DROUGHT DETECTION AND AGRICULTURAL SUGGESTIONS USING MACHINE LEARNING

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Abstract- This project is centered on providing valuable assistance to farmers by employing Machine Learning (ML) to anticipate the likelihood of drought and furnish tailored crop recommendations. To accomplish this, it harnesses the capabilities of the Weather API to collect essential parameters, including temperature, humidity, condition, wind speed, and precipitation. These vital data points are then inputted into the Random Forest Algorithm, facilitating the prediction of drought levels with precision. Consequently, the system is able to suggest crops that are best suited for varying probabilities of drought. Through meticulous evaluation of factors such as temperature, humidity, and precipitation, farmers are equipped to proactively assess drought risks and make well-informed decisions when planning their crops, thus effectively mitigating the detrimental impacts of drought on agricultural endeavours.

Keywords-ML (Machine Learning),API (Application Programming Interface), Random Forest Algorithm, gTTS- Google Text-to-Speech, Weather API.

1. Introduction

In the face of escalating global agricultural challenges, where the frequency and severity of droughts intensify due to climate change, innovative solutions become imperative. The convergence of technology and agriculture presents a promising avenue for addressing these pressing issues. By melding advanced Machine Learning (ML) techniques and data-driven algorithms with agricultural science, we can achieve precise monitoring of drought conditions and offer timely recommendations, marking a pivotal advancement in agricultural practices. Traditional methods of drought detection often lack the precision required for early intervention, leaving farmers vulnerable to crop losses. Moreover, the complexity of decision-making in selecting drought-resilient crops exacerbates the challenges faced by farmers.

Our proposed system seeks to revolutionize the landscape of agricultural resilience by focusing on two core objectives: early drought detection and ML-driven crop recommendations. To achieve this, we propose a robust framework that integrates crucial meteorological parameters such as temperature, humidity, wind speed, condition, and precipitation, gathered through Application Programming Interfaces (APIs). These parameters serve as inputs for our predictive model, powered by Random Forest algorithms, enabling accurate forecasting of drought conditions.

Key features of our system include real-time monitoring capabilities, facilitating prompt interventions to mitigate the impact of drought on crop yields. Additionally, our user-friendly interface provides farmers with access to drought forecasts and tailored cultivation advice, empowering them to make informed decisions and enhance their resilience against drought-induced adversities. Through this amalgamation of technology and agricultural profiecncy, our project aims to get into a new era of sustainable farming practices.

2. Objectives

Our project aims to accomplish several straightforward yet crucial objectives. First and foremost, we strive to predict droughts early, enabling farmers to prepare in advance. By incorporating various parameters such as temperature and humidity, we ensure our predictions are accurate and reliable. Moreover, we've designed our system to be user-friendly, ensuring farmers from any corner of India can easily access and interpret the data. Real-time analysis is another key aspect of our project, providing farmers with timely updates and actionable insights. Additionally, our system goes beyond prediction; it offers personalized crop recommendations tailored to the severity of the drought, empowering farmers to make informed decisions and safeguard their livelihoods.

3. Literature Survey

[1] This study provides a detailed examination of how Artificial Intelligence and Machine Learning (AIML) methods are applied, particularly in the context of monitoring drought in Iran. It thoroughly analyzes the combination of on-site observations and remote sensing data to track drought conditions. Additionally, it carefully evaluates the effectiveness of extensive remote sensing techniques in this context, while also discussing the potential limitations of these methods.

[4] This research focuses on a specific application of AIML in monitoring drought's impact on winter wheat crops. It offers a comprehensive investigation into a novel approach that utilizes spatially downscaled solar-induced chlorophyll fluorescence data. Through this analysis, the study aims to uncover the intricate details of how this innovative method can enhance our understanding of drought effects on specific agricultural crops.

[5] In this study, a probabilistic framework is developed for assessing drought conditions in South Korea using satellite data and deep learning models. The research delves into the practical implementation of this framework, providing a thorough exploration of its potential benefits and limitations. By examining the model's performance in depth, the study aims to provide valuable insights into the challenges and opportunities of applying AIML techniques to regional drought monitoring.

[6] The study introduces a new Comprehensive Drought Monitoring Index (CDMI) designed specifically for Mainland Southeast Asia. It offers a detailed analysis of the index's methodology, including the use of principal component analysis and multi-source remote sensing data. Through this examination, the study aims to elucidate both the capabilities and constraints of the CDMI in assessing drought conditions in the region.

[7] This section of the research focuses on a case study conducted in the Aegean Region of Turkey, where drought events are assessed using satellite-derived soil moisture data. The study examines the development and application of a soil moisture drought index over a significant period from 2000 to 2021. Additionally, it addresses various limitations associated with this approach, such as challenges related to land surface heterogeneity, and discusses implications for utilizing AIML techniques in regional drought assessments.

