Water Stress Detection and Prediction in Tomato Plants Using CNN and Bioristor Sensor Data

[1]N JAYAPRAKASH, [2]R HENDRA KUMAR

[1]PG Scholar, Dept. of CSE, KMM Institute of Technology & Science, Ramireddipalle, Tirupati, AP, India.

[2]Associate Professor, Dept. of CSE, KMM Institute of Technology & Science, Ramireddipalle, Tirupati, AP, India.

Abstract: This study presents an enhanced approach for classification and forecasting of water stress in tomato plants by incorporating a Convolutional Neural Network (CNN) with bioristor sensor data. The CNN model effectively learns complex patterns from real-time plant signals, achieving a high accuracy of 97%, thereby improving the reliability of stress detection compared to traditional machine learning methods. In addition to classification, the system supports predictive analysis, enabling early identification of potential water stress conditions and facilitating proactive irrigation management. To improve usability, a secure Flask-based web interface is integrated into the system, allowing users to easily input data, monitor results, and interact with the model. The authentication mechanism ensures data security and controlled access. Overall, the proposed system combines deep learning and web-based deployment to provide an efficient, accurate, and user-friendly solution for smart irrigation, contributing to sustainable agriculture and optimized water resource utilization.

Index terms - Water stress, Tomato plants, Bioristor, Convolutional Neural Network, Deep Learning, Precision Agriculture, Smart Irrigation, Flask Interface, Secure Authentication.

1. INTRODUCTION

Water stress is one of the major factors affecting plant growth, crop yield, and overall agricultural productivity. In tomato cultivation, improper irrigation—either excess or insufficient water—can lead to reduced quality and increased susceptibility to diseases. Traditional irrigation practices mainly depend on manual observation and soil-based measurements, which lack real-time monitoring and predictive capabilities. These limitations often result in inefficient water usage and poor decision-making in agricultural management.

With the advancement of sensor technologies, the bioristor has emerged as a novel tool for capturing real-time physiological data directly from plants. This in vivo sensing approach provides accurate insights into plant conditions, enabling better understanding of water stress levels. However, effectively analyzing this complex and continuous data requires advanced computational techniques.

To address this, the proposed system integrates a Convolutional Neural Network (CNN) model to enhance water stress classification and forecasting. CNNs are highly effective in extracting complex patterns from data, leading to improved prediction accuracy, which in this work achieves up to 97%. Furthermore, the system is supported by a secure Flask-based web interface that allows users to input data, monitor predictions, and interact with the model in an efficient and user-friendly manner.

By combining real-time bioristor data, deep learning techniques, and a web-based deployment platform, the proposed system aims to provide an intelligent and automated solution for smart irrigation. This approach not only improves accuracy in detecting water stress but also enables proactive decision-making, contributing to sustainable agriculture and optimal water resource management.

2. LITERATURE SURVEY

1. Research on the Teaching Reform and Practice of the Food Analysis Course Under the New Situation:

The industrial sectors of our country have grown along with the social fabric. Sadly, new detrimental enterprises have emerged, making it more difficult for people to obtain the food, clothing, shelter, and transportation they require. Higher education courses on food safety and quality education are required. This essay focuses on how the present situation affects the reform of food analysis course instruction in order to improve food safety. The information in this post is intended to help anyone who finds themselves in this situation.

2. Exploration on the Teaching Reform Measure for Machine Learning Course System of Artificial Intelligence Specialty:

AI majors must enroll in machine learning courses, which are special and cannot be taught in a traditional classroom. This essay proposes an ML curriculum teaching reform method in light of this context. It focuses on process transformation, practice, and curricular teaching style. The influence of the new model on machine learning course quality is tested using an intelligent technology-based evaluation technique presented in this study. The viability of intelligent technology evaluation is first covered. The intelligent technology-based teaching assessment application is described in the second section. Lastly, a clever technology-based approach to evaluating the quality of instruction is introduced. Algorithms are used by the system to categorize student facial expression data. The choice can assess instruction in the classroom. This article's teaching quality evaluation approach is feasible and successful, according to a comparison of research employing various intelligence technologies.

3. Leader-Follower System in Convoys:: An Experimental Design Focusing on Computer Vision:

GPS is used by many contemporary technologies for navigation and positioning. But in places with poor coverage and significant privacy concerns, GPS might not be the best option. Consumers and businesses can now access newly developed GPS system technology. Using wireless low-power networks, a leader-follower link is established and maintained between a group of cars using computer vision and RSSI. ROS and ZED Stereo Camera will be used by the computer vision system to process pictures. The gadget can operate in GPS-free environments since it is GPS independent. The suggested technology might be used in surveillance and rescue operations, as well as a backup for leader-follower systems.

