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Ensemble RF-KNN Model for Accurate Prediction of Drought Levels

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Abstract: The increasing frequency and severity of droughts represent a critical threat to agricultural systems worldwide, disrupting food production, and supply chains. Accurate and timely prediction of drought conditions is essential for ensuring agricultural sustainability and enabling proactive mitigation strategies. This study proposes a novel ensemble model that combines Random Forest (RF) and K-Nearest Neighbors (KNN) using soft voting to predict drought conditions based on meteorological data. The dataset consists of drought classifications for six levels, ranging from no drought to five drought severity levels using meteorological indicators from various U.S. counties. The performance of the proposed model was evaluated against several state-of-the-art machine learning models, including Logistic Regression, Decision Tree, and Artificial Neural Networks, using various evaluation metrics including accuracy, precision, recall, and F1-score. The results demonstrate the effectiveness of the proposed ensemble approach, achieving superior accuracy and reliability in predicting drought severity. This research highlights the transformative potential of machine learning in supporting agricultural systems and addressing climate change challenges through data-driven drought monitoring and mitigation strategies.

Keywords: Drought Prediction; Machine Learning; Ensemble Models; Random Forest; K-Nearest Neighbors; Climate Change.

1. Introduction

Drought is one of the most significant natural disasters affecting agriculture, with widespread impacts on crop production, water availability, and food security [1, 2]. The increasing occurrence of droughts, driven by climate change, has put immense pressure on agricultural systems, making it critical to predict and mitigate their effects [3]. When crops fail due to water scarcity, it disrupts local food supplies, global trade, and livelihoods. Thus, timely and accurate prediction of drought conditions is vital for reducing risks and enabling farmers and policymakers to prepare effectively [4]. Traditional methods for monitoring drought, such as the Standardized Precipitation Index (SPI) or the Palmer Drought Severity Index (PDSI), rely heavily on region-specific climatic data. While these indices have been effective in some areas, their limitations include the inability to generalize to diverse geographic regions and their limited ability to capture complex relationships among drought-related factors [5]. This gap necessitates the development of advanced tools that can process vast datasets and identify intricate patterns to predict drought with greater accuracy.

The advancements in artificial intelligence (AI) and machine learning (ML) provide a promising avenue to address these challenges. It enables machines to simulate human intelligence, learn from data, adapt to new inputs, and perform tasks that traditionally require human expertise [6]. Machine learning is a subset of AI, that focuses on developing algorithms that allow computers to identify patterns and make decisions without explicit programming. These models excel in handling large, complex datasets, making them ideal for analyzing meteorological indicators and predicting drought

[7]. Machine learning models, such as Random Forest (RF), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN), are particularly powerful due to their ability to process high-dimensional data, uncover nonlinear relationships, and adapt to diverse data distributions. They can leverage historical meteorological data to predict future drought conditions, even in the presence of missing or noisy data [8]. Furthermore, the integration of advanced techniques like ensemble learning enhances their accuracy and robustness, as it combines the strengths of multiple models to mitigate individual weaknesses [9]. Unlike traditional approaches, which often rely on predefined equations and region-specific assumptions, ML models can generalize well across different regions and climatic conditions. This adaptability makes them highly scalable, offering solutions that can be applied to diverse agricultural systems worldwide [10, 11].

This paper presents a data-driven framework to predict drought conditions, emphasizing its critical importance for agriculture. A new ensemble model, which combines Random Forest and K-Nearest Neighbors using soft voting is proposed to improve predictive performance. This model utilized the meteorological data across six drought classification levels to ensure high accuracy and adaptability. To validate its effectiveness, the ensemble model is compared against state-of-the-art machine learning algorithms, including Logistic Regression, Decision Tree, and Artificial Neural Networks. The goal of this study is to provide a practical and robust approach to drought prediction that supports agricultural decision-making and enhances resilience to climate-related risks. By utilizing meteorological data and advanced ML techniques, this research contributes to the development of global drought monitoring systems that prioritize food security and sustainable agricultural practices.

