Real-Time Smart Irrigation Management with Extended Hybrid Regression and Neural Networks

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Abstract: A hybrid ensemble regression model with web-based deployment is added to the prediction framework to increase smart irrigation system accuracy and dependability. Gradient Boosting, XGBoost, and AdaBoost predict soil moisture, temperature, and humidity utilizing a Voting Regressor in the suggested expansion. A two-stage ANN with the suggested TANELU activation function uses these predicted properties to assess irrigation need and optimal watering time. A Flask-based web interface allows real-time data entry, analysis, and irrigation suggestions, making the system scalable, user-friendly, and adaptable to varied agricultural settings while decreasing water waste.

Index terms - *Hybrid ensemble regression, voting regressor, precision irrigation, artificial neural network, TANELU activation function, environmental parameter forecasting, smart agriculture, Flask-based web deployment, water resource optimization, sustainable irrigation*

1. INTRODUCTION

Agricultural systems are under growing pressure to produce more food with fewer natural resources as the world's population expands rapidly and the climate becomes increasingly unpredictable. Numerous recent studies have shown that population fluctuations and rising global temperatures have a major influence on water demand and agricultural sustainability [1]. This raises the risk of water-related and heat-related disasters. Agriculture employs the majority of freshwater resources worldwide, according to the Food and Agriculture Organization (FAO), which highlights that the future of food security is heavily dependent on the effective use of resources, notably water [2]. In addition to wasting a lot of water, inefficient irrigation methods can eventually reduce agricultural output and the overall health of the soil.

As a result, a detailed evaluation of the supply and demand for agricultural water resources has become an essential field of study. To anticipate agricultural water resources' carrying capacity and support sustainable irrigation planning, advanced modeling and stochastic simulation techniques have been investigated [3]. Due to their potential to increase agricultural output, water efficiency, and environmental sustainability in the face of changing climate conditions, precision irrigation technologies are also becoming increasingly important [4]. In order to maximize crop productivity while simultaneously reducing environmental effect, modern agriculture is progressively using techniques for water management, fertilizer control, biostimulants, and improved cultivation techniques [5]. These problems and developments underscore the need for data-driven intelligent irrigation systems that integrate machine learning, adaptive decision-making, and predictive modeling in order to achieve sustainable agricultural productivity.

2. LITERATURE SURVEY

1. Performance and Robustness Analysis of Advanced Machine Learning Models for Predicting the Required Irrigation Water Amount:

Given the substantial population expansion, the agricultural sector is essential to maintaining global food security. Crop output may not be able to keep up with the growing demand for food. One of the biggest issues facing the agriculture industry is water shortage, which is made worse by the ineffectiveness of conventional irrigation techniques. To solve this problem, plant water requirements must be accurately predicted. In order to precisely forecast the daily water amount (quantity) requirements of greenhouse plants utilizing different air and soil data characteristics, this research suggests sophisticated machine learning (ML) and deep learning (DL) algorithms. The data was prepared for the suggested models using a variety of data preparation methods. Additionally, two distinct data splitting techniques (simple data preparation for the ML models and time series data preparation for the time series DL models) were utilized to divide the data into inputs and outputs due to the distinct nature of the suggested models.The Multi-Layer Perceptron (MLP) model demonstrated greater stability and efficiency across several data optimization phases, consistently outperforming other models, according to the results. Furthermore, in many data optimization settings, both ML and Long-Short Term Memory (LSTM) models demonstrated high performance. Parameter sensitivity analysis was used to assess robustness, and the results showed that ML models were typically more resilient than DL models. This resilience is explained by the fact that ML models have fewer parameters than DL models, which improves their dependability. This study guarantees that the suggested models have the capacity to maximize irrigation techniques, consequently resolving water shortage problems and raising agricultural output.