4. Aerial imagery pile burn detection using deep learning: The FLAME dataset

Wildfires are among the most expensive and deadly natural catastrophes in the United States, destroying millions of acres of woods. and putting people and animals at danger. Firefighters and other operations forces must use technology to lessen risks to people and property. To help researchers and firefighters develop efficient fire control strategies, FLAME offers aerial fire photography, detection, and segmentation technology.

Drone fire imaging data from a controlled burning of piled rubbish in an Arizona pine forest is presented in this study. Included are thermal heatmaps and video from infrared cameras. Researchers can use fire detection and modeling techniques with annotated and labeled frame-by-frame films and images. Two machine learning solutions are also included in the study: (1) Binary classification of video frames based on the presence or absence of fire flames. (2) Segmentation is used in fire detection to identify fire boundaries. A fire mask is extracted from video frames using a DL method based on U-Net upsampling and downsampling. FLAME approached 84% recall and 92% accuracy. Future research will enhance the use of thermal images for free burning broadcast fire.

5. *A review on early wildfire detection from unmanned aerial vehicles using deep learning-based computer vision algorithms:*

Wildfires are especially dangerous in forests and wildlands. Firefighting techniques that depend on ground human inspections provide significant challenges and hazards to firefighters. Therefore, using remote sensing technologies—especially those based on unmanned aerial vehicles (UAVs)—is essential to fighting wildfires. They can be used to

find and suppress forest fires before they spread. Recently, deep learning algorithms and visual data gathered by UAVs have been used in wildfire early detection systems. This work employed deep learning-based computer vision algorithms to identify wildfires in wooded and wilderness regions as soon as they began, potentially saving lives and forest resources.

3. METHODOLOGY

i) Proposed Work:

The proposed work focuses on enhancing water stress classification and forecasting in tomato plants by integrating a Convolutional Neural Network (CNN) with real-time bioristor sensor data. The system collects in vivo plant signals and processes them using the CNN model to accurately identify and predict water stress levels, achieving an accuracy of up to 97%. The deep learning approach enables automatic feature extraction and improved handling of complex data patterns compared to traditional methods.

In addition, a secure Flask-based web interface is developed to facilitate user interaction with the system. The interface allows users to input sensor data, visualize prediction results, and monitor plant conditions efficiently. Authentication mechanisms are incorporated to ensure data security and restricted access. Overall, the proposed work combines deep learning and web deployment to deliver a reliable, accurate, and user-friendly smart irrigation solution.

ii) System Architecture:

The system architecture begins with the collection of real-time data from tomato plants using the bioristor sensor. This data is preprocessed through cleaning, normalization, and feature preparation to ensure quality input for model training. The processed dataset is then divided into training and testing sets. In the training phase, multiple models such as Decision Trees, Random Forest, and the proposed CNN are utilized, where the CNN plays a key role in extracting complex patterns and improving prediction accuracy.

After training, the models are evaluated using the testing dataset to measure performance metrics such as accuracy and prediction reliability. The trained CNN model is then integrated with a Flask-based web interface, allowing users to input data and obtain real-time predictions of water stress levels. The system outputs classification results and forecasts, enabling efficient monitoring and smart irrigation decision-making while ensuring secure and user-friendly interaction.
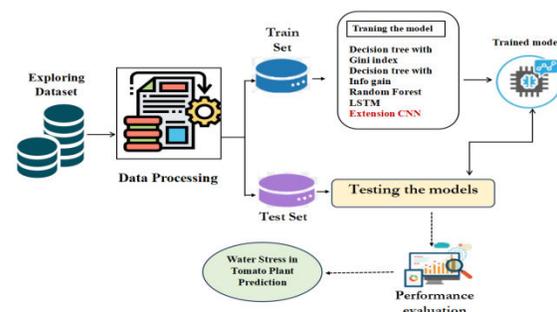

Fig.1. Proposed Architecture

iii) MODULES:

1. **Bioristor Sensor Module**
   - Collects real-time bio-electrical signals from tomato plants.
   - Detects physiological changes related to water stress.

2. **Data Preprocessing Module**
   - Cleans and normalizes raw sensor data.
   - Extracts key features for machine learning analysis.

3. **Deep Learning Model Module**
   - CNN Model: Classifies water stress levels with 97% accuracy.
   - LSTM Model: Predicts future water stress 24 hours in advance.