The remainder of this paper is structured as follows: Section 2 reviews the literature and discusses related work. Section 3 outlines the methodology, including the proposed ensemble model and its components. Section 4 presents experimental analysis, covering the dataset, preprocessing methods, experimental setup, and evaluation metrics. Section 5 discusses the results, comparing the performance of the proposed model with other machine learning approaches. Finally, Section 6 concludes the paper with key insights and recommendations for future research.

2. Related Work

The prediction of drought conditions is a critical aspect of environmental management, agricultural planning, and disaster preparedness. Over the years, various machine learning techniques have been employed to predict droughts with varying degrees of success. In this section, we review the existing literature on drought prediction using machine learning models, highlighting the strengths and limitations, and better understanding the effectiveness of the existing methods.

The use of machine learning for drought prediction in Pakistan was explored in [12], where Support Vector Machine (SVM), ANNs, and KNN models were applied to predict drought severity levels (moderate, severe, and extreme) during two major cropping seasons. Data from the NCEP/NCAR reanalysis database was used, and Recursive Feature Elimination (RFE) enhanced predictor accuracy. SVM outperformed other models by effectively capturing temporal and spatial drought patterns, identifying key predictors such as relative humidity, temperature, and wind speed. Short-term drought forecasting has also been explored. In Ethiopia's Awash River [13], the authors focused on short-term drought forecasting using the Standardized Precipitation Index (SPI). They compared ANNs, support vector regression (SVR), and coupled wavelet-ANN models. The coupled wavelet-ANN model delivered the most accurate SPI 3 and SPI 6 predictions over 1- and 3-month lead times, demonstrating the benefits of integrating wavelet transforms with ANN for enhanced forecasting.

In [14], researchers investigated groundwater levels in drought-prone areas of northwestern Bangladesh using historical data from 1981 to 2017. Seven machine learning models, including Random Tree (RT) and Random Forest (RF), were evaluated with metrics such as RMSE and correlation coefficient (CC). Ensemble methods like Bagging-RT and Bagging-RF achieved the most accurate predictions, showcasing their potential for sustainable groundwater resource management. Another study [15] applied machine learning models, including Random Forest (RF), Extreme Gradient Boost (XGB), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM), to estimate drought events on the Tibetan Plateau. Using the Standardized Precipitation Evapotranspiration Index (SPEI), XGB and RF excelled at SPEI-3 estimation, while LSTM and XGB performed best for SPEI-6. These findings highlight the adaptability of these models for decision-making in water resource management.

The authors in [8] examined drought indices (SPI and SPEI) at multiple timescales, employing Random Forest, Voting Regressor, AdaBoost Regressor, and K-Nearest Neighbors Regressor. Random Forest and Voting Regressor achieved high accuracy, with NSE values ranging from 0.74 to 0.93, while KNN showed weaker performance. This study underscores the need for advanced algorithms and improved data collection for precise drought prediction. In addition, Agricultural drought vulnerability in Bangladesh's Barind Tract was analyzed in [16], utilizing Landsat satellite imagery and multiple indices like NDVI and VHI. The Cellular Automata-Artificial Neural Network (CA-ANN) model forecasted significant increases in extreme drought conditions by 2026 and 2031, driven by reduced vegetation and rising temperatures. The study emphasizes the need for proactive measures to enhance agricultural resilience.

Hydrological drought prediction was addressed in [17] by modeling three drought indices (SPI, SSI, and SPEI) using SVR, Gene Expression Programming (GEP), and M5 model trees (MT). The MT model excelled in SSI predictions with a correlation coefficient (CC) of 0.8195 and RMSE of 0.8186, demonstrating its effectiveness for hydrological drought modeling. The effectiveness of hybrid approaches, such as wavelet-boosting ANN (WBS-ANN) and wavelet-boosting SVR (WBS-SVR), has also been demonstrated in [18], the authors combine wavelet transforms with ensemble techniques for drought prediction in Ethiopia. The results showed that hybrid models like wavelet-boosting ANN (WBS-ANN) and wavelet-boosting SVR (WBS-SVR) provided the most accurate SPI predictions, highlighting the potential of hybrid approaches in enhancing drought forecasting.

