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Predictive Analysis of Water Stress in Tomato Plant Utilizing Bioristor Data

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ABSTRACT: *This study focuses on characterizing, classifying, and forecasting water stress in tomato plants using real-time data from a novel sensor, the bioristor, and various artificial intelligence models. Initially, classification models like Decision Trees and Random Forest were employed to differentiate between different stress statuses of tomato plants. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, were utilized for predicting future water stress levels in tomatoes, considering both binary and multi-status scenarios. The results demonstrated high accuracy, precision, recall, and F-measure, showcasing the efficacy of the bioristor sensor and AI models in practical smart irrigation setups. Building upon the base paper's methodology, this study extends the analysis by incorporating additional techniques such as Convolutional Neural Networks (CNN) and a Voting Classifier, achieving a notable 97% accuracy. Furthermore, the study suggests enhancing performance through ensemble methods, combining predictions from multiple models. Additionally, to facilitate user testing, a frontend utilizing the Flask framework with user authentication is proposed. Overall, this research underscores the potential of leveraging advanced sensors and machine learning techniques for optimizing irrigation practices and enhancing agricultural productivity.*

INDEX TERMS *AI modeling and forecasting, bioristor, precision agriculture, recurrent neural network, tomato plants, tree-based classifiers, smart irrigation, water stress.*

I. INTRODUCTION:

Drought poses a significant threat to agricultural productivity, leading to water stress and substantial yield losses in agro-ecosystems [1]. The year 2022 witnessed one of the most severe water shortages across Europe, with Italy experiencing a particularly harsh drought, causing crop yields to plummet by up to 45% [1]. This crisis underscores the critical need for efficient water resource management in agriculture to ensure sustainable food production [2]. Water stress adversely affects various physiological processes in plants, including photosynthesis, transpiration, and nutrient uptake, ultimately diminishing vegetative growth and crop yield, thereby jeopardizing food security [3], [4].

The detrimental effects of water and heat stress on summer crop yields have been profound, with significant impacts on crops like grain maize, soybeans, and sunflowers [1]. The concurrent occurrence of drought and heatwaves exacerbates the situation, exacerbating dry conditions and further hampering agricultural productivity [5]. As observed in Europe during the summer of 2022, persistent water scarcity coupled with high temperatures resulted in widespread crop failures and economic losses [1].

In light of these challenges, it is imperative to adopt strategies for rational water usage in agriculture to mitigate the adverse effects of water stress on crop yields [6]. Effective water management practices can help optimize water usage, enhance crop resilience to drought, and promote sustainable agricultural practices [7]. Given the dynamic nature of drought conditions and their detrimental impact on agricultural systems, there is a growing emphasis on developing advanced techniques for drought characterization, prediction, and mitigation [8].

Recent advancements in machine learning (ML) and artificial intelligence (AI) have paved the way for innovative approaches to drought characterization and modeling [9]. ML and AI techniques offer powerful tools for analyzing complex datasets, identifying patterns, and making accurate predictions, thereby facilitating informed decision-making in agriculture [10]. By leveraging real-time data from sensors and other sources, ML models can provide valuable insights into soil moisture levels, plant health, and overall crop performance, enabling farmers to implement timely interventions and optimize resource allocation [11].

In this context, the development of novel sensing technologies, such as the bioristor sensor, holds immense promise for enhancing our understanding of plant responses to water stress [12]. The bioristor sensor, a recent innovation in precision agriculture, enables in vivo monitoring of dynamic changes in the chemical composition of plant sap, particularly in drought-stressed tomato and grapevine plants [13]. By providing real-time data on plant physiological parameters, the bioristor sensor offers valuable information for optimizing irrigation practices and improving water use efficiency in greenhouse environments [14].