2. Artificial intelligence to optimize water consumption in agriculture: A predictive algorithm-based irrigation management system:

Water scarcity is one pressing global issue that has to be addressed. Only around 31% of people do not face water stress, according to the UN, suggesting that freshwater resources are not managed effectively and are distributed unfairly. This phenomenon is both natural and man-made as the human footprint is linked to several fields, with agriculture having the most impact. Scientific study indicates that 4.0 technologies are primarily responsible for reducing this industry's impact on critical resources like water and soil. Based on these presumptions, the proposed work aims to improve agricultural irrigation management by implementing a three-layer architectural system that maximizes water consumption and prevents situations when soil moisture levels exceed their capacity. By assessing the soil capacity point, experimental activities make it possible to determine a confidence interval that guides watering decisions. The latter interval, soil and environmental data, and three-day weather forecasts are merged to create a consistent dataset for training and testing three different machine learning algorithms based on a classification problem to anticipate the irrigation network's health. As a result, the built multi-layer perceptron neural network, support vector machine, and k-neighbors classifier achieved an accuracy of more than 99%. Despite this, the neural network produced more accurate decision region boundaries, which decreased the quantity of inaccurate predictions. A Monte Carlo simulation was then used to evaluate the water and energy savings, which were up to 27% and 57%, respectively. In conclusion, the predictive algorithm-based irrigation management system provides an economical method of optimizing water management in agriculture that is really scalable to any crop by figuring out the appropriate soil capacity level.

3. A Survey Towards Decision Support System on Smart Irrigation Scheduling Using Machine Learning approaches:

Over the past 10 years, big data analytics and machine learning have been significant research topics in the agricultural sector. Agriculture analytics is a data-intensive, interdisciplinary field. A vital tool for examining vast volumes of data is big data analytics. Controlling irrigation water is a challenging task for sustainable agriculture. Numerous climate, soil, and weather-related factors affect it. Accurately estimating a crop's water requirements requires strong modeling. Examining the use of intelligent learning methods in a big data-based decision support system framework for sustainable water irrigation management is the aim of this study. We examined how these developments may be used to build and deploy the next generation of data, models, analytics, and decision support tools for agricultural irrigation water systems. In order to develop applications based on analytical modeling methodologies, water irrigation management must also swiftly incorporate state-of-the-art big data and ICT information technologies. An overview of the area is given in this study, which covers crop water model needs, irrigation scheduling methods, smart agricultural irrigation water management, decision support systems, and research motivation.

4. The Outcomes of Smart Irrigation System using Machine Learning to minimize water usage within the Agriculture Sector:

The issue of water scarcity today poses a worldwide threat to food security and the whole agricultural value chain. Improvements to intelligent irrigation infrastructure are necessary since saving water is the most challenging job confronting farmers. whether making decisions on agricultural complexity, such as whether to irrigate, farmers rely on information about soil type, available water supply, soil moisture, and climate factors. In order to solve the complex problems that agriculture faces, deploying field sensors through IoT, a data-driven technology, requires fusing state-of-the-art technologies with modern methods. IoT has made it simpler to gather long-term data, and since data is easily accessible, applying 4IR to machine learning and logistic regression in the agriculture industry reveals several perspectives that help solve complex issues. This article proposes a 4IR-enabled Smart Irrigation System that lowers water use in the agriculture industry by providing farmers with real-time data on soil moisture, weather API, crop water capacity, and plugging sensors to predict when farmers may irrigate or not.

