the standardized precipitation evapotranspiration index based on a huge dataset of over sixty years. The prediction of drought conditions through this study from 1965 to the end of 2022 has therefore been enhanced and taken to another level. The study further showed that integrating the relevant climatic information and artificial intelligence, especially machine learning, enables accurate prediction of drought in areas that are highly sensitive to climate change. The authors also studied several meteorological factors and drought conditions by developing and employing machine learning classifiers such as Random Forest Classifier, Gradient Boosting Classifier, and MLP Classifier, with an accuracy of classification between 80% and 88%. The Multi-Model Drought Forcaster and Drought Anticipation Super Model predicted droughts with 92% and 96% accuracy, respectively. Even more precisely, we discovered that Drought Anticipation Models outperformed basic solo models in drought prediction by successfully merging several regression and classification approaches. The Drought Anticipation Super Model outperforms, indicating that ensemble learning approaches may learn the critical, often more complex, nonlinear mappings observed during droughts.It should be noted that feature engineering and employing several algorithms combined to increase the density of drought forecasts. Thus, the use of the hybrid model highlights the need for more research in the drought forecasting framework, particularly in terms of exploring a deeper ensemble approach and maybe including supplementary data, such as soil moisture and satellite data. As a result, the study raises important questions concerning Bangladesh's methods and paradigms for struggling with or accepting climate change, agricultural land use, water availability, and so on. Accordingly, the following study areas are recommended based on the research conclusions of the current study: This study made substantial improvements in the early prediction of drought using a machine learning technique. In-depth research is needed to uncover various uses of deep learning models, increase the accessibility of multi-type datasets, and apply the paradigm in various climate-sensitive domains.

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