These studies highlight the rapid advancements in applying machine learning models to drought prediction across diverse regions and contexts. While individual models such as SVM, ANN, and RF have shown strong performance, ensemble techniques, and hybrid models provide further improvements by leveraging the strengths of multiple approaches. This body of research opens the way for developing novel ensemble models, such as the proposed RF-KNN approach, to enhance accuracy and scalability in drought prediction tailored to agricultural systems.

3. Methodology

This section presents the methodological framework employed in this study to predict drought using machine learning. Initially, five machine learning models were implemented and evaluated, including Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Artificial Neural Networks (ANN). Subsequently, the two best-performing models, RF and KNN, were selected to develop an ensemble model using a soft voting mechanism to enhance prediction accuracy. The methodology is divided into two subsections: the first provides an overview of the individual ML models used, and the second elaborates on the proposed ensemble model.

3.1 Machine Learning Models

To identify the most effective algorithms for drought prediction, five machine learning models were employed. Each model offered unique strengths that addressed specific aspects of the prediction task. The first model is the decision tree (DT) [19], this algorithm served as a starting point, creating a tree-like structure by splitting the dataset into subsets based on feature values. While its simplicity and interpretability are notable advantages, DT models are prone to overfitting, especially without proper pruning. To overcome these limitations, the Random Forest (RF) model, an advanced ensemble learning technique, was employed [20]. RF generates multiple decision trees during training and combines their predictions, either by averaging (for regression) or by voting (for classification). Configured with 50 estimators and a max depth of 80, RF demonstrated robustness in handling non-linear relationships and reducing overfitting, making it a strong contender for drought prediction.

Next, the K-Nearest Neighbors (KNN) algorithm which, is a non-parametric technique also tested in this study [21]. KNN classifies data points based on the majority class of their k-nearest neighbors, with k=5 chosen for this study. Its simplicity and effectiveness in capturing local patterns were advantageous, although the model's performance is sensitive to the choice of k and the distance metric used. The Logistic Regression (LR) model, commonly employed for binary classification, was adapted for this study to handle multi-class drought prediction. As a statistical model estimating the probability of categorical outcomes based on input features, LR provided a solid baseline for comparison with more complex approaches.

Lastly, the Artificial Neural Network (ANN) model, inspired by biological neural structures, was evaluated [22]. The ANN configuration consisted of input, hidden, and output layers. Known for their ability to model complex, non-linear patterns, ANNs require careful parameter tuning but proved valuable in exploring the dataset's intricate relationships. This exploration of machine learning techniques provided a foundation for selecting the two most effective models, RF and KNN. Their complementary strengths were subsequently combined in a novel ensemble model to enhance predictive accuracy.

3.2 Proposed Ensemble Model

Based on the evaluation of individual models, RF and KNN emerged as the top-performing algorithms. To capitalize on their complementary strengths, an ensemble model was developed using a Voting Classifier with soft voting. The ensemble approach integrates the predictive capabilities of RF and KNN, resulting in a more accurate and generalized model. The concept of soft voting involves averaging the predicted probabilities of individual models, giving more weight to confident predictions, as opposed to hard voting, which relies on majority decisions. This allows the ensemble model to make predictions that reflect the confidence levels of its constituent algorithms. The mathematical formulation of the soft voting mechanism is given by:

$$P(y_k) = \frac{1}{n}\sum_{i=1}^{n} P_i(y_k) \tag{1}$$

where $P_i(y_k)$ is the predicted probability of class y_k By the $i-th$ model, and n is the total number of models. This approach ensures a more balanced prediction when dealing with imbalanced datasets. Fig 1 illustrates the architecture of the proposed Voting Classifier, showing how the outputs of Random Forest and K-Nearest Neighbors are combined to produce the final prediction.

