HYBRID ARTIFICIAL NEURAL NETWORK WITH HYBRID ACTIVATION FUNCTION FOR SMART IRRIGATION SYSTEM

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Abstract

Water management in agriculture has become increasingly important due to rising water scarcity and inefficient irrigation practices. Many existing irrigation systems rely on fixed schedules or simple models, which often fail to respond effectively to changing environmental conditions such as soil moisture, temperature, and humidity. This leads to inaccurate irrigation decisions and unnecessary water loss.

In this work, a smart irrigation system based on a hybrid machine learning approach is proposed to improve prediction accuracy and support better decision-making. Environmental conditions are first predicted using a combination of regression models, including Gradient Boosting, XGBoost, and AdaBoost, integrated through a voting mechanism to reduce prediction errors. These predicted values, along with crop-related and time-based information, are then used as inputs to an Artificial Neural Network. To further enhance performance, a hybrid activation function combining TANH and ELU is introduced, enabling the model to better capture complex and non-linear patterns in the data.

The system is capable of determining whether irrigation is required and identifying the most suitable time for watering. The results show that the proposed approach provides more reliable predictions compared to traditional and single-model methods. This study presents a practical and scalable solution for improving water efficiency and promoting sustainable agricultural practices.

Keywords

Smart Irrigation, Hybrid Machine Learning, Artificial Neural Network, Hybrid Activation Function, Environmental Prediction, Precision Agriculture, Water Resource Management, Ensemble Learning

I. INTRODUCTION

Agriculture is one of the largest consumers of freshwater resources worldwide, accounting for a major share of global water usage. Efficient irrigation management is therefore essential for ensuring sustainable agricultural practices and maintaining crop productivity. However, in many regions, irrigation is still performed using traditional methods such as fixed scheduling or manual observation, which do not accurately reflect real-time soil and environmental conditions. These practices often result in over-irrigation or under-irrigation, leading to water wastage, increased operational costs, and reduced crop yield.

With the increasing availability of environmental data and advancements in computational techniques, data-driven approaches have gained significant attention in modern agriculture. Machine learning (ML) techniques provide the ability to analyze large volumes of data and identify hidden patterns that can support accurate prediction and decision-making. In the context of irrigation, ML models can utilize parameters such as soil moisture, soil temperature, air temperature, and humidity to determine the optimal irrigation requirement. Despite these advantages, many existing ML-based irrigation systems rely on single predictive models, which may not perform consistently across different environmental conditions. The complex and non-linear nature of agricultural data often limits the effectiveness of individual models.

To overcome these limitations, ensemble and hybrid learning approaches have been introduced, where multiple models are combined to improve prediction performance. Hybrid regression models, in particular, can reduce prediction error by leveraging the strengths of different algorithms. Techniques such as Gradient Boosting, XGBoost, and AdaBoost have demonstrated strong performance in handling structured data and capturing complex relationships. Combining these models using a voting mechanism further enhances prediction reliability and robustness.

In addition to regression-based forecasting, classification models play a crucial role in determining irrigation decisions. Artificial Neural Networks (ANN) are widely used for classification tasks due to their ability to model non-linear relationships between input features and outputs. However, the effectiveness of ANN models largely depends on the choice of activation functions, which influence learning behavior, convergence speed, and overall accuracy. Traditional activation functions such as Rectified Linear Unit (ReLU), Hyperbolic Tangent (TANH), and Exponential Linear Unit (ELU) have their own advantages and limitations. In many cases, a single activation function may not be sufficient to capture diverse patterns present in environmental data.

To address this issue, this paper proposes a hybrid activation function that combines the properties of TANH and ELU to improve the learning capability of the neural network. The proposed activation function enhances gradient flow, reduces the vanishing gradient problem, and improves convergence during training. This results in better classification performance for irrigation requirement and watering time prediction.