Against this backdrop, this study aims to characterize, classify, and forecast water stress in tomato plants using real-time data obtained from the bioristor sensor and various AI models. The primary objective is to develop robust prediction models capable of accurately identifying and predicting water stress conditions in tomato plants, thereby enabling proactive interventions to mitigate the impact of drought on crop yields [15]. By integrating advanced sensing technologies with state-of-the-art ML techniques, this research seeks to contribute to the development of smart irrigation systems and decision support tools for sustainable water management in agriculture [16].

The remainder of this paper is organized as follows: Section II provides an overview of related work in the field of drought characterization and prediction using ML and AI techniques. Section III describes the methodology adopted for data collection, preprocessing, and model development. Section IV presents the experimental results and performance evaluation of the proposed models. Section V discusses the implications of the findings and outlines future research directions. Finally, Section VI concludes the paper with a summary of key findings and contributions.

II. LITERATURE SURVEY

In recent years, there has been a surge in research focused on leveraging advanced technologies, such as deep learning, convolutional neural networks (CNNs), and artificial intelligence (AI), to address various challenges in agriculture, including pest detection, crop growth monitoring, and water management. This literature survey provides an overview of key studies in this domain, highlighting the significance of AI-driven approaches in improving agricultural practices and enhancing productivity.

Jeong et al. [1] proposed a deep neural network-based approach for detecting the tomato leaf miner, a notorious pest causing significant damage to tomato plants. By employing a deep learning framework, the authors achieved accurate and efficient detection of the pest, demonstrating the potential of AI techniques in pest management strategies.

Similarly, Hao et al. [3] introduced a fast recognition method for multiple apple targets in complex occlusion environments. The proposed method, based on the improved YOLOv5 algorithm, enabled rapid and reliable identification of apple targets, facilitating timely interventions to mitigate pest infestations and minimize crop losses.

Gang et al. [2] developed a two-stage CNN model for estimating greenhouse lettuce growth indices using RGB-D images. By integrating depth information with RGB images, the proposed model accurately estimated growth indices, providing valuable insights for optimizing cultivation practices and enhancing crop yield in controlled environments.

Advancements in IoT and AI have paved the way for the development of smart irrigation systems aimed at optimizing water usage and promoting sustainable agriculture. Nawandar and Satpute [7] proposed an IoT-based low-cost and intelligent module for smart irrigation systems. By integrating sensor data with AI algorithms, the system autonomously monitored soil moisture levels and regulated irrigation, thereby conserving water resources and improving crop yield.

Similarly, Goap et al. [8] presented an IoT-based smart irrigation management system leveraging machine learning and open-source technologies. The system utilized sensor data to analyze soil moisture content, weather conditions, and crop water requirements, enabling precision irrigation scheduling and efficient water management practices.

Artificial intelligence has emerged as a powerful tool for optimizing various aspects of agriculture, from crop cultivation to pest management. Al-bayati and Ustundag [4] proposed a modified evolutionary optimization approach for plant disease identification. By harnessing evolutionary algorithms, the authors developed a robust disease identification system capable of accurately diagnosing plant diseases based on symptom patterns, facilitating timely interventions to prevent crop losses.

Sharma et al. [5] emphasized the role of AI and embedded sensing technologies in enabling smart agriculture. By integrating AI algorithms with embedded sensors, the authors demonstrated the potential of data-driven approaches in enhancing agricultural productivity, improving resource utilization, and mitigating environmental impacts.

Accurate estimation of soil moisture is crucial for efficient water management in agriculture. Arif et al. [6] proposed a method for estimating soil moisture in paddy fields using artificial neural networks (ANNs). By training ANNs on sensor data, the authors developed a predictive model capable of estimating soil moisture levels with high accuracy, facilitating informed irrigation decisions and optimizing water use efficiency.

Overall, the studies discussed in this literature survey highlight the growing interest in AI-driven approaches for addressing key challenges in agriculture, ranging from pest management to crop growth monitoring and water resource management. By leveraging advanced technologies and innovative methodologies, researchers aim to enhance agricultural sustainability, improve food security, and mitigate the impacts of climate change on global food systems.