This ensemble model combines RF's strength in capturing global patterns and relationships with KNN's ability to detect local data structures. By integrating these strengths, the ensemble model demonstrated superior predictive performance compared to its components. This approach underscores the potential of ensemble learning to enhance the accuracy and reliability of machine learning models in drought prediction.

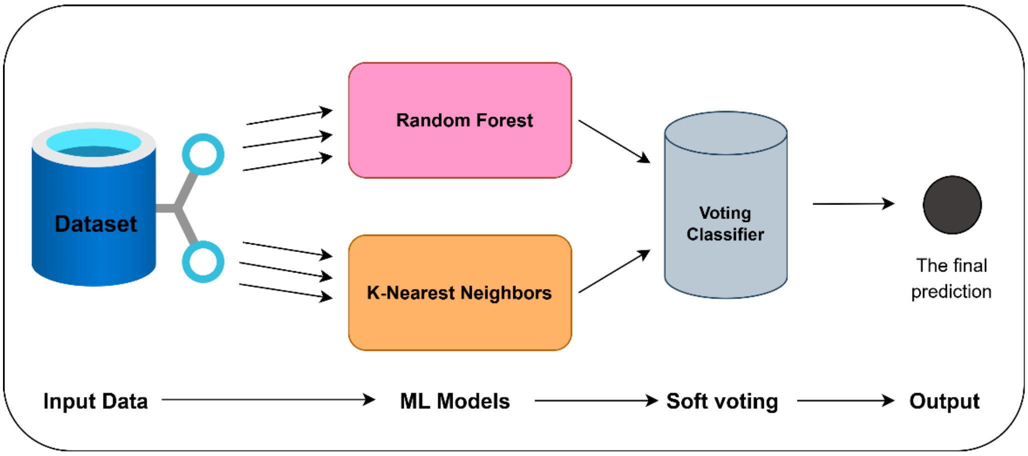

Figure 1. The architecture of the proposed RF-KNN ensemble model.

4. Experimental Analysis

4.1 Dataset

The dataset used in this study is derived from the U.S. Drought Monitor and incorporates meteorological data provided by the NASA POWER Project and the U.S. Drought Monitor [23]. It is a classification dataset aimed at predicting six levels of drought severity, ranging from "No Drought" (None) to "Exceptional Drought" (D4). It includes 18 meteorological indicators, such as precipitation, temperature, humidity, and wind speed, which are essential for capturing the conditions leading to drought. Each data entry represents the drought level at a specific point in time for a given U.S. County, the drought severity levels are classified as shown in Table 1. The dataset serves as a valuable resource for investigating the feasibility of predicting drought conditions using meteorological data. Its insights could potentially lead to generalized drought prediction models applicable beyond the U.S.

Table 1. Drought severity levels in the dataset

Category	Description	Possible impacts
(None)	No Drought	- Short-term dryness slows planting, growth of crops or pastures
(D0)	Abnormally Dry	- Some lingering water deficits - Pastures or crops not fully recovered
(D1)	Moderate Drought	- Some damage to crops, pastures - Streams, reservoirs, or wells low, some water shortages developing or imminent
(D2)	Severe Drought	- Crop or pasture losses likely - Water shortages are common - Water restrictions imposed
(D3)	Extreme Drought	- Major crop/pasture losses - Widespread water shortages or restrictions
(D4)	Exceptional Drought	- Exceptional and widespread crop/pasture losses - Shortages of water in reservoirs, streams, and wells create water emergencies.