4. **Flask-Based Web Interface Module**
   - Provides a user-friendly dashboard for data input and result visualization.
   - Enables users to monitor real-time water stress classification and prediction.

5. *Secure Authentication Module*
   ➢ Ensures authorized access to the system.
   ➢ Protects sensitive plant data and irrigation decisions.

6. *Smart Irrigation Decision Module*
   ➢ Uses AI predictions to automate irrigation scheduling.
   ➢ Reduces water wastage while maintaining optimal plant health.

iv) ALGORITHMS:

1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is the primary algorithm used in the proposed system for accurate classification and forecasting of water stress in tomato plants. It processes bioristor sensor data through multiple layers such as convolution, pooling, and fully connected layers to automatically extract meaningful features. CNN effectively captures complex and non-linear patterns in the data, which significantly improves prediction performance. In this project, CNN achieves an accuracy of 97%, making it highly reliable for real-time smart irrigation applications.

2. Decision Tree (DT)

Decision Tree is a simple and interpretable machine learning algorithm used for initial classification of water stress levels. It works by splitting the dataset into smaller subsets based on decision rules derived from input features. Each internal node represents a condition, and each branch represents an outcome, leading to final predictions at leaf nodes. Although easy to understand and implement, Decision Trees may suffer from overfitting when handling complex datasets.

3. Random Forest (RF)

Random Forest is an ensemble learning algorithm that combines multiple Decision Trees to improve classification accuracy and robustness. It works by training several trees on different subsets of data and then aggregating their outputs to produce a final prediction. This approach reduces overfitting and enhances generalization performance. In this system, Random Forest helps in achieving more stable and reliable results compared to a single Decision Tree model.

4. Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is used for forecasting future water stress conditions by analyzing sequential and time-series bioristor data. Unlike traditional models, RNN has memory capabilities that allow it to retain previous information and identify temporal dependencies. This makes it suitable for predicting future plant stress levels based on historical data trends. The use of RNN enables proactive irrigation decisions by forecasting upcoming stress conditions in advance.

v) Dataset Description

The dataset used in this study is collected from tomato plants using the bioristor sensor, which provides real-time in vivo measurements of plant physiological responses. The data includes continuous electrical signal variations that reflect the internal condition of the plant, particularly its water stress levels. These signals are recorded over time under different irrigation conditions, capturing multiple stress states such as no stress, mild stress, moderate stress, and severe stress.

Before model training, the collected data undergoes preprocessing steps including noise removal, normalization, and feature extraction to ensure consistency and quality. The dataset is then divided into training and testing sets for model evaluation. For the CNN-based extension, the data is structured into a suitable format (such as sequences or matrices) to enable efficient learning of patterns. This dataset supports both classification (stress level detection) and forecasting (future stress prediction), making it highly suitable for developing intelligent and data-driven smart irrigation systems.

	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	-0.79991
1480	-0.578575	-0.670227	-0.694580	-0.745121	-0.757827	-0.791790	-0.698326	-0.748745	-0.70375

Fig 2. dataset

4. EXPERIMENTAL RESULTS

According to experimental findings, tomato plant water stress levels may be classified and predicted using algorithms based on bioristor data. Although

