RESEARCH PAPER

A Hybrid AI-Based Framework for Irrigation Classification, Optimal Irrigation Time Prediction, and Water Resource Management

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ABSTRACT

Irrigation is essential in agriculture for world food production. However, this poses a problem because water is a finite resource and as the population grows, there is a bigger need for fresh water which can lead to water shortages if too much is used for irrigation. Conventional irrigation techniques often result in a large amount of water being wasted with low control of the distribution of resources. To address these difficulties, this article uses two datasets: one publicly shared irrigation dataset from GitHub and a synthetically created dataset based on basic features. The data were processed extensively in order to work with both LSTM and stacking classifier models; null values were removed, duplicate data were removed, feature augmentation was performed, and normalisation was performed using both MinMax Scaler and SMOTE with StandardScaler for LSTM and stacking classifier models in best-time classification.

ANN with activation functions TanELU, ReLU, Tanh and ELU were used to classify the images, as well as LSTM networks and stacking classifiers for irrigation and best-time classification, and RF, XGBoost, AdaBoost, stacking regressor and voting regressor for forecasting regression tasks. Evaluation metrics used for classification were accuracy, precision, recall, F1 score and training time, while for regression MSE, RMSE and MAE were used for the evaluation. The obtained results demonstrate the improvement of the stacking classifier in the best-time classification by 99.9%, in the irrigation classification by 99.6%, and an RMSE of 0.288 in forecasting regression. We demonstrated considerable increase in water-efficient agricultural irrigation management by utilising explainable artificial intelligence approaches (such as LIME and SHAP) to explain the value of features and a Flask-based user interface to enable real-time prediction based on user input.

Keywords: Smart Irrigation, Machine Learning, Artificial Neural Networks, Stacking Classifier, Forecasting Regression, Explainable AI

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I. INTRODUCTION

Agricultural irrigation is the key to global food security and productivity of crops in the face of increasing population pressure. The world population growth is estimated to be 9.8 billion people by 2050, which will result in a significant increase in the need for food production and agricultural resources [1]. This demand needs to be met by the effective utilization of the arable land and water resources. Water is also a vital input in agriculture, which directly affects crop growth, yield and quality [2]. However, in many locations, irrigation practices are still based on old approaches such as human monitoring and fixed scheduling which frequently lead to inefficient water use and excessive consumption [3].

Old irrigation systems may have structural and operational issues, including poor soil moisture management, a lack of flexibility in response to environmental changes, and other issues. Typically, such systems are based on open-loop systems that do not involve real-time monitoring or automatic decision making, causing high water losses and inefficient use of resource [4]. Climate change is an additional factor that makes these problems even worse, as the variations in precipitation, as well as the rise in temperature and the increase in rates of evaporation, pose a threat to the agricultural viability and water supply [5]. Modern irrigation technologies such as drip and sprinkler systems minimise water wastage but still require clever management strategies

for optimal water distribution and maintenance of suitable soil moisture levels [6].

The key goal of the project is to develop an intelligent and adaptive irrigation management system for efficient utilization of water for agricultural production. The proposed method combines field measurements of environmental and soil conditions with data-driven decision support tools for better management of irrigation scheduling and water allocation. The aim is to improve the accuracy of irrigation need predictions, to better utilize resources and to enable farmers to make better decisions for optimum crop management. The framework ensures greater confidence in irrigation decision making by taking into account the dynamic soil and environmental conditions, and promotes sustainable agriculture practices [7]. Flexibility and scalability are emphasized to adapt to the agricultural conditions and crop types [8]. The results are in accordance with food security [9, 10]..

II. LITERATURE REVIEW

Recent innovations in precision irrigation aim at the water-use efficiency through the use of sensor technology, data analytics and intelligent decision making. Water savings and yield improvements were significant under sustainable precision irrigation, which was demonstrated in this study using remote sensing and data-driven methods, as shown by Baruah et al. However, their methods are not widely applicable due to the general limitation of the methods when making a transition to other climatic and soil conditions [11]. The study by Gómez-Chabla et al. [12] offers a comprehensive assessment of IoT applications in agriculture, highlighting the benefits of sensor-driven monitoring and connectivity while also tackling the challenges of scalability, interoperability, and real-time decision-making.

Closed loop and auto-irrigation system has been examined to minimize the inefficiencies. Wang et al. suggested a closed loop IoT based irrigation system for sugarcane crop field which was crop and environment specific and controlled soil moisture well, but water wastage was reduced [13]. Mishra discussed the scarcity of fresh water all over the world and spoke about the agricultural sector being the biggest consumer of water and the need for adopting smart water management plans. There were no irrigation control systems in operation [14].

