CLASSIFICATION AND FORECASTING OF WATER STRESS IN TOMATO PLANTS USING BIORISTOR DATA

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Abstract - The main goal of this study is to describe, classify, and predict water stress in tomato plants by using real-time data from a new monitor called the bioristor and different AI models. At first, classification models like Decision Trees and Random Forest were used to tell the difference between tomato plants that were in different levels of stress. We used Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, to guess how much water tomatoes would need in the future, taking into account both one- or more-state situations. The results showed that the bioristor sensor and AI models work well in real-world smart watering systems by showing high accuracy, precision, memory, and F-measure. This study builds on the approach used in the base paper by adding more methods, like Convolutional Neural Networks (CNN) and a Voting Classifier, to the analysis. It was able to achieve an impressive 97% accuracy. The study also shows that success can be improved by using ensemble methods, which combine estimates from different models. A frontend built on the Flask framework with user authentication is also suggested to make testing easier for users. Overall, this study shows how modern devices and machine learning can be used to improve farming output and make watering more efficient.
Index Terms: AI modeling and forecasting, bioristor, precision agriculture, recurrent neural network, tomato plants, tree-based classifiers, smart irrigation, water stress.

1 INTRODUCTION

Agricultural output is greatly affected by drought, which causes water stress and large crop losses in agro-ecosystems [1]. One of the worst water droughts in Europe's history happened in 2022. Italy was hit especially hard, with food yields dropping by up to 45% [1]. This situation shows how important it is for farmers to handle water resources well so that food production can continue [2]. Water stress makes many physiological processes in plants worse, such as photosynthesis, transpiration, and nutrient uptake. This lowers crop yield and vegetative growth, which threatens food security [3, 4].

Extreme heat and lack of water have had very bad affects on summer crop output, especially on products like grain corn, soybeans, and sunflowers [1]. When droughts and heat waves happen at the same time, they make things worse by making it even drier and less productive for farming [5]. As happened in Europe in the summer of 2022, chronic lack of water and high temperatures caused many crops to fail and the economy to lose money [1].

Because of these problems, it is important to come up with smart ways for farmers to use water so that water stress doesn't hurt food yields too much [6]. Good water management can help farmers use water more efficiently, make crops more resistant to drought, and encourage environmentally friendly farming methods [7]. There is a rising focus on creating more advanced methods for identifying, predicting, and reducing droughts [8]. This is because droughts are always changing and have negative effects on farming systems.

New developments in machine learning (ML) and artificial intelligence (AI) have made it possible for new ways to describe and model droughts [9]. Machine learning and artificial intelligence (AI) are strong ways to look at large datasets, find trends, and make accurate predictions. This helps farmers make better decisions [10]. ML models can give farmers useful information about soil wetness levels, plant health, and general crop performance by using real- time data from monitors and other sources [11]. This lets farmers act quickly and make the best use of their resources.

In this situation, the creation of new monitoring technologies like the bioristor sensor has a huge potential to help us learn more about how plants react to water stress [12]. The bioristor sensor is a new development in precision agriculture that lets scientists watch changes in the chemical makeup of plant sap while the plants are still alive [13]. This is especially useful for tomato and grapevine plants that are suffering from drought. By giving real-time data on plant physiological factors, the bioristor monitor is useful for better water use efficiency in greenhouses and finding the best ways to water plants [14].

In this situation, the study's goal is to describe, label, and predict tomato plant water stress using real-time data from the bioristor sensor and different AI models. The main goal is to make strong forecast models that can correctly find and predict when tomato plants are experiencing water stress. This will allow for proactive actions to lessen the effects of drought on food yields [15]. By using cutting- edge sensing tools Using cutting-edge machine learning methods, this study aims to help create smart watering systems and decision-making tools for long-term water control in farming [16].