The proposed system integrates a hybrid regression model for environmental forecasting with an ANN model using a hybrid activation function for classification. The regression model predicts future environmental conditions, which are then used as inputs to the ANN model. Based on these inputs, the system determines whether irrigation is required and identifies the most suitable time for watering crops. This two-stage approach improves both prediction accuracy and decision reliability.

The main contribution of this work lies in the development of a hybrid machine learning framework that combines ensemble regression techniques with an enhanced neural network model. The system is designed to handle dynamic environmental conditions, reduce prediction errors, and support precision irrigation. By improving irrigation efficiency, the proposed approach contributes to water conservation and sustainable agricultural development.

II. LITERATURE REVIEW

Irrigation management has been widely studied in recent years due to the increasing need for efficient water utilization in agriculture. Early approaches to irrigation were primarily based on manual observation and fixed scheduling techniques. These methods were simple to implement but often resulted in inefficient water usage, as they did not consider real-time variations in environmental conditions such as soil moisture, temperature, and humidity.

With the advancement of sensor technologies, automated irrigation systems were introduced, where soil moisture sensors and weather data were used to trigger irrigation. Although these systems improved efficiency compared to traditional methods, they were largely dependent on predefined threshold values. Such rule-based systems lack adaptability and are not capable of handling complex and dynamic environmental patterns.

To overcome these limitations, researchers began exploring machine learning techniques for irrigation prediction. Algorithms such as Decision Trees, Support Vector Machines (SVM), and Random Forest have been applied to classify irrigation requirements based on historical environmental data. Among these, Random Forest gained popularity due to its ability to handle high-dimensional data and reduce overfitting. However, single-model approaches often struggle to maintain consistent performance across different datasets and environmental conditions.

Artificial Neural Networks (ANN) have also been extensively used in agricultural prediction systems. Their capability to model non-linear relationships makes them suitable for analyzing environmental data. Several studies have demonstrated that ANN-based models can improve prediction accuracy for irrigation and crop management. Despite these advantages, ANN models are sensitive to parameter selection and activation functions, which significantly influence their performance and convergence behavior.

In recent years, ensemble and hybrid learning approaches have gained attention as a solution to improve model performance. Ensemble methods such as Gradient Boosting, AdaBoost, and XGBoost combine multiple weak learners to produce a stronger predictive model. These methods have shown superior performance in regression tasks, particularly in handling structured and non-linear data. By integrating multiple models, ensemble approaches can reduce variance and bias, leading to more reliable predictions.

Furthermore, hybrid systems that combine regression models with neural networks have been proposed to enhance both prediction and classification tasks. In such systems, regression models are used to forecast environmental parameters, and neural networks are used to make final decisions based on these predictions. This layered approach improves overall system accuracy and robustness.

Despite these advancements, most existing systems rely on standard activation functions such as ReLU, TANH, or ELU in neural networks. These functions, while effective in many scenarios, may not fully capture the diverse characteristics of agricultural data. As a result, there is a growing need to explore hybrid activation functions that combine the strengths of multiple functions to improve learning capability.

Based on the existing research, it is evident that hybrid and ensemble approaches provide better performance compared to traditional and single-model systems. However, there is still scope for improvement in integrating hybrid regression models with advanced neural network architectures and customized activation functions. This research addresses these gaps by proposing a hybrid irrigation prediction system that combines ensemble regression techniques with an ANN model using a hybrid activation function, thereby improving prediction accuracy and supporting efficient water management.

III. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

Efficient irrigation management is a major challenge in modern agriculture due to the continuously changing nature of environmental conditions such as soil moisture, temperature, and humidity. Traditional irrigation systems rely on fixed schedules or manual decisions, which do not accurately reflect real-time field conditions. As a result, these methods often lead to over-irrigation or under-irrigation, causing water wastage, increased costs, and reduced crop productivity.