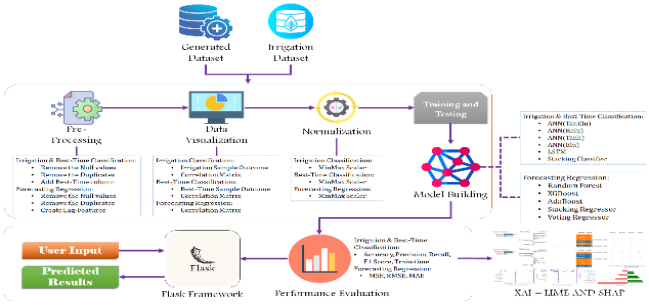
The use of data-driven intelligence has also greatly enhanced the management of irrigation systems. Abioye et al. evaluated the precision irrigation techniques using a ML approach and digital agriculture platforms, finding higher water use efficiency and yield gains, but limited transparency and adaptability to field variability [15]. Bhoi et al., suggested IoT based intelligent irrigation recommendation system employing predictive decision support. But it was inflexible in the face of dynamic settings due to its reliance on a fixed list of configurations [16].

Other studies have focused on hybrid IoT and learning frameworks. Vij et al. introduced an IoT-based smart irrigation farm automated system to minimize human labor, but didn't compare their model to datasets [17]. Raghuvanshi et al. [18] have explored the security in IoT for smart irrigation systems, but irrigation optimisation was not discussed.

Recent research has been in the realm of distributed intelligence, real-time analysis. Munir et al. presented a smart irrigation system with edge computing to enable low latency judgements, however the complexity of the infrastructure and the restricted comparative evaluation are still a worry [19]. Glória et al. suggested an irrigation system that can be implemented using real-time data from the sensors and intelligent analysis, which would lead to lower water consumption and more accurate monitoring but would still pose problems with the accuracy of decisions and the adaptability of the system [20]. These gaps motivate the current work on an intelligent irrigation architecture that is scalable, flexible, and reliable.

III. MATERIALS AND METHODS

To enhance irrigation efficiency, we propose a system that can predict the optimal irrigation schedule and environmental information based on two datasets: one is an open-source irrigation dataset available from GitHub, and the other is a synthetic irrigation dataset created from key irrigation parameters. The system is an organised process of data input, transformation, normalisation and segmentation of datasets to classify and predict. For irrigation and best-time classification, the advanced ML methods such as ANN with optimised activation function, LSTM-based network and Ensemble classifiers (Stacking) are introduced. The regression forecasting is done using RF, XGBoost, ADABoost, stacking and voting regressors to increase the prediction stability. Model generalisation is enhanced by class balance SMOTE and feature scaling with StandardScaler, and XAI techniques like LIME and SHAP offer insights into feature influence. An online user interaction and prediction delivery is provided by a Flask deployment framework.Real time user interaction and prediction delivery is supported by a Flask deployment framework. The system is designed to optimize the precision and efficiency of irrigation and decision making, making it sustainable and accurate.



"Fig. 1. Proposed Architecture"

The proposed system architecture illustrates the end-to-end irrigation data analytics system, including generated and real irrigation datasets. At the initial stages of the process some preprocessing is carried out such as noise reduction, missing value treatment, data normalisation and data visualisation. Different ML and DL techniques are used to train and test models for irrigation type classification and water requirement prediction. Performances are evaluated according to usual standard measures and a flask structure is designed to interact with a user and to visualize the results. LIME and SHAP are examples of explainable AI methods that enhance the interpretability and transparency of models.

A) Dataset Collection

The data used for irrigation in this work was obtained from a public available GitHub repository and comprises 3,589 samples with nine attributes. Besides the classification

of the irrigation requirement and the duration of irrigation, which are the classification labels, the dataset also contains numerical environmental and soil parameters like soil temperature, soil moisture, humidity, ambient temperature, crop type and temporal soil features. The data set contains the temporal features as well as multi-feature environmental variability that can serve as the basis for forecasting and can be a reliable aid in the development of water-saving and intelligent irrigation management systems.