5. An Innovative Smart Irrigation Using Embedded and Regression-Based Machine Learning Technologies for Improving Water Security and Sustainability:

Key concerns for global agriculture include resource conservation, water management, and food security. Water scarcity brought on by climate change demands more productive agriculture. Water is wasted by conventional, incorrect irrigation methods. Food security and sustainability may be increased by optimizing irrigation for local conditions and crop requirements using embedded systems and machine learning. To improve irrigation efficiency, this study suggests utilizing real-time data and prediction algorithms. In order to improve water management, this study proposes an integrated irrigation system that makes use of sensors and algorithms. By adjusting irrigation to crop needs, the technique promotes more sustainable water management. Precise irrigation level prediction based on sensor data is made possible by using machine learning methods such as linear regression to estimate environmental factors and crop water requirements. An autonomous and effective system for gathering data and making decisions in real time has been produced by combining embedded systems like the ESP32 with temperature, humidity, and water level sensors. With an MAE of 0.8434, RMSE of 0.8434, and R2 Score of 0.4044, the proposed model forecasts soil moisture. The training and prediction times for our model are 0.00253 and 0.00117 seconds, respectively. These results show that the proposed model is more accurate and computationally efficient than certain other studies. According to the report, water resource management has improved and water use has significantly decreased. Discussions reveal that by offering more accurate and flexible water resource management, embedded systems utilizing machine learning algorithms can improve irrigation efficiency and agricultural sustainability. Particularly in areas affected by climate change, this study promotes sustainable water management and food security.

3. METHODOLOGY

The suggested approach uses Internet of Things sensors and meteorological application programming interfaces to collect real-time data on soil moisture, soil temperature, air temperature, and humidity. The quality of the data may be enhanced by creating time-series features, handling missing values, and normalizing the data. A hybrid ensemble voting regressor is used in conjunction with Random Forest, XGBoost, and AdaBoost regression models to predict environmental factors. This reduces the amount of error that occurs throughout the prediction process. The proposed TANELU hybrid activation function allows a two-stage artificial neural network to learn the desired characteristics. The first stage of the artificial neural network (ANN) determines the irrigation requirements, while the second stage determines the watering schedules. Among the factors influencing irrigation choices include rainfall, soil moisture, and time restrictions. In conclusion, real-time irrigation recommendations and alarms are provided using a Flask-based web interface to accomplish efficient, adaptable, and environmentally responsible irrigation management.

i) Proposed Work:

To decrease agricultural water waste, a two-stage artificial neural network and hybrid ensemble regression are used in the proposed intelligent precision irrigation architecture. IoT sensors and meteorological services provide real-time observations of temperature, humidity, soil moisture, and air temperature. Ecological parameters are predicted using machine learning regression models including Random Forest, XGBoost, and AdaBoost, as well as a hybrid voting regressor that combines Gradient Boosting and AdaBoost to increase prediction accuracy. These anticipated characteristics are used by the decision-making module to create proactive, data-driven irrigation strategies.

A two-stage ANN architecture with the recommended TANELU hybrid activation function is used in the decision layer. The first stage assesses if irrigation is necessary based on present and future conditions, while the second stage establishes the ideal watering time for crop health and water efficiency. To cut down on needless watering, time-window validation, rainfall detection, and soil moisture thresholds are combined. A web interface developed on Flask provides farmers with real-time instructions and notifications. Accurate forecasting, adaptability in a range of agricultural scenarios, and sustainable water resource use are all provided by this integrated method.

ii) System Architecture:

The proposed system design makes intelligent irrigation decisions by utilizing linked layers. IoT sensors in the data collection layer measure soil temperature, humidity, soil moisture, and air temperature in real time. Machine learning models such as XGBoost for environmental forecasting and two ANN models with the designated TANELU activation function for best-time prediction and irrigation demand are trained and stored using these features. By storing and loading learned models throughout runtime to forecast environmental variables, proactive irrigation planning may be accomplished. To enhance decision-making, the system modifies input parameters and forecasts environmental aspects.

Expected environmental conditions, crop kind, day and time, city location, and real-time weather data from an external API are all taken into account by the decision and control layer. Unnecessary watering may be avoided by time-window validation, rainfall detection, and comparison of soil moisture thresholds. Watering and irrigation schedules are determined by the two-stage ANN outputs. The action layer provides farmers with irrigation management and SMS alerts. This system manages water and maintains agricultural irrigation using human interaction, prediction, and decision-making.