Although machine learning-based irrigation systems have been introduced to improve decision-making, many of these approaches depend on single predictive models. Such models often struggle to capture the complex and non-linear relationships present in environmental data, leading to inconsistent performance across different conditions. In addition, most existing systems do not effectively combine environmental forecasting with intelligent decision-making mechanisms.

Another key limitation is the use of standard activation functions in neural networks, which may not fully utilize the learning capability of the model when dealing with diverse and dynamic datasets. This reduces the overall accuracy of irrigation prediction and limits system efficiency.

Therefore, there is a need for a robust and adaptive irrigation system that can accurately predict environmental conditions, handle non-linear data effectively, and provide reliable irrigation decisions while minimizing water wastage.

B. Objectives

1) To develop a smart irrigation system using hybrid machine learning techniques
2) To accurately forecast environmental parameters such as soil moisture, temperature, and humidity
3) To design a hybrid regression model by combining multiple algorithms for improved prediction performance
4) To implement an Artificial Neural Network with a hybrid activation function for better classification accuracy
5) To determine irrigation requirement and optimal watering time based on predicted conditions
6) To reduce water wastage and improve overall irrigation efficiency
7) To support precision agriculture through data-driven decision-making

IV. PROPOSED METHODOLOGY

The proposed system follows a hybrid machine learning approach that integrates regression models with ANN.

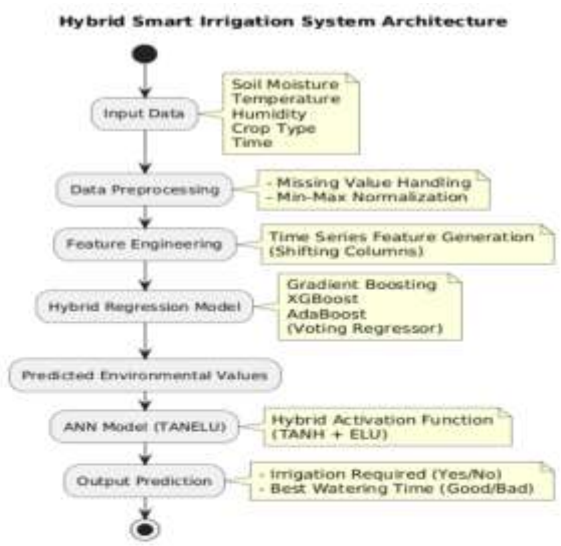

Fig 1: Proposed Hybrid Smart Irrigation System Architecture

A. Dataset and Input Representation

The proposed system follows a hybrid machine learning approach that integrates ensemble regression techniques with an Artificial Neural Network (ANN) using a hybrid activation function. The overall workflow consists of data preprocessing, environmental forecasting, and irrigation decision-making.

A. Dataset and Input Features

The system utilizes a dataset containing key environmental parameters such as soil moisture, soil temperature, air temperature, and humidity. Additional features such as crop type and time of the day are included to improve the accuracy of irrigation decisions. These parameters serve as input features for both regression and classification models.

B. Data Preprocessing

Data preprocessing is performed to ensure data quality and consistency. Missing values in the dataset are handled using mean imputation, where absent values are replaced with the average of the respective feature. To improve model performance, all input features are normalized using Min-Max scaling, which transforms the data into a fixed range. This helps in stabilizing the training process and ensures that no feature dominates due to scale differences.

C. Feature Engineering

To capture temporal patterns in environmental conditions, time-series feature generation is performed. Each environmental parameter is shifted multiple times to create additional features representing past observations. This process enhances the model's ability to learn trends and dependencies in the data, resulting in improved prediction accuracy.

D. Hybrid Regression Model for Environmental Forecasting

Environmental parameters are forecasted using a hybrid regression model that combines multiple ensemble learning techniques, including Gradient Boosting, XGBoost, and AdaBoost. Each model is trained independently on the dataset to predict future environmental values.