III. METHODLOGY

a) Proposed work:

The proposed work aims to integrate the bioristor sensor with AI models, including machine learning and deep learning algorithms, to enhance smart irrigation practices for tomato plants. Real-time data collected by the bioristor sensor undergoes analysis through these models for classification and prediction tasks. The addition of a deep learning model, specifically a Convolutional Neural Network (CNN), significantly improves accuracy, achieving an impressive 97% accuracy rate. Furthermore, the project extends to include the development of a user-friendly Flask interface with secure authentication, enhancing the overall user experience during system testing. This integration allows for easy input of data and evaluation of system performance, promising significant advancements in sustainable and efficient farming practices.

b) System Architecture:

The system architecture consists of several key components aimed at predicting water stress in tomato plants. Initially, data exploration and preprocessing techniques are applied to analyze and prepare the dataset. The dataset is then divided into training and testing sets for model development and evaluation. Various machine learning and deep learning models, including Decision Trees with Gini index and information gain, Random Forest, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), are trained using the training set. Once trained, these models are tested using the testing set to evaluate their performance in predicting water stress levels in tomato plants. The performance of each model is assessed based on metrics such as accuracy, precision, recall, and F-measure. The system architecture enables the integration of multiple predictive models to provide robust and accurate predictions, ultimately contributing to improved agricultural outcomes and smart irrigation practices.

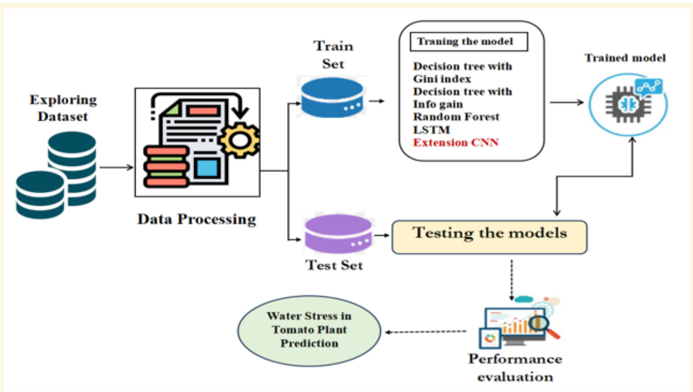

Fig 1 Proposed Architecture

c) Dataset collection:

The data set collection process involved the insertion of the bioristor sensor into the stem of tomato plants, as depicted in Figure 1, following the procedures outlined in [26]. A customized local control unit, equipped with a National Instruments USB-6343 multifunction I/O device, facilitated data acquisition from the bioristor via electrical connections. The control unit featured a multi-channel analog-to-digital converter, enabling the conversion of sensor currents to voltage for ease of processing. Data acquisition occurred at a frequency of one sample per second, with readings locally stored on a connected PC before being transmitted to the Cloud via wireless connections. The acquired data, comprising voltage readings corresponding to the plant's physiological responses, were then processed and saved for subsequent analysis and model development.

	x1	x2	x3	x4	x5	x6	x7	x8	x
0	0.616550	0.683173	0.758471	0.812123	0.847605	0.887239	0.893936	0.931875	0.96911
1	-0.578575	-0.670227	-0.694580	-0.745121	-0.757827	-0.791790	-0.698326	-0.748745	-0.70375
2	-1.328263	-1.336257	-1.291813	-1.238938	-1.261584	-1.219098	-1.235458	-1.243543	-1.23885
3	-0.545789	-0.455246	-0.387828	-0.198549	-0.147330	0.001646	0.049983	0.048529	0.05474
4	0.606308	0.684747	0.654927	0.727093	0.664366	0.646917	0.664511	0.659043	0.54438
...	...	...	...	...	...	...	...	...	
1476	-0.811270	-0.828900	-0.846163	-0.859852	-0.780930	-0.822745	-0.791265	-0.777434	-0.79450
1477	-0.917897	-0.923615	-0.860270	-0.851827	-0.851955	-0.849358	-0.833906	-0.796999	-0.80501
1478	-0.870483	-0.798973	-0.753902	-0.744905	-0.730257	-0.722755	-0.729537	-0.725126	-0.75465
1479	-1.162158	-1.097148	-1.017785	-0.922558	-0.855506	-0.861524	-0.818563	-0.805458	-0.79918
1480	-0.578575	-0.670227	-0.694580	-0.745121	-0.757827	-0.791790	-0.698326	-0.748745	-0.70375