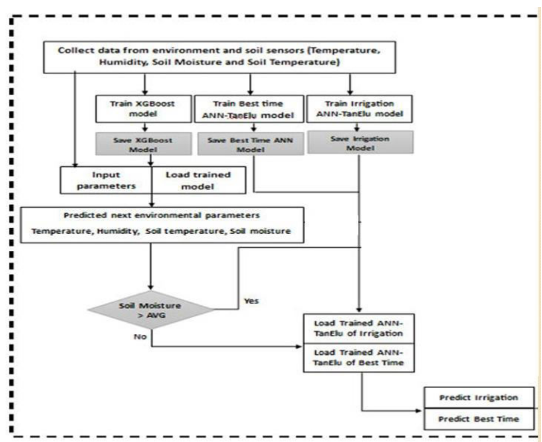

Fig.1. Proposed Architecture

iii) MODULES:

a) Importing the packages: All pertinent Python modules and packages needed for web deployment, machine learning, data management, and visualization are imported by this module. Packages that include tools for numerical computation, data processing, graph visualization, model construction, assessment, and managing Flask server operations may make the entire irrigation prediction workflow go smoothly.

b) Exploring the dataset: This module loads and examines the irrigation dataset, evaluating the distribution of optimal and poor watering times as well as the quantity of irrigation and non-irrigation episodes. Prior to preprocessing and model training, it assists in identifying broad trends, feature types, and data structures.

c) Visualization: The dataset is represented graphically in this module, which shows irrigation class distributions, ideal watering times, and other environmental factors. To improve prediction accuracy, visualization helps identify imbalances, trends, and anomalies that influence feature engineering, preprocessing, and model selection.

d) Pre-processing: Cleaning and getting the dataset ready for modeling are part of preprocessing. Moving columns create new time-series features, missing values are filled in, and categorical variables like crop type are encoded. For training prediction models, this ensures consistent, high-quality input.

e) Normalizing: Value normalization techniques such as MinMax normalization are used to scale all environmental and time-series parameters. This ensures that different models interpret data consistently for precise irrigation and watering predictions, removes bias in learning, and encourages convergence during training.

f) Split the data into train & test: Typically, 80% of the dataset is used for training and 20% is used for testing. This enables models to evaluate performance and generalization on unidentified test data for reliability while learning patterns from the training set.

g) Model training: To predict irrigation needs and optimal watering times, many algorithms are trained. Regression models that predict environmental features include Random Forest, XGBoost, and AdaBoost. Current RELU and suggested TANELU activation functions are used by ANN models to determine irrigation needs and offer the best watering schedules.

h) Evaluation: Measures like accuracy, precision, recall, and F1-score for classification models and MAE, MSE, and RMSE for regression models are used to assess model performance. Evaluation ensures that the best-performing model is selected and validates the hybrid strategy's effectiveness.

i) Flask Server: The irrigation prediction system is hosted on a web server that is set up by the Flask module. Through a browser-based interface, users may interact with the trained models, enter data files, and get real-time irrigation and watering forecasts.

j) User Login: For secure system access, this module oversees user authentication. By ensuring that only authorized individuals may carry out irrigation and watering forecasts, users' login credentials improve data privacy and system security.

k) Predict Irrigation & Watering: For secure system access, this module oversees user authentication. By ensuring that only authorized individuals may carry out irrigation and watering forecasts, users' login credentials improve data privacy and system security.

l) Logout: After usage, the logout module safely ends the user session, ensuring that no unauthorized access occurs. It clears session data and reroutes visitors to the login page to protect confidential irrigation forecast data and maintain system integrity.

iv) ALGORITHMS:

a) Random Forest:

The Random Forest ensemble learning method uses many decision trees to improve prediction accuracy and durability. During training, it builds many decision trees and outputs the majority vote for classification or the average prediction for regression. When compared to a single decision tree, it minimizes overfitting and efficiently manages high-dimensional data. By predicting environmental factors like temperature, humidity, and soil moisture, Random Forest offers reliable inputs for irrigation prediction in this irrigation system. Accurate water requirement prediction is made possible by its ability to take into account complex, nonlinear relationships among environmental elements. It is perfect for altering crop kinds and conditions while keeping consistent performance under a variety of settings since it balances bias and variance by employing many trees.

b) XGBoost:

A gradient boosting method called XGBoost was created for effective, high-performance prediction tasks. Decision trees are built sequentially, with each tree enhancing accuracy by correcting the errors of its predecessors. The method uses regularization to prevent overfitting and permits parallel processing for faster training. In irrigation management, XGBoost predicts future climatic factors including temperature, humidity, and soil moisture—all of which are critical for scheduling watering and determining the optimal times to do so. Its precision in managing complex datasets yields regression results with minimal error. Because of its scalability and robustness, which allow it to adapt to different crops and temporal circumstances, the algorithm is a reliable tool for forecasting environmental elements required for intelligent water management and waste reduction.

c) AdaBoost:

Adaptive Boosting, often known as AdaBoost, is an ensemble technique that combines many weak learners to create a strong prediction. Each student receives instruction gradually, paying more attention to instances that were previously incorrectly identified. Accuracy and generalization are improved by this repeated method. AdaBoost forecasts temperature, humidity, and soil moisture to help with irrigation and watering schedule decisions in the irrigation system. Its adaptability increases the accuracy of irrigation scheduling by enabling more efficient handling of nonlinear patterns and environmental unpredictability. Prediction reliability is increased via AdaBoost's weighted learning method, which ensures that difficult circumstances are compensated for. By combining its output with other models, the technique maximizes irrigation efficiency by obtaining a trustworthy and precise estimate of water requirements for different crops.

d) Extension Hybrid Model:

The Extension Hybrid Model uses a Voting Regressor to combine many regression algorithms, such as Gradient Boosting, XGBoost, and AdaBoost. The ensemble selects the best-performing forecasts for irrigation decisions after each algorithm evaluates environmental conditions. By combining the best features of many models, this hybrid approach reduces prediction errors and increases consistency in a variety of environmental contexts. It forecasts temperature, humidity, and soil moisture, making it possible to classify irrigation needs and determine the best times to irrigate. Hybridization increases overall prediction accuracy by enabling the algorithm to adjust to different crop kinds and environmental conditions. This technique reduces water loss and improves resource efficiency in agriculture by offering a solid and comprehensive foundation for intelligent irrigation control.

e) Existing ANN with RELU Irrigation:

For the binary classification of irrigation demands, the existing Artificial Neural Network with RELU activation is a feedforward neural network. The network can learn complex connections between input properties like crop kind and ambient circumstances because to RELU's incorporation of nonlinearity. The network assesses whether irrigation is required at a given time based on temperature, humidity, and soil moisture. Its primary goal is to accurately classify irrigation occurrences and offer helpful data for watering schedules. RELU activation speeds up quick convergence by removing vanishing gradient issues during training. This tool helps save water while maintaining crop health by using trends in historical environmental data to produce reliable forecasts for irrigation decisions.

f) Existing ANN with RELU Best Water:

This neural network classifies the optimal times to water crops using the RELU activation function. To determine if the current time of year is ideal for irrigation, it looks at variables including soil moisture, air temperature, humidity, and crop kind. The RELU function helps the model learn nonlinear patterns efficiently while minimizing vanishing gradient problems. Its main function is to determine the best time of day for irrigation so that water is used effectively. By examining historical environmental trends, it provides recommendations for timely irrigation, increasing water consumption efficiency, and preventing waste. The network produces very accurate predictions for water management decisions by acting as a classification model.

g) Propose ANN with TANELU Irrigation:

To improve learning, convergence, and nonlinear representation, the proposed ANN with TANELU activation uses a hybrid function that combines TANH and ELU. It classifies whether irrigation is required based on input factors such as soil moisture, temperature, humidity, crop type, and time. By allowing the network to more effectively capture complex connections than traditional activation functions, TANELU increases prediction accuracy. By accurately determining when watering is necessary, the model's sophisticated irrigation scheduling helps reduce water loss. It adapts to changing crop and soil conditions by integrating environmental and temporal data, ensuring constant classification of irrigation requirements while improving generalization across diverse scenarios.

h) Propose ANN with TANELU Best Water:

This model uses the TANELU hybrid activation function of an ANN to categorize the best times to irrigate crops. Soil moisture, temperature, humidity, crop type, and the time of day are examples of inputs. By integrating TANH and ELU, the network may learn intricate nonlinear connections between irrigation time and environmental data, improving accuracy and convergence. By predicting when watering is suitable, it guarantees efficient water application. The system provides precise recommendations for the right irrigation period in response to various crop conditions and environmental variability. The network reduces forecast errors by using TANELU, which results in improved agricultural productivity and sustainable water management.

4. EXPERIMENTAL RESULTS

The proposed system was evaluated using real-world environmental and irrigation variables, including soil moisture, soil temperature, air temperature, and humidity parameters. For environmental forecasting, Random Forest, AdaBoost, XGBoost, and the hybrid ensemble voting regressor were analyzed using MAE, MSE, and RMSE. With an MAE of 0.00525 (0.52%), XGBoost was the model with the lowest prediction error. Combining various regression algorithms improved the accuracy and stability of the hybrid ensemble voting regressor, bringing the error down to 0.00475 (0.47%).

The suggested two-stage ANN with TANELU activation function was compared to ReLU-activated ANN models for irrigation decision-making. Classification abilities were assessed using accuracy, precision, recall, and F-score. The TANELU-based ANN discovered the optimal watering time under ideal conditions with 99% accuracy and forecasted irrigation demands with 93% accuracy. These results suggest that the hybrid activation function enhances convergence, learning efficiency, and classification reliability. Experimental findings show that the hybrid regression and ANN-based system minimizes water waste and permits precise watering.

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..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