	Time	crop type	soil temperature	soil moisture	Humidity	Temperature	Irrigation	Hour	Best Time
0	2025-01-01 00:00:00	1	15.760437	19.270443	55.608559	27.045541	1	0	0
1	2025-01-01 01:00:00	2	29.924145	19.103156	47.245352	32.799676	1	1	0
2	2025-01-01 02:00:00	1	28.180711	35.643144	40.935005	35.254287	1	2	0
3	2025-01-01 03:00:00	1	31.042611	52.239879	75.099950	32.671066	1	3	0
4	2025-01-01 04:00:00	1	17.107351	13.980254	71.950914	37.797349	1	4	0

"Fig.2 Load the Irrigation dataset"

This study relies on a publicly available irrigation dataset from the GitHub repository, and the data has 3,589 observations and nine features. It includes numerical data of the environment and soil like soil temperature, soil moisture, humidity, ambient temperature, crop type etc. and time based information of the day in hours, and the target information of irrigation need and optimal irrigation time. The data captured is multi-parameter environmental variability and time-dependent features that can be used for model predictions, and can be used to design intelligent, data-driven and water-efficient irrigation management solutions.

	Time	crop type	soil temperature	soil moisture	Humidity	Temperature	Irrigation	Hour	Best Time
0	2025-01-01 00:00:00	1	15.760437	19.270443	55.608559	27.045541	1	0	0
1	2025-01-01 01:00:00	2	29.924145	19.103156	47.245352	32.799676	1	1	0
2	2025-01-01 02:00:00	1	28.180711	35.643144	40.935005	35.254287	1	2	0
3	2025-01-01 03:00:00	1	31.042611	52.239879	75.099950	32.671066	1	3	0
4	2025-01-01 04:00:00	1	17.107351	13.980254	71.950914	37.797349	1	4	0

"Fig.3 Load the Generated dataset"

B) Pre-Processing

The preprocessing step intends to ready the real and synthetic irrigation datasets to guarantee the data reliability and modelling efficiency. The noisiness and inconsistencies are first eliminated by discarding the missing data and the duplicate records. A derived Best-Time attribute is generated to complement the information relevant to making a decision for irrigation and best-time classification-related tasks. In an effort to capture temporal dependencies and trends for forecasting regression, lag-based features are created. These pre-processing techniques help to ensure the consistency of the data, enhance feature representation and support accurate classification and prediction in all irrigation related learning tasks.

C) Data Visualization:

It provides visualization of data stage to provide analytical understanding of real and synthetic irrigation datasets for decision making on modeling. We show the distribution of classes in the irrigation and best-time prediction problems as examples, and discuss patterns and potential class imbalance. Correlation matrices are built for each categorisation and each forecasting scenarios to investigate the relationships and the dependencies among features. These visual analyses can help in understanding the data structure, evaluating the significance of features, and determining the factors that have a significant impact on the model, thus enhancing the interpretability, reliability, and predictive accuracy of the model.

D) Normalization:

We normalise irrigation and synthetic datasets for irrigation classification, best-time classification and forecasting regression tasks to have consistent feature scaling. To avoid that features with larger magnitudes would dominate the learning process, all the numerical attributes are scaled by using the Min–Max scaling strategy to have a similar range. This phase brings a numerical stability, accelerates the convergence of the model, and facilitates comparative learning from feature to feature. Normalization of the normalized uniform helps to train the model fairly, to develop a better generalisation ability and to obtain more reliable classification and regression results.

C) Training and Testing:

The model is trained and tested using both synthetic and real datasets, to assess its performance and generalisation capability. The preprocessed and normalised data is divided into a training set and a testing set to ensure a fair testing. The model is trained using the data in the training set to learn the pattern, and then the accuracy is confirmed on the data in the testing set by the model. This separation helps to prevent information leakage, to evaluate the performance of the system reliably, and to guarantee robustness of classification and forecasting models in real-life situations.

D) Algorithms

Classification Models:

ANN with TanELU Activation: ANN are enhanced by TanELU activation functions, which combine the limitedness and unboundedness of activation functions, enabling learning of non-linear representations. This hybrid behaviour can result in an optimized gradient flow, in a more stable convergence, and in a higher degree of generalization of the model, which will lead to reliable classification performance in complex and highly variant input pattern.

ANN with ReLU Activation: ANN with ReLU activation function are more efficient in computation and can train faster and overcome the vanishing gradient problem. This piecewise activation enables sparse activation of neurones thus enabling efficient hierarchical feature extraction, scalable classification performance on high dimensional and nonlinear data distribution.