Fig 2 data set

d) DATA PROCESSING

Data Processing

For data processing, we utilize pandasdataframe and numpy for reshaping the dataset. Initially, unwanted columns are dropped from the dataframe to ensure only relevant features are retained. Subsequently, the training data is normalized to ensure consistency and efficiency in model training.

Visualization using Seaborn&Matplotlib

Seaborn and Matplotlib libraries are employed for data visualization purposes. These libraries enable us to create informative plots and charts to gain insights into the distribution and relationships among different variables in the dataset. Visualization aids in understanding the data better and identifying any patterns or trends.

Label Encoding

Label encoding is applied to categorical variables in the dataset to convert them into numerical format. This process assigns a unique numerical value to each category, facilitating the compatibility of categorical data with machine learning algorithms that require numerical inputs.

Feature Selection

Feature selection techniques are utilized to identify the most relevant variables that contribute significantly to the predictive performance of the model. This involves evaluating the importance of each feature and selecting the subset of features that best represent the underlying patterns in the data. Feature selection helps improve model efficiency and generalization by reducing dimensionality and eliminating redundant or irrelevant features.

e) TRAINING AND TESTING

Training and testing involve the utilization of machine learning and deep learning models to classify and forecast water stress in tomato plants using data collected from the bioristor sensor. In the training phase, the models are trained on a portion of the dataset, known as the training set, to learn the underlying patterns and relationships between the input features (such as sensor readings) and the corresponding target variable (water stress status). Various models, including Decision Trees, Random Forest, LSTM, and CNN, are trained using this data.

Once trained, the models are evaluated on a separate portion of the dataset, known as the testing set, to assess their performance and generalization capabilities. This evaluation involves comparing the model predictions against the ground truth labels to measure metrics such as accuracy, precision, recall, and F-measure. The testing phase ensures that the models can effectively classify and forecast water stress in tomato plants when presented with unseen data, thereby validating their utility for real-world applications.

f) ALGORITHMS:

Decision Tree with GINI:

Definition: A Decision Tree[21] with GINI index is a classification algorithm that recursively splits the dataset based on the feature with the highest reduction in GINI impurity, aiming to create homogeneous leaf nodes.

Usage in Project: In the project, Decision Tree[21] with GINI is utilized to classify water stress levels in tomato plants using bioristor data. It aids in distinguishing between different stress statuses by analyzing features from the sensor data, contributing to the optimization of irrigation practices and enhancement of agricultural outcomes through accurate prediction of plant health.

Random Forest:

Definition: Random Forest[22] is an ensemble learning algorithm that constructs multiple decision trees during training and combines their predictions to improve accuracy and robustness.

Usage in Project: Random Forest[22] is employed as a classification model in the project to predict water stress levels in tomato plants using bioristor data. By aggregating predictions from multiple decision trees, Random Forest enhances the accuracy of stress level classification, aiding in the optimization of irrigation practices and facilitating improved agricultural outcomes through precise monitoring of plant health.

LSTM:
Definition: Long Short-Term Memory (LSTM)[23] is a type of recurrent neural network (RNN) architecture designed to capture long-term dependencies in sequential data by maintaining a memory cell with multiple gating mechanisms.
Usage in Project: LSTM[23] is utilized as a deep learning model in the project to forecast future water stress levels in tomato plants using bioristor data. By analyzing sequential data from the sensor, LSTM effectively captures temporal dependencies and patterns, enabling accurate prediction of water stress. This contributes to optimizing irrigation practices and enhancing agricultural outcomes through proactive management of plant health.