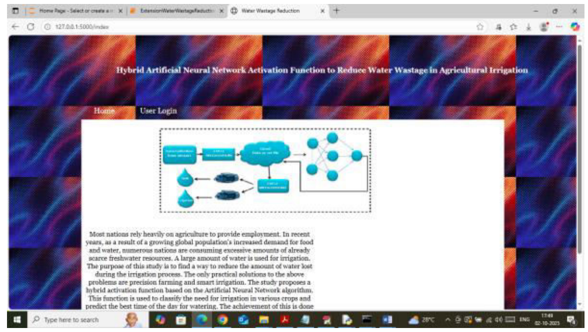

Fig2 home screen

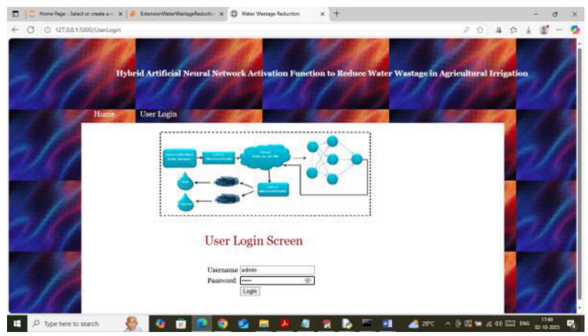

Fig 3 User Login

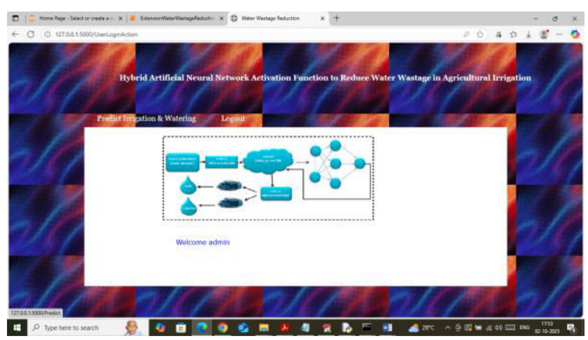

Fig4 User home page

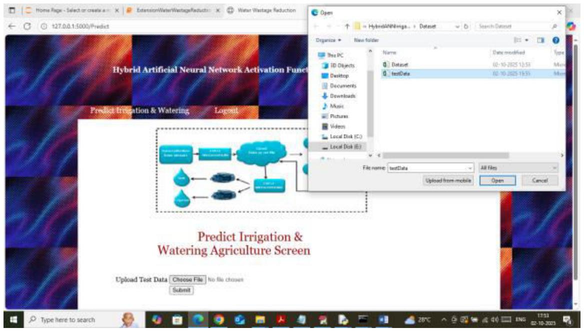

Fig5 Uploading test image

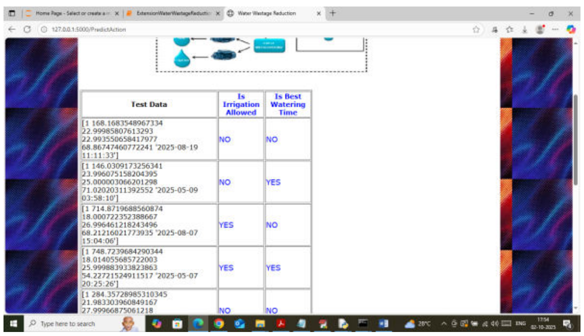

Fig6 Prediction result

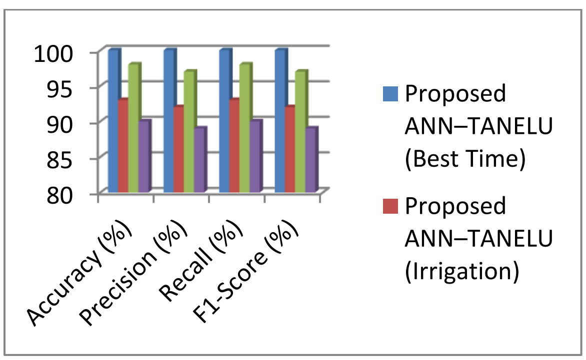

Fig7 Performance Comparison of Forecasting Algorithms

5. CONCLUSION

A web-based deployment platform and a hybrid ensemble regression model were used to improve the smart irrigation system's forecast accuracy and usability. Predictions of soil moisture, temperature, and humidity were enhanced using Gradient Boosting, XGBoost, and AdaBoost in a voting regressor. Because the predicted characteristics were more accurate, the two-stage ANN utilizing the suggested TANELU activation function was able to precisely determine irrigation requirements and estimate watering times.

Farmers may easily utilize the updated framework for real-time data processing, visualization, and irrigation recommendations thanks to its Flask-based web interface. The hybrid regression extension increases adaptability across a wide range of crops and climates while lowering forecasting uncertainty and water waste. An intelligent and scalable irrigation control system is created by combining agricultural applications with contemporary ensemble learning techniques.

6. FUTURE SCOPE

Future studies might focus on enhancing the irrigation prediction system by using more advanced hybrid learning methods and real-time adaptive mechanisms. The accuracy of irrigation scheduling may be increased by taking into account other environmental factors including sun radiation, wind speed, and rainfall. IoT-enabled smart sensors might be expanded to track soil salinity and nitrogen levels to provide comprehensive crop management. Edge computing and cloud-based analytics may be utilized for faster processing and decision-making. Furthermore, the system may be modified to support other crop varieties using dynamic crop development models. While mobile applications may be improved for better usability and farmer advice, reinforcement learning techniques may be explored to enable autonomous irrigation choices, further reducing water loss and boosting sustainable agricultural practices.

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