The rest of this paper is organized in this way: In Section II, we look at similar work that has been done on using machine learning and artificial intelligence to describe and predict droughts. In Section III, we talk about the methods used to collect data, prepare it for analysis, and build the model. In Section IV, the testing data and performance reviews of the suggested models are given. In Section V, we talk about what the results mean and where we think future study should go. Finally, Section VI wraps up the paper with a list of the most important results and inputs.

2 LITERATURE SURVEY

A lot of research has been done in the past few years on how to use advanced technologies like deep learning, convolutional neural networks (CNNs), and artificial intelligence (AI) to help farmers with problems like finding pests, tracking crop growth, and managing water. This literature review looks at some of the most important studies that have been done in this area. It shows how important AI-based methods are for making farming better and more productive.

Jeong et al. [1] suggested using a deep neural network to find the tomato leaf miner, a well-known pest that does a lot of damage to tomato plants. The authors were able to accurately and quickly find the pest by using a deep learning system. This shows that AI methods can be useful in pest control strategies.

Hao et al. [3] also came up with a quick way to recognize multiple apple objects in settings with a lot of obstacles. The suggested method, which was based on the better YOLOv5 algorithm, made it easy to quickly and accurately find apple targets. This made it possible to take action quickly to stop pests from getting in and reducing crop losses. With RGB-D pictures, Gang et al. [2] created a two- stage CNN model for figuring out greenhouse lettuce growth indices. The suggested model correctly predicted growth indices by combining depth information with RGB pictures. This gave growers useful information for improving food yields in controlled settings and making farming methods more efficient.

Improvements in IoT and AI have made it possible to create smart watering systems that use water more efficiently and support farming that lasts. Nawandar and Satpute [7] suggested a cheap and smart IoT gadget for smart watering systems. By combining sensor data with AI algorithms, the system automatically checked the amount of moisture in the soil and controlled watering, which saved water and increased food growth. In the same way, Goap et al. [8] showed an Internet of Things-based smart watering control system that uses open-source and machine learning technologies. The system used monitor data to look at the amount of water in the land, the weather, and how much water each crop needed. This allowed for accurate timing of watering and better water management.

Artificial intelligence has become a strong tool for improving many areas of agriculture, from growing crops to getting rid of pests. Al-bayati and Ustundag[4] suggested a changed version of evolutionary optimization as a way to find plant diseases. The writers used evolutionary algorithms to create a strong disease identification system that can correctly identify plant diseases based on patterns of symptoms. This allows for quick actions to be taken to stop crop losses.

Sharma et al. [5] talked a lot about how AI and integrated tracking technologies can make farming smart. By combining AI algorithms with built-in monitors, the authors showed how data-driven methods can be used to improve resource use, boost farming output, and lessen environmental damage.

For farmers to use water efficiently, it is important to get a good idea of how wet the soil is. Arif et al. [6] suggested using artificial neural networks (ANNs) to figure out how wet the soil is in paddy areas. By teaching ANNs on sensor data, the authors created a prediction model that can accurately guess the amount of wetness in the soil. This lets farmers make better decisions about when to water and how to use water most efficiently.

In general, the studies we looked at show that people are becoming more interested in using AI to solve some of agriculture's biggest problems, like controlling pests, keeping an eye on food growth, and managing water resources. Researchers want to make farming more sustainable, make sure everyone has enough food, and lessen the effects of climate change on food systems around the world by using new tools and methods.

3 METHODLOGY

a) Proposed work:

The goal of the suggested work is to improve smart watering for tomato plants by combining the bioristor sensor with AI models, such as machine learning and deep learning methods. The bioristor monitor collects data in real time, and these models are used to sort and predict that data. When a deep learning model, especially a Convolutional Neural Network (CNN), is added, accuracy goes up by a huge amount, reaching an amazing 97% rate. In addition, the job includes making a Flask interface that is easy to use and has safe login. This will improve the general user experience while trying the system. Integration makes it easy to enter data and check how well the system is working, which could lead to big improvements in farming methods that are both safe and effective.

b) System Architecture:

The design of the system is made up of several important parts that work together to predict when tomato plants will be too dry. At first, methods like data analysis and preparation are used to look at and get ready the information. The information is then split into training sets and testing sets so that a model can be built and tested. The training set is used to teach different machine learning and deep learning models, such as Random Forest, Long Short-Term Memory (LSTM), Decision Trees with Gini index and information gain, and Convolutional Neural Networks (CNN). After being taught, the testing set is used to see how well the models can predict the levels of water stress in tomato plants. Metrics like accuracy, precision, memory, and F-measure are used to judge how well each model works. Multiple forecasting models can be combined in the system's design to make predictions that are strong and accurate. This leads to better farming results and smarter watering practices.