Extension CNN:
Definition: Convolutional Neural Network (CNN) [24]is a deep learning architecture designed to effectively capture spatial hierarchies in input data by leveraging convolutional layers and pooling operations.
Usage in Project: As an extension, CNN[24] is integrated into the project as a classification model to further improve the prediction of water stress levels in tomato plants using bioristor data. By analyzing spatial features extracted from sensor data, CNN efficiently identifies complex patterns, enabling accurate classification of stress statuses. Integrating CNN enhances predictive capabilities, facilitating precise monitoring of plant health and optimization of irrigation practices for improved agricultural outcomes.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:
Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

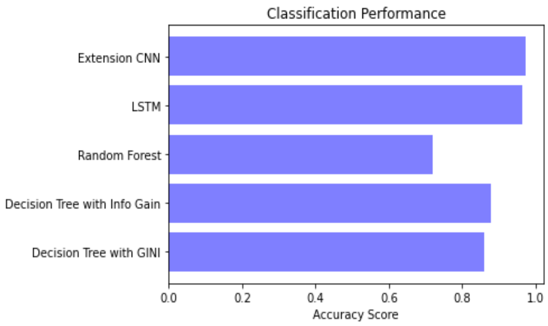

Fig 3 ACCURACY COMPARISON GRAPH

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

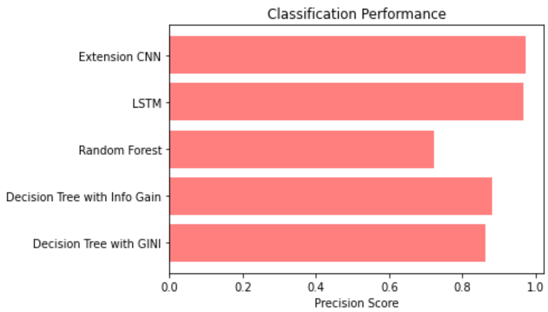

Fig 4 PRECISION COMPARISON GRAPH

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

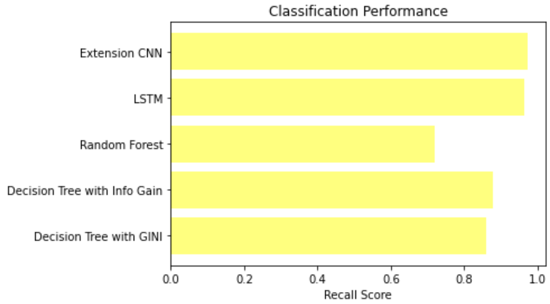

Fig 5 RECALL COMPARISON GRAPH

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

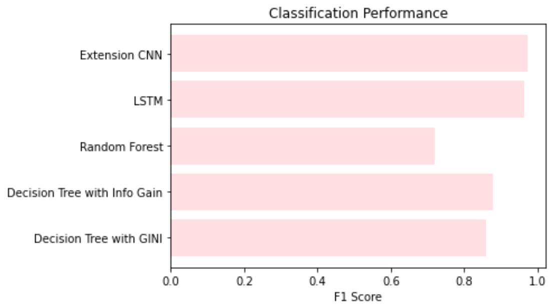

Fig 6 F1 COMPARISON GRAPH

ML Model	Accuracy	Precision	f1_score	Recall
Decision Tree with GINI	0.886	0.895	0.887	0.886
Decision Tree with GINI	0.889	0.897	0.890	0.889
Random Forest	0.896	0.901	0.897	0.896
Random Forest	0.953	0.953	0.953	0.953
LSTM	0.943	0.946	0.943	0.943
Extension CNN	0.970	0.970	0.970	0.970