4.2 Experimental Setup

The meteorological indicator values in the dataset were normalized using standard scaling to ensure that all features had a similar scale, improving the performance of distance-based algorithms like K-Nearest Neighbors [24]. Then the dataset is divided into training and testing subsets, with 80% of the data used for training and 20% reserved for testing. The experiments were conducted using Python (version 3.10.13) with the Scikit-learn library [25]. Each machine-learning model was initially trained and evaluated using default hyperparameters. Subsequently, fine-tuning was performed to optimize their performance. For the ensemble model, Scikit-learn's Voting Classifier was employed to integrate the predictions of the top-performing models. All experiments were executed on the Kaggle platform, leveraging an Nvidia Tesla P100 GPU with 30 GB of RAM, ensuring efficient computation for both training and testing.

4.3 Evaluation Metrics

To assess the performance of the machine learning models and the proposed ensemble approach, four evaluation metrics were employed: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the models' capabilities, particularly in addressing the challenges posed by imbalanced datasets.

Accuracy measures the proportion of correctly classified instances to the total number of instances in the dataset. It is calculated as:

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \tag{2}$$

Precision evaluates the correctness of positive predictions by determining the ratio of true positive predictions to the total number of positive predictions. It is expressed as:

$$\text{Precision} = \frac{TP}{(TP + FP)} \tag{3}$$

Recall, also known as sensitivity or true positive rate, measures the ability of the model to correctly identify all positive instances. It is defined as:

$$\text{Recall} = \frac{TP}{(TP + FN)} \tag{4}$$

F1-Score is the harmonic means of precision and recall, providing a balanced evaluation of the model's performance, especially when dealing with imbalanced data. It is calculated as:

$$F1\ \text{Score} = 2 \times \frac{\text{recall} \times \text{Precision}}{\text{recall} + \text{Precision}} \tag{5}$$

While accuracy offers an overall performance indicator, it can be misleading in cases where one class dominates the dataset. So, we need the other metrics. In the context of Precision, high precision indicates that the model has a low false-positive rate, making it suitable for tasks where false alarms carry significant costs. High recall indicates that the model minimizes false negatives, making it valuable in scenarios where missing positive cases is critical. Finally, A higher F1 score reflects a better trade-off between precision and recall. These metrics collectively offer a nuanced evaluation of the models, highlighting their strengths and limitations in drought prediction tasks.

5. Results and Discussion

This section presents and analyzes the performance of the machine learning models employed for drought prediction, as well as the proposed ensemble model. The experiments aimed to evaluate the models across key metrics including accuracy, precision, recall, and F1-score while highlighting the strengths and limitations of each algorithm. The proposed model, combining Random Forest and K-Nearest Neighbors, was expected to outperform individual models due to its ability to leverage the complementary strengths of its components. The results are summarized in Table 2, which provides a comparative overview of the models' performance.

Table 2. Performance metrics of machine learning models for drought prediction.

Model	Accuracy	Precision	Recall	F1-Score
Decision tree (DT)	0.7754	0.7743	0.7754	0.7749
Random Forest (RF)	0.8126	0.8083	0.8126	0.8104
K-Nearest Neighbors (KNN)	0.7987	0.7983	0.7987	0.7985
Logistic Regression (LR)	0.6579	0.5545	0.6579	0.6024
Artificial Neural Networks (ANN)	0.7180	0.7245	0.6921	0.7079
Proposed model (RF- KNN)	**0.8252**	**0.8155**	**0.8221**	**0.8188**

The performance of the machine learning models varied significantly, reflecting their strengths and limitations in handling the drought prediction task. The Decision Tree (DT), with an accuracy of 77.54%, offered simplicity and interpretability but struggled with overfitting, which Random Forest (RF) addressed effectively. RF outperformed DT, achieving 81.26% accuracy due to its ensemble approach that better handles non-linear relationships and reduces overfitting. Similarly, K-Nearest Neighbors (KNN) demonstrated its ability to capture local patterns with an accuracy of 79.87%, though its reliance on parameter tuning, such as the choice of k and distance metrics, may limit its robustness in higher dimensions.