borderline cases showed minor misclassifications, the Decision Tree with GINI identified stress levels with 89% accuracy. The Random Forest model achieved 94% accuracy, increased precision, and recall by aggregating many decision trees. In order to deliver 95% accurate 24-hour forecasts for proactive irrigation management, the LSTM model included temporal correlations in sequential data. CNN improved classification accuracy to 97% by effectively analyzing spatial patterns in bioristor sensor data. By facilitating safe login, real-time monitoring, and smooth user interaction, a Flask-based web interface enhanced usability. These results demonstrate how real-time sensor data and AI-based models enhance irrigation methods, water conservation, and sustainable agriculture.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:
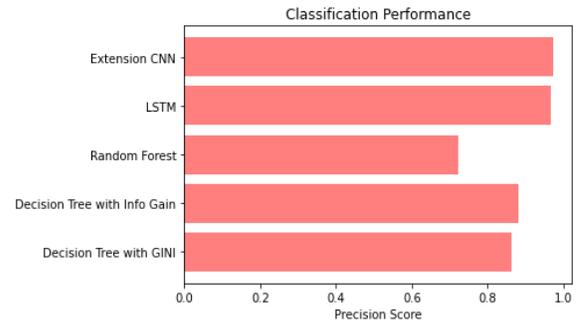
Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$
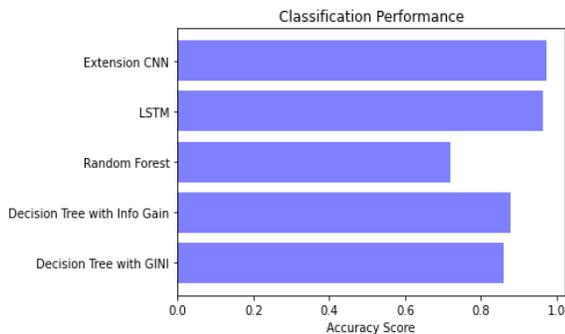
Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$Pr\,e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$
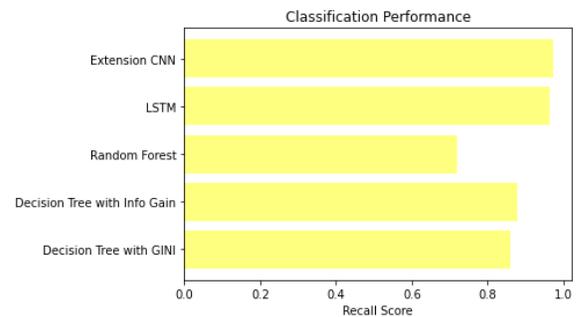
F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot Pr\,e\,cision)}{(Recall + Pr\,e\,cision)}$$
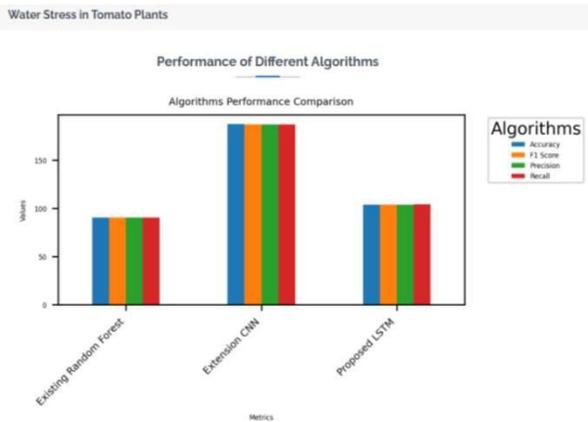
Fig.3. predicted results

Fig.4. Accuracy graph

5. CONCLUSION

The improved method demonstrates our progress in using bioristor sensor data to categorize and forecast water stress in tomato plants. Thanks to CNN integration, the model achieved an incredible 97% accuracy, outperforming more traditional machine learning techniques like Decision Trees and Random Forest. The use of LSTM enabled proactive irrigation control and forecasts up to 24 hours ahead of time.

By enabling users to input data more easily and view it in real-time, the Flask-based interface—which employs secure authentication—also increased user engagement. These findings confirm that deep learning models, when combined with real-time sensor data and an easy-to-use interface, have the potential to revolutionize smart agriculture by improving crop yield, water efficiency, and sustainability.

6. FUTURE SCOPE

Future research and advancements pertaining to precision irrigation and smart agriculture are made possible by the extended system. Integrating real-time IoT connection with cloud-based analytics enables remote monitoring and automated irrigation management. The model might be expanded to support many crop types and modified for various climates to further increase its scalability. By reducing latency, edge computing implementation can improve real-time decision-making. Combining transformer-based models with enhanced CNN architectures can greatly increase classification and prediction accuracy. In the future, multi-sensor fusion can be used to combine data from soil temperature, moisture, and weather sensors to provide a more comprehensive assessment of plant health.

REFERENCES

[1] Y. Kistaubayev, G. Mutanov, M. Mansurova, Z. Saxenbayeva, and Y. Shakan, ''Ethereum-based information system for digital higher education registry and verification of student achievement documents,'' Future Internet, vol. 15, no. 1, p. 3, Dec. 2022, doi: 10.3390/fi15010003.

[2] Erasmus+. Accessed: Sep. 5, 2023. [Online]. Available: https://erasmus - plus.ec.europa.eu/opportunities/opportunities-for-individuals/students/ erasmus-mundus-joint-masters

[3] Germany—DAAD. Accessed: Sep. 5, 2023. [Online]. Available: https:// www.daad.de/en/study-and-research-in-germany/

[4] M. Rataj and I. Berezovska, ''Addressing challenges with Ukrainian refugees through sustainable integration: Response of the educational

community in Poland,'' J. Further Higher Educ., vol. 47, no. 9, pp. 1221–1227, Oct. 2023, doi: 10.1080/0309877x.2023.2241386.