[2] The study critically examines the methodology employed to evaluate drought events in Turkey's Aegean region, using remote sensing techniques and time-frequency analysis. It provides a detailed exploration of the Vegetation Health Index (VHI) derived from satellite data and the Standardized Precipitation Evapotranspiration Index (SPEI) obtained from meteorological station data. Furthermore, the study discusses potential limitations, including the need for comparison with other satellite-based drought indices and the consideration of external factors such as climate change and human activities in drought assessment.

[8] This section meticulously analyzes a study proposing a method for identifying drought stress in tomato seedlings through chlorophyll fluorescence imaging. It offers a comprehensive examination of the methodology's intricacies, including its strengths and limitations. Additionally, the study explores broader implications for AIML applications in understanding crop responses to drought stress, transcending the specific context of the research.

[9] The study focuses on contrasting responses of canopy structure and leaf physiology to drought in Southwest China. It provides a detailed analysis of the methodologies employed, along with critical examination of

their limitations. Moreover, the study discusses broader implications for AIML applications in understanding the complex relationship between plant physiology and drought, extending beyond the specific case study.

[3] This section examines a study that classifies drought events based on onset timing and duration in South Africa's Eastern Cape Province. It offers a detailed exploration of the methodologies used, accompanied by critical analysis of their limitations. Additionally, the section discusses broader implications for AIML applications in predicting drought events at regional scales.

[10] The study evaluates drought conditions in Bangladesh using various satellite and ground-based indices. It provides a thorough examination of the methodologies employed, including an exploration of their limitations. Furthermore, the study discusses broader implications for AIML applications in classifying and assessing drought risks at the national level.

4. Methodology

4.1 API Implementations:

This project leverages an API (Application Programming Interface) to retrieve weather data. An API acts as a messenger between two software applications. Here, it fetches weather information from an external service (WeatherAPI.com) upon receiving a user's location.
The code defines a function named "get_weather" that interacts with the API using a provided API key and the user-specified location. If successful, the function returns various weather details like temperature, humidity, and wind speed. This retrieved weather data is then employed within the project's logic for drought analysis.

4.2 Random Forest Algorithm Usage:

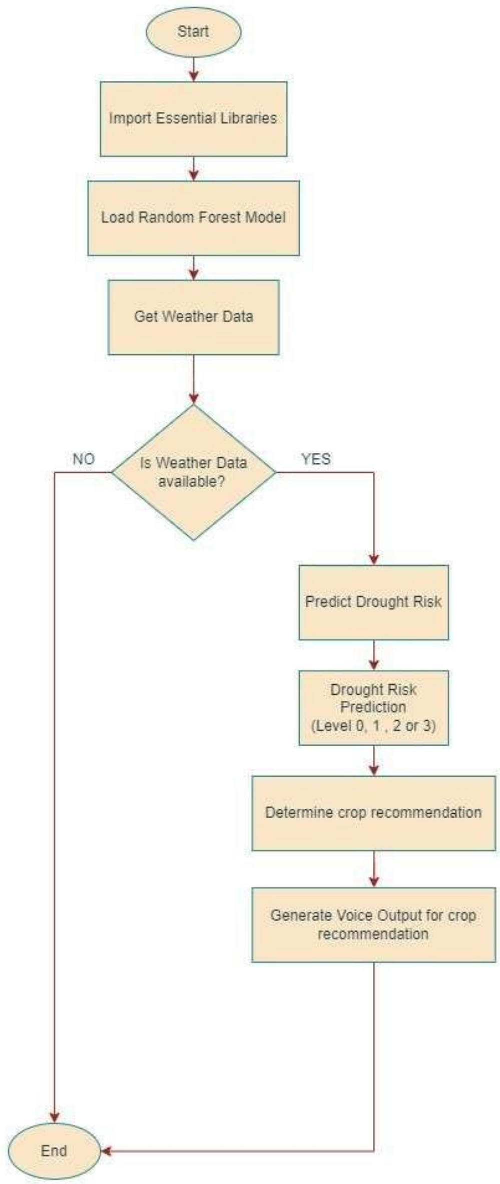
The code incorporates a machine learning technique called a random forest to analyze the likelihood of drought at a given location. Imagine a random forest as a group of decision trees, each containing a set of rules based on various weather factors. These factors, in this case, include temperature, humidity, wind speed, and precipitation.
When a user submits their location, the code retrieves weather data using an API. This data is then fed into each tree in the random forest individually. Each tree, based on its internal rules, makes a prediction about the drought risk. Finally, the code combines the predictions from all the trees in the forest to arrive at a final, more robust prediction.
The final prediction categorizes the drought risk into four classes: no risk, low risk, moderate risk, and high risk. Based on this risk category, the code recommends a selection of three crops that are more likely to thrive in those specific weather conditions. This approach helps users make informed decisions about their crop choices considering the potential drought risk.

4.3 Dataset Overview:

In this project, the dataset is prepared by associating different combinations of parameters with various drought levels. For each drought level, 1000 combinations of temperature, rain condition, humidity, wind speed, and precipitation are fed into the random forest model. These parameters are categorized based on their ranges and conditions. For instance, temperature ranges, rain conditions like "Rainy or Heavy Clouds," humidity levels, wind speed ranges, and precipitation amounts in millimeters are considered to determine drought severity.