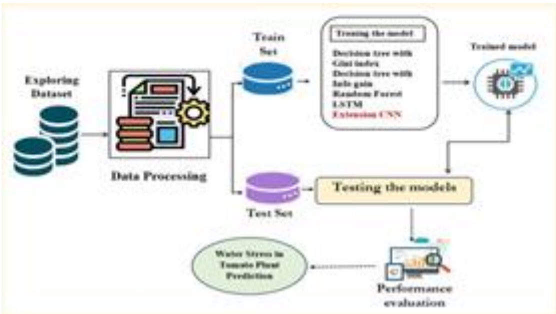

Fig. 1 Proposed Architecture

c) Dataset collection:

To collect the data set, the bioristor sensor was put into the stem of tomato plants, as shown in Figure 1. This was done by following the steps in [26]. A homemade local control unit with a National Instruments USB-6343 multifunction I/O device made it easier to get data from the bioristor by connecting to it electrically. The control unit had a multi-channel analog-to-digital converter that turned sensor currents into voltage so they could be processed more easily. One sample was taken every second, and results were saved locally on a PC that was linked before being sent to the cloud over wifi links. The collected data, which included electricity readings that showed how the plant was reacting physiologically, was then processed and saved so that it could be analyzed later and used to build a model.

	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	-1.23888
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	-0.729637	-0.725126	-0.75468
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

We use pandas data frame and numpy to process the data and reshape the dataset. At first, columns that aren't needed are removed from the data frame to make sure that only important features are kept. After that, the training data is standardized to make sure that the training process is consistent and effective.

Visualization using Seaborn & Matplotlib

For data display, the Seaborn and Matplotlib tools are used. With these tools, we can make useful plots and charts that show how the different factors in the dataset are distributed and how they relate to each other. Visualization helps you understand the data better and find patterns or trends.

Label Encoding

In the dataset, label encoding is used to turn qualitative factors into number ones. This process gives each group a unique number value. This makes it easier for categorical data to be used with machine learning methods that need numerical inputs.

Feature Selection

Feature selection methods are used to find the most important factors that make a big difference in how well the model predicts the future. To do this, you have to figure out how important each feature is and pick the group of features that best show the trends in the data. Getting rid of unnecessary or duplicate features and lowering the number of dimensions is one way that feature selection helps improve model efficiency and generalization.

e) Training and Testing

Using data from the bioristor sensor for training and testing, machine learning and deep learning models are used to classify and predict tomato plants that are experiencing water stress. During the training phase, the models are taught on the training set, which is a subset of the dataset. They learn the patterns and connections between the input features (like sensor values) and the target variable (water stress state). This data is used to train many models, such as Decision Trees, Random Forest, LSTM, and CNN.

After being trained, the models are tested on a different part of the dataset, called the testing set, to see how well they work and how well they can generalize. In this test, the model forecasts are compared to the ground truth labels to find out how accurate, precise, recallable, and F-measured they are. During the testing process, it is made sure that the models can correctly identify and predict tomato plant water stress when given new data. This proves that they can be used in the real world.

f) Algorithms:

Decision Tree with GINI:

A Decision Tree with GINI is a classification method that splits the dataset over and over again based on the feature that reduces GINI impurity the most, with the goal of making leave nodes that are all the same.