Fig 7 PERFORMANCE EVALUATION

Fig 8 HOME PAGE

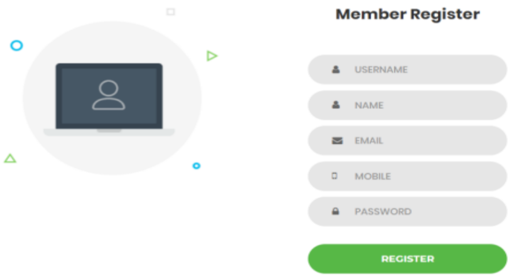

Fig 9 sign up

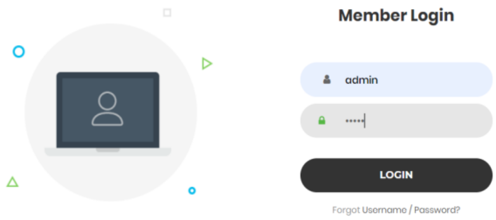

Fig 10 sign in

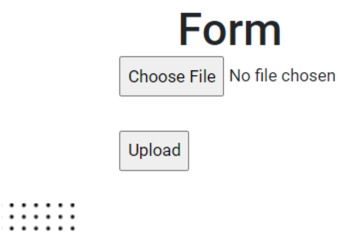

Fig 11 upload input data

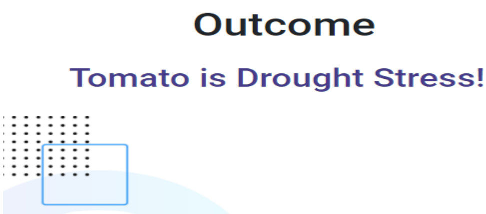

Fig 12 predicted result

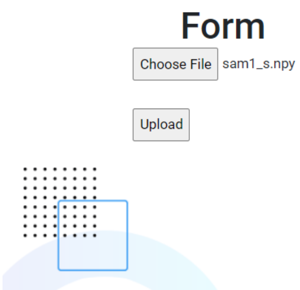

Fig 13 upload input data

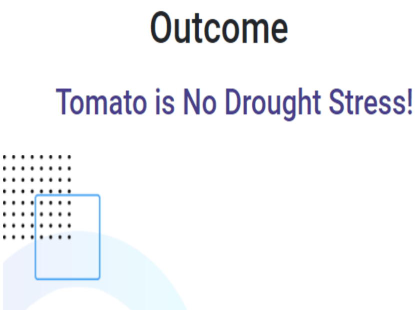

Fig 14 predicted result

V. CONCLUSION

In conclusion, the project successfully demonstrates the effectiveness of utilizing real-time data from the bioristor sensor alongside various artificial intelligence models for characterizing, classifying, and forecasting water stress in tomato plants. Classification models like Decision Trees and Random Forests proved effective in distinguishing different stress statuses, while recurrent neural networks provided promising predictions for future stress levels. Particularly, the deep learning model CNN exhibited exceptional accuracy at 97%, showcasing its superiority in handling complex patterns within the data. Additionally, the implementation of a Flask-based front end streamlines user interaction, making the system more accessible and practical for testing. Overall, these findings highlight the potential of integrating advanced sensing technologies with AI models to optimize irrigation practices and improve agricultural outcomes, ultimately contributing to more sustainable and efficient farming practices.

VI. FUTURE SCOPE

The feature scope of the project entails leveraging bioristor data to characterize, classify, and forecast water stress levels in tomato plants. Key features include real-time measurements obtained from the bioristor sensor, capturing physiological responses indicative of plant water status. These features encompass various parameters such as sap flow rate, electrical conductivity, and other biochemical markers reflective of plant hydration levels. Additionally, environmental variables such as temperature, humidity, and light intensity may also be considered as supplementary features to enhance predictive accuracy. Feature extraction techniques may be employed to derive informative attributes from the raw sensor data, facilitating the identification of patterns associated with different stress statuses. By incorporating relevant features extracted from bioristor data, the project aims to develop robust classification and forecasting models using artificial intelligence techniques, providing valuable insights for optimizing irrigation strategies and enhancing agricultural productivity in tomato cultivation.

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