Logistic Regression (LR) exhibited the weakest performance, with an accuracy of 65.79%, due to its inability to model complex, non-linear patterns in the data. In contrast, Artificial Neural Networks (ANN) showed moderate success, achieving 71.80% accuracy, highlighting its potential to handle non-linear relationships but revealing the need for further optimization to improve its performance. The proposed ensemble model, which combines RF and KNN, delivered the highest accuracy of 82.52% and the best F1-score of 0.8188, demonstrating its effectiveness in leveraging the complementary strengths of its components to provide a balanced and robust solution for drought prediction. Figure 2 provides a visual comparison of the accuracy of all models, highlighting the superior performance of the proposed ensemble model.

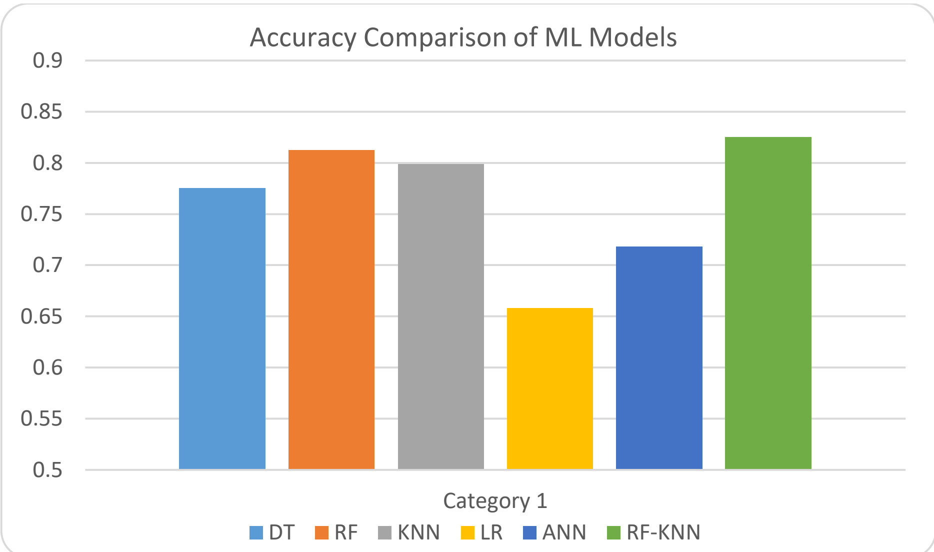

Figure 2. Comparison of performance metrics across machine learning models.

The proposed model's performance highlights the potential of ensemble learning to improve the accuracy of drought prediction. By integrating two complementary algorithms, the ensemble model provides a more generalized and robust solution. This underscores the importance of leveraging diverse machine-learning techniques for complex environmental problems.

6. Conclusion and Future Work

This study explored the use of machine learning models to predict drought severity levels using meteorological data. Five individual algorithms including Decision Tree, Random Forest, K-Nearest Neighbors, Logistic Regression, and Artificial Neural Networks were initially evaluated to identify their suitability for this task. Among these, Random Forest and K-Nearest Neighbors emerged as the top-performing models, demonstrating robust predictive capabilities and complementing each other in terms of capturing both global and local data patterns. To enhance accuracy, an ensemble model was developed by integrating Random Forest and K-Nearest Neighbors through a soft voting mechanism. The ensemble approach effectively leveraged the strengths of its constituent models, achieving superior performance compared to individual models. The experiments, conducted using a standardized dataset normalized for consistency, demonstrated the reliability of the proposed methodology. The evaluation metrics, including accuracy, precision, recall, and F1-score, provided a comprehensive analysis of the model’s predictive abilities and highlighted the advantages of ensemble learning in addressing the complexities of drought prediction. This research contributes to the growing field of data-driven drought prediction, emphasizing the potential of machine learning in mitigating the impacts of drought through early detection. However, the study primarily relied on historical meteorological data, and further work is needed to incorporate additional variables such as soil moisture and vegetation indices. Future research should also explore the generalizability of the proposed ensemble model to other geographical regions and its adaptability to real-time prediction systems.

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare no competing interests in the research.

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Author Contribution

All authors contributed equally to this research.

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