Usage in Project: Bioristor data is used to use a Decision Tree[21] with GINI to sort tomato plants' amounts of water stress into groups. By looking at traits from the sensor data, it helps tell the difference between different levels of stress. This helps improve farming results by making accurate predictions about plant health and improving watering methods.

Random Forest:
Random Forest is an ensemble learning method that builds many decision trees during training and then joins their results to make the system more accurate and stable.

Usage in Project: Bioristor data is used to use Random Forest [22] as a classification model to guess how much water stress tomato plants are under. By combining estimates from several decision trees, Random Forest improves the precision of stress level classification. This helps farmers get better results from their watering methods and keeps an eye on plant health more accurately.

LSTM:
What it means: Long Short-Term Memory (LSTM)[23] is a type of recurrent neural network (RNN) architecture that keeps a memory cell with various control methods to find long-term relationships in sequential data.
Usage in Project: Bioristor data is used to train LSTM [23], a deep learning model, to predict how much water stress tomato plants will experience in the future. LSTM successfully catches time relationships and trends by studying sequential data from the sensor. This makes it possible to accurately predict water stress. This helps improve farming results by taking an active role in managing plant health and making watering more effective.

Extension CNN:
What it means: The Convolutional Neural Network (CNN) [24] is a type of deep learning framework that uses convolutional layers and pooling processes to successfully record spatial relationships in input data.
Usage in Project: To make the project even better, CNN[24] is added as a classification model to help guess how much water stress tomato plants are under using bioristor data. CNN quickly finds complicated patterns by looking at spatial features taken from sensor data. This lets it accurately classify stress levels. Adding CNN improves the ability to predict the future, which makes it easier to keep a close eye on plant health and find the best ways to water crops for better results in farming.

4 EXPERIMENTAL RESULTS
Accuracy: The correctness of a test is how well it can tell the difference between weak and strong examples. To figure out how accurate a test is, we should keep track of the very small number of real positive and negative results in all cases that were looked at. This could be shown with numbers as:

Accuracy = TP + TN TP + TN + FP + FN.

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

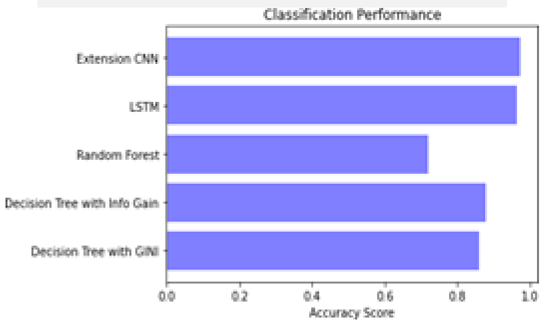

Fig. 3 Accuracy Comparison Graph

Precision: Precision is the percentage of correctly classified events or samples that are among the hits. So, the following method can be used to figure out the accuracy:

$$\text{Precision} = \text{True positives} / (\text{True positives} + \text{False positives}) = TP / (TP + FP)$$

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

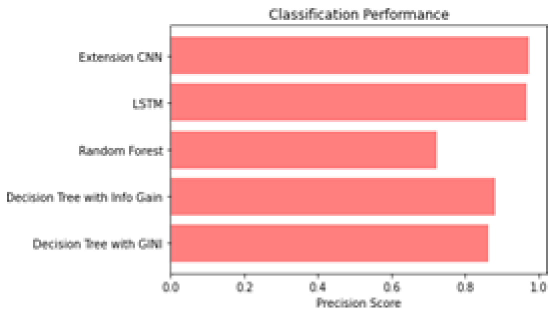

Fig 4 Precision Comparison Graph

Recall: Recall is a machine learning variable that measures how well a model can recognize all relevant examples of a certain class. It's the percentage of expected positive feelings that turn out to be real positive feelings. This tells us how well a model can catch instances of a certain class.