4.4 Methodology Flowchart

This flowchart illustrates the workings of our project, which predicts drought risk and suggests crops. The process initiates by obtaining essential libraries for web development and machine learning tasks. Subsequently, a pre-trained model, adept at predicting drought risk, is loaded. Users then specify their location, triggering the retrieval of weather data through an external API. The flowchart then determines the success of this data retrieval. If successful, the system extracts relevant weather parameters and feeds them into the model to predict the drought risk. Based on this prediction, the application recommends crops likely to flourish under those specific weather conditions. Finally, a voice output listing the recommended crops is generated for the user.



Details of each step in the flowchart are as follows:

1. Start: The process begins here.
2. Import Essential Libraries: This step involves importing necessary libraries like Flask, requests, and pickle. These libraries are crucial for functions like web framework, API requests, and loading a pre-trained model.
3. Load Random Forest Model: A random forest model, which is a machine learning model trained to predict drought risk, is loaded here.
4. Get Weather Data: The code retrieves weather data for the user-specified location by interacting with an external API service (WeatherAPI.com) using an API key.
5. Is Weather Data Available?: The code checks if the weather data was successfully fetched from the API.
6. NO (if weather data is not available): If the data retrieval fails, the program redirects the user to a "try_again.html" page.
7. YES (if weather data is available): If the weather data is retrieved successfully, the following steps are carried out:

- Extract Weather Parameters:The relevant weather parameters like temperature, humidity, wind speed, and precipitation are extracted from the acquired weather data.

8. Predict Drought Risk: The extracted weather data is fed into the loaded random forest model to predict the drought risk. The model's output is a numerical value between 0 and 3, indicating the level of drought risk (0: No Risk, 1: Low Risk, 2: Moderate Risk, 3: High Risk).
9. Determine Crop Recommendation: Based on the predicted drought risk level, the code recommends three crops that are more likely to thrive under those specific weather conditions. The logic behind the crop recommendations is:

- No Risk (0): Crops that require ample water throughout the growing season, like rice, sugarcane, banana, etc.
- Low Risk (1): Crops that are moderately resistant to drought conditions, like wheat, barley, peas, etc.
- Moderate Risk (2): Crops that are relatively drought-tolerant, like maize, sorghum, millet, etc.
- High Risk (3): Crops that are highly drought-tolerant, like rye, oats, flaxseed, etc.

10. Generate Voice Output for Crop Recommendation: The code creates a voice output listing the three recommended crops using a text-to-speech library (gTTS).
11. End: The process concludes here, and the user is presented with the predicted drought risk, weather data, and voice output for crop recommendations.

5. Conclusion

Our project facilitates farmers by precisely evaluating drought risks and suggesting suitable crops. We evaluated various algorithms, including Decision Tree, SVM, and Random Forest, which yielded accuracies of approximately 91%, 98%, and nearly 99% respectively. Given Random Forest's superior performance, we adopted it for our system. Leveraging Random Forest, our platform delivers real-time drought assessments and crop recommendations, empowering farmers to make informed decisions. This capability supports proactive drought management and optimal crop selection, enhancing agricultural resilience and food security. In summary, our project provides critical assistance for sustainable farming practices, helping farmers mitigate risks and thrive in challenging environments.

6. References

[1] Sepideh Jalayer., et al. (2023) 'Assessment of Spatiotemporal Characteristic of Droughts Using In Situ and Remote Sensing-Based Drought Indices'.

[2] Bhuiyan, M. M. R., et al. (2020) 'Monitoring of Drought Condition and Risk in Bangladesh Combined Data From Satellite and Ground Meteorological Observations'.

[3] Chen, H., et al. (2020) 'Drought Prediction Based on Feature-Based Transfer Learning and Time Series Imaging'.

[4] Qiu Shen., et al. (2022) 'Exploring the Potential of Spatially Downscaled Solar-Induced Chlorophyll Fluorescence to Monitor Drought Effects on Gross Primary Production in Winter Wheat'.

[5] Zhaoxu Zhang., et al. (2021) 'Establishment of a Comprehensive Drought Monitoring Index Based on Multisource Remote Sensing Data and Agricultural Drought Monitoring'.

[6] Mishra, A. K., et al. (2022) 'Satellite-Based Assessment of Meteorological and Agricultural Drought in Mainland Southeast Asia'.

[7] SEMRA KOCAASLAN., et al. (2021) 'Evaluating Drought Events by TimeFrequency Analysis: A Case Study in Aegean Region of Turkey'.

[8] YAN LONG., et al. (2021) 'Recognition of Drought Stress State of Tomato Seedling Based on Chlorophyll Fluorescence Imaging'.

[9] Hongfan Gu., et al. (2023) 'Satellite-Detected Contrasting Responses of Canopy Structure and Leaf Physiology to Drought'.

[10] Valerie Graw., et al. (2020) 'Timing is Everything–Drought Classification for Risk Assessment'.