ANN with Tanh Activation: ANN with tanh activation offers symmetric output distribution which allows for balanced propagation of gradients and constant learning. The activation makes the model sensitive to different features, and helps relating differently shaped patterns to each other in a precise, nonlinear fashion, resulting in stable classification performance and improved stability of the model.

ANN with ELU Activation: ANN with ELU activation mechanism offers controlled negative outputs, thus stabilising the training process by reducing the shift of the bias in the activations of the neurones. The activation enhances the gradient flow and speeds up the convergence, which helps to learn from complex nonlinear relationships robustly and enhances the reliability of classification under different data scenarios.

Long Short-Term Memory (LSTM): LSTMs have memory cells and gates that selectively remember past information, introducing temporal dependencies. This is an advantage in being able to learn from sequences, and improves the consistency of predictions, the capacity to see patterns over long sequences, and the accuracy of classification in situations where input is temporally dependent and dynamically changing.

Stacking Classifier: The stacking classifier is a combination of a set of heterogeneous base models with a meta-learner that learns to combine the separate predictions into a final prediction. The ensemble approach benefits from the complementary of the models, reduces variance, expands generalisation and enhances overall classification accuracy and the reliability of decision making.

Forecasting Regression Models:

Random Forest Regressor: RF regression is a kind of bagging technique of the decision trees in which the feature selection and data sampling are performed randomly. Combining the predictions of different trees increases robustness, decreases overfitting and allows for good modelling of nonlinear interactions, resulting in consistent and dependable forecast performance.

XGBoost Regressor: XGBoost regression is based on iterative boosting, which attempts to make more accurate predictions in each iteration and reduces the residual error. The learning framework it proposes are regularised, have higher prediction accuracy, efficiently represent the interaction among features, and have superior generalisation ability, so that it can work well in complex forecasting scenarios.

ADABoost Regressor: ADABoost regression is an adaptive-weighted combination of weak learners, giving more weight to instances that make more mistakes in the predictions. An iterative refinement that makes the detection of hard patterns more sensitive, reduces bias, and enhances the overall quality of forecasts and forecast robustness in data context scenarios where patterns are heterogeneous.

Stacking Regressor: Stacking regressor is a model which mixes the outcome of various regression models and uses them to train a meta-learner which learns how to combine the predictions in the best possible manner. The layered ensemble approach captures the diversity of data patterns, minimises limits of individual models, and improves the predictive accuracy and the generalisation ability of complex regression tasks.

Voting Regressor: Voting regressor uses a set of regression models and combines the prediction results using averaging methods. This ensemble approach leads to diversity of models, minimises variance, smoothens prediction fluctuations and increases stability and reliability in forecasting dynamic environmental parameters.

IV. Experimental Results

Accuracy: The ability of the test to correctly distinguish patients from healthy people. We should calculate the proportion of true positive and true negative in all the cases analysed to measure the accuracy of a test. Mathematically this can be represented as:

$$"Accuracy = \frac{TP + TN}{TP + FP + TN + FN} (1)"$$

Precision: (Percentage of accurately identified instances or samples that are identified as positive out of total number of instances or samples identified as positive). Thus, the formula to calculate the precision is:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)"$$

Recall: Recall in ML is a measure of a model's ability to identify all the examples belonging to a certain class. It is the percentage correctly predicted positive observations divided by the number of actual positive observations, giving some indication of the comprehensiveness of a model in capturing observations from a particular class.

$$"Recall = \frac{TP}{TP + FN} (3)"$$

F1-Score: F1 score is one of the statistics used in ML for assessing the correct behavior of a model. Combines Precision and Recall of a model. The only thing accuracy metric is – is the number of times the model predicted the whole data set correctly.

$$"F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100(1)"$$

MSE: A measure of error of statistical models. It is the mean of the squares of the differences between the measured and the expected values. If a model is absolutely correct, the MSE will be equal to 0. The more the model error, the higher its value. Mean squared error is sometimes referred to as mean squared deviation (MSD).

$$"MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \quad (5)"$$

RMSE: The average of the squares of the differences between the values forecasted by the statistical model and the actual values. It is numerically the standard deviation of the residuals. The distances between the points of data and the regression line are called residuals.

$$"RMSE = \sqrt{\frac{\sum_{i=1}^{n} ||y(i) - \hat{y}(i)||^2}{N}} \quad (6)"$$

MAE: he amount of error that your measurements have. This is the discrepancy between the measured value and the "actual" value. For example if a scale reads 90 pounds but you know that you weigh 89 pounds then the scale has an absolute inaccuracy of 90 lbs - 89 lbs = 1 lbs.