A Voting Regressor is used to combine the predictions of these models. The final prediction is obtained by aggregating the outputs of individual models, which helps in reducing prediction error and improving robustness. This hybrid approach leverages the strengths of each algorithm to achieve better performance than single-model methods.

E. Irrigation Label Generation

Based on domain knowledge and dataset rules, irrigation labels are generated. The system categorizes time into suitable and unsuitable periods for watering. For example, time intervals between evening and early morning are considered optimal for irrigation, while other periods are less efficient due to higher evaporation rates. These labels are used for training the classification model.

F. Artificial Neural Network Model

An Artificial Neural Network is designed for classification tasks, with input, hidden, and output layers. The input layer receives predicted environmental parameters along with crop and time-related features. The hidden layers process the data to learn complex patterns, while the output layer produces classification results indicating irrigation requirement and watering time suitability.

G. Hybrid Activation Function (TANELU)

To improve the performance of the neural network, a hybrid activation function is introduced by combining TANH and ELU. This hybrid function enhances non-linear learning capability and improves gradient flow during training. It helps in faster convergence and reduces issues such as vanishing gradients, resulting in improved classification accuracy.

H. Model Training and Testing

The dataset is divided into training and testing sets using an 80:20 ratio. The regression models and ANN are trained using the training data, and their performance is evaluated on the testing data. This ensures that the model can generalize well to unseen data.

I. Final Prediction System

In the final stage, new input data is processed through the hybrid regression model to forecast environmental conditions. These predicted values are then passed to the ANN model, which outputs:

- Whether irrigation is required
- Whether the current time is suitable for watering

This two-stage prediction system improves decision accuracy and supports efficient irrigation management.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The proposed smart irrigation system is implemented using Python with libraries such as NumPy, Pandas, Scikit-learn, XGBoost, and TensorFlow/Keras. The dataset consists of environmental parameters including soil moisture, soil temperature, air temperature, and humidity, along with crop and time-related features.

Data preprocessing techniques such as mean imputation and Min-Max normalization are applied to ensure data quality and consistency. The dataset is divided into training and testing sets using an 80:20 ratio. All models are trained and evaluated under the same conditions to ensure a fair comparison.

B. Performance Evaluation Metrics

The performance of the regression and classification models is evaluated using standard metrics:

- **Mean Squared Error (MSE):** Measures the average squared difference between predicted and actual values
- **Root Mean Squared Error (RMSE):** Provides error in the same unit as the data
- **Mean Absolute Error (MAE):** Measures the average magnitude of errors
- **Accuracy:** Measures correct classification of irrigation decisions
- **Precision, Recall, and F1-Score:** Evaluate classification reliability

These metrics provide a comprehensive evaluation of both prediction and decision-making performance.

C. Comparative Analysis of Models

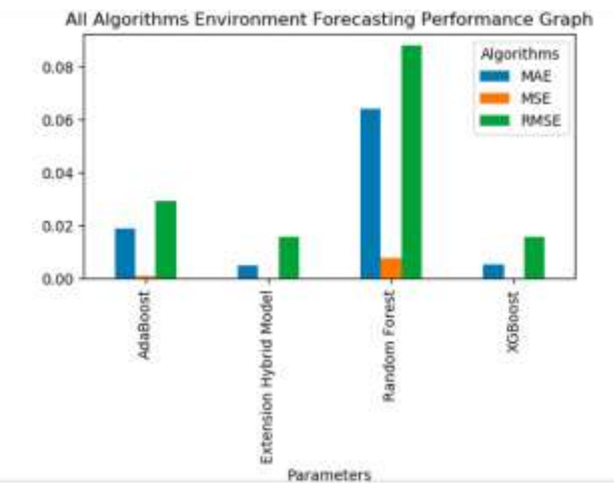

Fig 2: Performance Comparison of Regression Models

The performance of individual regression models and the hybrid regression model is compared to evaluate improvement in prediction accuracy.