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

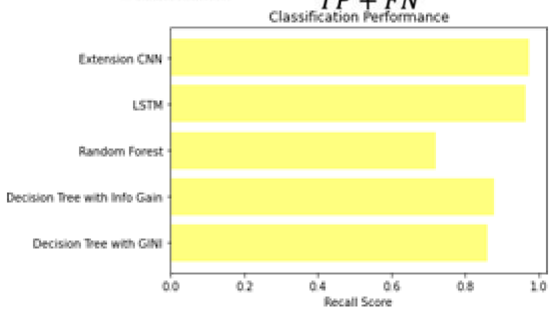

Fig. 5 Recall Comparison Graph

F1-Score: There is a machine learning rating tool called the F1 score that measures how accurate a model is. It adds up the accuracy and review scores of a model. The accuracy measurement figures out how often, across the whole collection, a model correctly predicted what would happen.

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

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

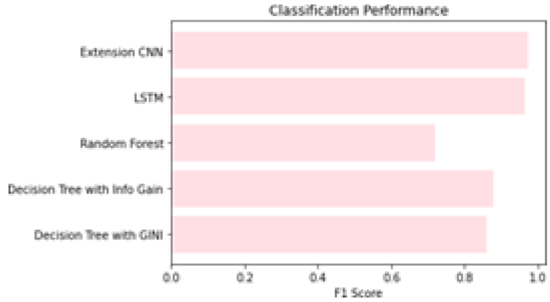

Fig. 6 F1 Comparison Graph

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

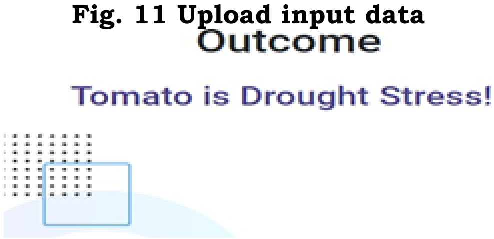

Fig. 12 Predicted result

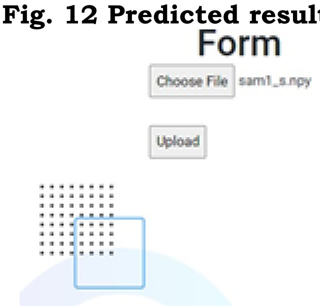

Fig. 13 Upload input data

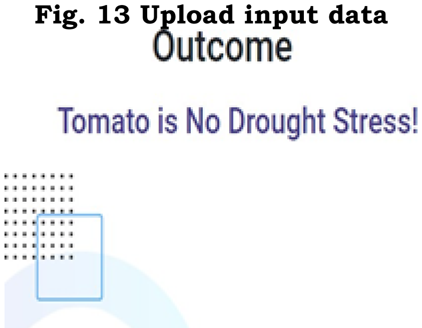

Fig. 14 Predicted Result

5 CONCLUSION

Finally, the project shows that using real-time data from the bioristor sensor along with different AI models can effectively describe, classify, and predict tomato plant water stress. Classification models like Decision Trees and Random Forests were good at telling the difference between different amounts of stress, and recurrent neural networks were good at predicting how stressed people would be in the future. In particular, CNN's deep learning model was very accurate (97%), showing that it was better at dealing with complex patterns in the data. In addition, using a Flask-based front end makes it easier for users to work with the system, which makes it easier to test. Overall, these results show that combining advanced sensing technologies with AI models could help improve farming results and make watering methods more effective, leading to more sustainable and efficient farming methods.

6 FUTURE SCOPE

Using bioristor data to describe, classify, and predict tomato plant water stress levels is part of the project's main goal. Some of the most important features are the real-time readings from the bioristor monitor, which record bodily reactions that show how much water the plant has. These traits include things like the rate at which sap flows, how well electricity flows through the plant, and other biological signs that show how much water the plant has. Environmental factors like temperature, humidity, and light strength could also be used as extra data to improve the accuracy of predictions. Feature extraction methods can be used to get useful information from the raw sensor data. This makes it easier to find trends that are linked to different levels of stress. As part of the project, relevant features from bioristor data will be used to create strong classification and forecasting models using artificial intelligence. These models will give valuable information for improving tomato cultivation productivity and irrigation strategies.

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