$$"MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (7)"$$

"Table. 1. Performance Evaluation Table – Best-Time Classification"

ML Model	Accuracy	Precision	Recall	F1-Score
ANN (TanELU)	0.681	0.472	0.681	0.557
ANN (ReLU)	0.688	0.473	0.688	0.561
ANN (Tanh)	0.678	0.506	0.678	0.559
ANN (ELU)	0.685	0.577	0.685	0.565
LSTM (ReLU)	0.997	0.997	0.997	0.997
Extension Stacking	0.999	0.999	0.999	0.999

A comparative performance evaluation is shown in Table 1 . Extension Stacking and Extension LSTM achieved almost optimal results in terms of accuracy, precision, recall and F1-scores in comparison with ANN models. Extension Stacking is also quicker to train.

"Table.2 Performance Evaluation Table – Irrigation Classification"

ML Model	Accuracy	Precision	Recall	F1-Score
ANN (TanELU)	0.965	0.965	0.965	0.965
ANN (ReLU)	0.979	0.979	0.979	0.979
ANN (Tanh)	0.953	0.953	0.953	0.953
ANN (ELU)	0.969	0.970	0.969	0.969
LSTM (ReLU)	0.971	0.971	0.971	0.971
Extension Stacking	0.996	0.996	0.996	0.996

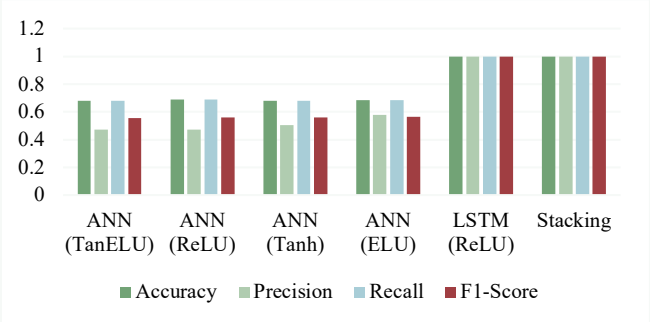
The model performances are summarized in 2, showing that Extension Stacking is the most superior model with the highest accuracy, F1-score and the lowest training time followed by ANN and Extension LSTM.

"Table.3 Performance Evaluation Table – Irrigation Classification"

ML Model	MSE	RMSE	MAE
RandomForest	0.09114	0.30174	0.25741
XGBoost	0.08419	0.29012	0.25032
ADA	0.12751	0.34423	0.29237
Stacking	0.08305	0.28816	0.24922
Extension Voting	0.08316	0.28834	0.24934

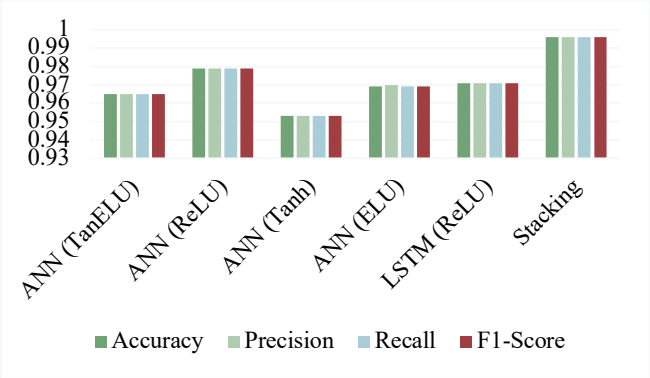
The summary of regression performance is shown in Table 3. The prediction accuracy of Extension Stacking and Extension Voting is better than random forest, XGBoost and AdaBoost with the lowest values of MSE, RMSE and MAE.

"Fig. 4. Comparison Graph - Best-Time Classification"



It can be seen from the Graph.1 that the accuracy, precision, recall and F1-score of ANN variants and extension models are good, but ANN variants have much less training time.

"Fig 5. Comparison Graph – Irrigation Classification"

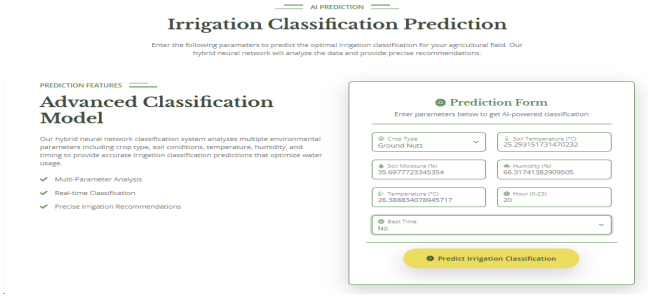


The accuracy, precision, recall, F1-score, and training time are the same but the computing costs are different in ANN activation functions and extension models as shown in Graph.2.