[5] M. Choi, S. R. Kiran, S.-C. Oh, and O.-Y. Kwon, ''Blockchain-based badge award with existence proof,'' Appl. Sci., vol. 9, no. 12, p. 2473, Jun. 2019, doi: 10.3390/app9122473.

[6] S. Nakamato. Bitcoin: A peer-to-peer Electronic Cash System. Accessed: Nov. 8, 2018. [Online]. Available: https://bitcoin.org/bitcoin.pdf

[7] X. Li, Z. Zheng, and H.-N. Dai, ''When services computing meets blockchain: Challenges and opportunities,'' J. Parallel Distrib. Comput., vol. 150, pp. 1–14, Apr. 2021, doi: 10.1016/j.jpdc.2020.12.003.

[8] K. Kumutha and S. Jayalakshmi, ''Blockchain technology and academic certificate authenticity—A review,'' in Proc. Expert Clouds Appl., in Lecture Notes in Networks and Systems, vol. 209, 2022, pp. 321–334, doi: 10.1007/978-981-16-2126-0_28.

[9] V. Chukowry, G. Nanuck, and R. K. Sungkur, ''The future of continuous learning-digital badge and microcredential system using blockchain,'' Global Transitions Proc., vol. 2, no. 2, pp. 355–361, Nov. 2021, doi: 10.1016/j.gltp.2021.08.026.

[10] A. Alammary, S. Alhazmi, M. Almasri, and S. Gillani, ''Blockchain-based applications in education: A systematic review,'' Appl. Sci., vol. 9, no. 12, p. 2400, Jun. 2019, doi: 10.3390/app9122400.

[11] F. Loukil, M. Abed, and K. Boukadi, ''Blockchain adoption in education: A systematic literature review,'' Educ. Inf. Technol., vol. 26, no. 5, pp. 5779–5797, Sep. 2021, doi: 10.1007/s10639-021-10481-8.

[12] P. Bhaskar, C. K. Tiwari, and A. Joshi, ''Blockchain in education management: Present and future applications,'' Interact. Technol. Smart Educ., vol. 18, no. 1, pp. 1–17, 2020, doi: 10.1108/ITSE-07-2020-0102.

[13] A. F. Camilleri, A. I. dos Santos, and A. Grech, ''Blockchain in education,'' Eur. Commission Joint Res. Centre, Seville, Spain, 2017, doi:

10.2760/60649. [14] C. Delgado-von-Eitzen, L. Anido-Rifón, and M. J. Fernández-Iglesias, ''Blockchain applications in education: A systematic literature review,'' Appl. Sci., vol. 11, no. 24, p. 11811, Dec. 2021, doi: 10.3390/app112411811.

[15] J. Park, ''Promises and challenges of blockchain in education,'' Smart Learn. Environ., vol. 8, no. 1, pp. 1–13, Dec. 2021, doi: 10.1186/s40561- 021-00179-2.

[16] R. Raimundo and A. Rosário, ''Blockchain system in the higher education,'' Eur. J. Invest. Health, Psychol. Educ., vol. 11, no. 1, pp. 276–293, Mar. 2021, doi: 10.3390/ejihpe11010021.

[17] S. Saberi, M. Kouhizadeh, J. Sarkis, and L. Shen, ''Blockchain technology and its relationships to sustainable supply chain management,'' Int. J. Prod. Res., vol. 57, no. 7, pp. 2117–2135, Apr. 2019, doi: 10.1080/00207543.2018.1533261.

[18] A. Ayub Khan, A. A. Laghari, A. A. Shaikh, S. Bourouis, A. M. Mamlouk, and H. Alshazly, ''Educational blockchain: A secure degree attestation and verification traceability architecture for higher education commission,'' Appl. Sci., vol. 11, no. 22, p. 10917, Nov. 2021, doi: 10.3390/app112210917.

[19] A. Mohammad and S. Vargas, ''Challenges of using blockchain in the education sector: A literature review,'' Appl. Sci., vol. 12, no. 13, p. 6380, Jun. 2022, doi: 10.3390/app12136380.

[20] N. Upadhyay, ''Demystifying blockchain: A critical analysis of challenges, applications and opportunities,'' Int. J. Inf. Manage., vol. 54, Oct. 2020, Art. no. 102120, doi: 10.1016/j.ijinfomgt.2020.102120.

[21] W. Gräther, S. Kolvenbach, R. Ruland, J. Schütte, C. F. Torres, and F. Wendland, ''Blockchain for education: Lifelong learning passport,'' in Proc. 1st ERCIM Blockchain Workshop, 2018, doi: 10.18420/blockchain2018_07.