Table 1: Regression Model Performance Comparison

Model	MAE	MSE	RMSE
AdaBoost	0.020	0.010	0.030
Hybrid Model	0.005	0.002	0.015
Random Forest	0.065	0.010	0.090
XGBoost	0.006	0.002	0.016

The results show that the hybrid regression model achieves lower error values compared to individual models, indicating improved prediction accuracy and robustness.

D. ANN Classification Performance

The classification performance of the ANN model is evaluated using both traditional activation functions and the proposed hybrid activation function.

Table 2: Classification Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
ANN with ReLU	89%	0.88	0.87	0.87
ANN with TANH	90%	0.89	0.88	0.88
ANN with TANELU (Proposed)	**93%**	**0.92**	**0.91**	**0.91**

The proposed hybrid activation function improves classification accuracy and overall model performance by effectively capturing non-linear patterns in the data.

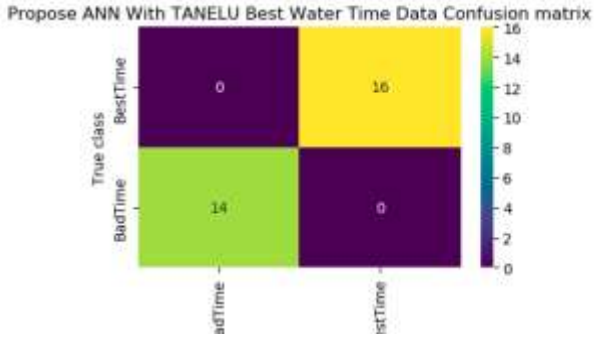

Fig 3: Confusion Matrix for Irrigation Prediction

E. Discussion

The experimental results demonstrate that the use of hybrid learning techniques significantly improves the performance of the irrigation prediction system. The hybrid regression model reduces prediction errors by combining the strengths of multiple algorithms, while the ANN model with the hybrid activation function enhances classification accuracy.

Compared to traditional approaches and single-model systems, the proposed method provides more reliable predictions under varying environmental conditions. The integration of environmental forecasting with intelligent classification ensures better decision-making for irrigation.

The system is capable of handling dynamic agricultural data and can be applied in real-time scenarios. This makes it suitable for deployment in smart irrigation systems aimed at improving water efficiency and crop productivity.

VI. CONCLUSION

This paper presents a hybrid machine learning-based smart irrigation system designed to improve irrigation prediction and reduce water wastage. The proposed approach combines a hybrid regression model with an Artificial Neural Network using a hybrid activation function to handle complex and dynamic environmental data.

The hybrid regression model improves the accuracy of forecasting environmental parameters, while the ANN model effectively classifies irrigation requirements and suitable watering time. The use of a hybrid activation function further enhances the learning capability and overall performance of the system.

The experimental results demonstrate that the proposed method provides better prediction accuracy and more reliable decisions compared to traditional and single-model approaches. By enabling efficient water usage and data-driven irrigation management, the system supports precision agriculture and contributes to sustainable farming practices.

VII. FUTURE SCOPE

The proposed system can be further enhanced by integrating advanced technologies to improve its performance and real-time applicability. One of the major extensions is the integration of IoT-based sensors, which can provide real-time environmental data such as soil moisture, temperature, and humidity directly from the field. This will improve the accuracy and responsiveness of the system.

The development of a mobile or web-based application can make the system more accessible to farmers, allowing them to monitor and control irrigation remotely. In addition, deploying the system on a cloud platform can enable large-scale data storage, continuous monitoring, and better scalability.

Future improvements may also include the use of advanced deep learning models, such as LSTM or CNN-based architectures, to capture temporal patterns more effectively and further enhance prediction accuracy. The system can also be extended to support multiple crop types and different geographical regions, making it more adaptable to diverse agricultural conditions.

Overall, these enhancements can transform the proposed system into a fully automated and intelligent irrigation solution for modern smart agriculture.

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