"Fig 6. Comparison Graph – Forecasting Regression"



Compare the performance of RandomForest, XGBoost, ADA, Extension Stacking and Extension Voting with the first two measures MSE and RMSE, along with MAE. It can be shown that the ensemble extension model's error performance is more stable and balanced.



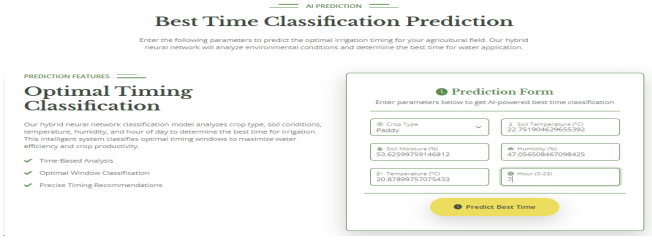
"Fig.7 Enter the input data"

It shows a user interface for irrigation classification prediction, with fields to enter the crop type, soil moisture, soil temperature, soil humidity, and growth stage, and a field to display the predictions of irrigation recommendations based on an advanced classification model.



"Fig.8 Predicted Result"

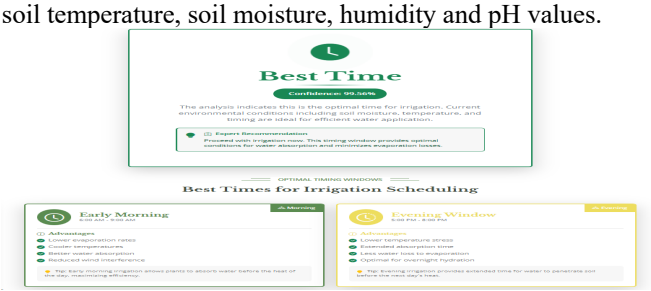
The model gives a confidence of 91.7% in predicting No Irrigation, meaning that climatic and soil moisture conditions are adequate to achieve crop development. It suggests to monitor the moisture content and advise appropriate crops according to the present field circumstances.



"Fig. 9 Enter the input data"

An AI-based best time classification input form is displayed in the interface which allows users to quickly

anticipate the optimal irrigation timing by entering crop type, soil temperature, soil moisture, humidity and pH values.



"Fig. 10 Predicted Result"

The algorithm forecasts the optimum time of irrigation with 99.56% certainty. The system recommends irrigation during favourable environmental factors like early morning or evening which ensures effective water absorption, less evaporation and better crop growth.

V. Conclusion

In conclusion, the proposed approach addresses one of the pressing challenges of this day and age: how to use water efficiently in agricultural irrigation so as to meet the ever-growing demand for food without depleting the limited freshwater resources. A publicly available irrigation dataset from GitHub and a synthetically created dataset on the base irrigation features are included in the methodology. The best time classification model was trained with SMOTE and StandardScaler, while the other classification models were preprocessed with a full pipeline that included the removal of null values, duplicate values, feature augmentation, and normalisation with a MinMax Scaler. The ML algorithms used are ANN with activation functions: tanelu, relu, tanh, elu, and lstm networks, as well as stacking classifiers and RF, xgboost, adaboost, stacking regressor and voting regressor for irrigation classification, best time classification and regression forecasting, respectively. Further, uses of XAI techniques like LIME and SHAP and a flask-based interface for real-time user input and prediction further advances the system. It is concluded that stacking classifier is outperforming other classifiers in terms of best time and irrigation classification with 99.9% and 99.6% accuracy respectively, and it also has a better RMSE for regression prediction of 0.288. In conclusion, the proposed system offers an effective, intelligible and efficient model for automated, data-driven water irrigation management decisions in agriculture.

The future goal of this system is to introduce other environmental and crop specific factors for a more accurate prediction of irrigation schedule. The generalisation of diverse agricultural regions can be studied with advanced hybrid models which include DL and ensemble techniques. By integrating sensors into IoT devices, real-time control of irrigation systems can be possible, reducing manual effort and water waste. There could be cloud-based deployment and mobile application interfaces to improve the accessibility and scalability for farmers. Moreover, advanced Explainable AI models could be used to delve deeper into feature interdependencies, assisting in making informed decisions and sustainable water management practices to optimize agricultural production and resource usage.

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