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Predictive and Explainable Machine Learning Framework for Sustainable Irrigation and Crop Water Optimization

B. Ravinder Reddy[1], Parvath Vaishnavi[2], G Charanya[3] and Bandari Bharath Chandra[4]
[1]Associate Professor, Department of Information Technology, SNIST Hyderabad, Telangana, India
Email: ravinder.b@sreenidhi.edu.in
[2-4]Student, Department of Information Technology, SNIST Hyderabad, Telangana, India
Email: 22311a12e2@it.sreenidhi.edu.in, 22311a12k1@it.sreenidhi.edu.in, 22311a12d7@it.sreenidhi.edu.in

Abstract*— Agricultural irrigation is critical in maintaining food production in the global arena yet excessive use of water is a huge challenge due to population pressures and scarce water resources. Conventional irrigation methods are usually very wasteful of water and they do not provide you with the precision in the utilization of the resources. In this document, two datasets are utilized, in order to address these problems: a free irrigation dataset on GitHub and a dataset which was created out of the base features. The datasets were highly preprocessed with many operations being done to them which included removing null values, duplicates, adding more features, normalization by MinMax Scaler, and the use of SMOTe with StandardScaler in both the LSTM and stacking classifier models in best-time classification. The tasks of classification such as irrigation and best-time classification were performed using ANN with TanELU, ReLU, Tanh, and ELU activation functions, LSTM networks, and stacking classifiers. Forecasting regression tasks were done using random forest, XGBoost, ADABoost, stacking regressor, and voting regressor. Accuracy, precision, recall, F1-score and training time were used as metrics to classify. Measures to be used in regression were MSE, RMSE and MAE. Stacking classifier performed better than the other two and obtained 99.9% best time classification, 99.6% irrigation classification and 0.288 RMSE predicting regression. The most important features were demonstrated by explainable AI methods, including LIME and SHAP. Real-time input-based prediction became possible with a Flask-based user interface, which demonstrated a tremendous difference in controlling less-water-intensive agricultural irrigation.

***Keywords*— Smart Irrigation, Machine Learning, Artificial Neural Networks, Stacking Classifier, Forecasting Regression, Explainable AI".**

I. Introduction

Agricultural irrigation is one of the major components of ensuring the food is sufficient to all and the production of crops high despite the increasing population. The population of the world is projected to reach nearly 9.8 billion individuals by the year 2050, a fact that will cause a colossal impact on the production of food and agricultural resources [1]. In a bid to fulfill this demand, arable land and water are likely to be used efficiently. Water plays a significant role in agriculture since it influences food production, productivity, and quality [2].

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However, irrigation in most areas is still conducted in the traditional manner, whereby there are various manual watch and set schedules, and this usually results in wastage and unnecessary consumption of water [3].
The conventional irrigation systems have issues with their design and mechanism such as the inability to regulate the quantity of water in the land well and inability to respond to environmental variations. In the vast majority of scenarios, these systems have an open-loop connection and, therefore, they lack real-time monitoring and automatic decision making. This implies that they waste a lot of water and are inefficient in their resources [4]. These issues are compounded by climatic change which alters the liquidity patterns, increases the temperature and accelerates the evaporation pace endangering the agriculture sustainability and availability of water [5]. The new irrigation methods such as sprinklers and drip irrigation systems use less water, although it still requires intelligent methods to ensure the water is distributed uniformly and the soil retains the appropriate size of moisture [6].
The primary objective of the research is to develop an intelligent and adaptable solution to the irrigation control that utilizes water more efficiently and produces higher harvests. The proposed system integrates real-time data on the environment and the land and data-driven tools to enable individuals make more effective decisions on when to water crops and what quantity of water to apply. It aims at achieving more accurate predictions of the amount of watering a crop will require, better utilization of resources and useful information to the farmer to manage crops well. The framework has enhanced reliability in the irrigation decisions because it relies on changing factors of the soil and environment, and it also promotes the environmentally friendly farming methods [7]. Flexibility and scalability are emphasised to ensure that it can be employed in various farming conditions and in various crops types [8]. The findings assist in ensuring that there is sufficient food [9, 10].

II. Literature Review

The latest trends in accurate irrigation are aimed at utilizing water in a better way with the help of sensing technologies, data analytics, and smart decision-making. Baruah et al. discussed the importance of remote sensing and data based techniques in sustainable precision irrigation. They discovered that these techniques conserved much water and yielded higher crop production although they are not simple to apply in large scale due to the fact that they should be able to adjust to various soil and climate conditions [11]. In their systematic study of the applications of IoT in agriculture, Gomez-Chabla et al. conducted this study [12]. They demonstrated that sensor-based monitoring and connectivity are effective, however, they also revealed issues with scalability, interoperability and real-time decision support [12].
Closed-loop and automated ways of irrigation have been considered in order to reduce wastage. Wang et al. developed a closed-loop watering system based on the IoT of sugarcane farms. This system enhanced better control of soil moisture and led into a reduction of water wastage, though it was specific to crops and environment [13]. Mishra discussed the shortage of freshwater in the world. He indicated that agriculture was the largest consumer, and he emphasized the necessity of intelligent water management approaches, yet he did not refer to the working methods of irrigation control [14].
Data-driven intelligence has enhanced the irrigation systems. Abioye et al. investigated the area of precision irrigation solutions that integrated ML and digital agriculture platforms. They discovered that these solutions enhanced the crop performance and water savings, they also discovered that these solutions were not so transparent and rigid to accommodate the changing field conditions [15]. Bhoi et al proposed an IoT-based intelligent irrigation recommendation system which would assist in making the decisions based on the forecasts but it would be less adjustable in the new environment since it would rely on the set up configurations [16].
Integrations that comprise both IoT and learning are also investigated. Vij et al. designed an automated system of irrigation in farms which utilized IoT technology and intelligent decisions to reduce the human input [17]. There was however not a robustness review across datasets in the system. Raghuvanshi et al. researched on security with IoT-enabled smart irrigation through intrusion detection based on ML, but did not investigate the method to enhance watering efficiency [18].
Emerging research subjects include distributed intelligence and real-time data. Munir et al. proposed a smart irrigation system involving edge computing as an idea that would enable rapid decision-making, although the concern is how complex the infrastructure would be and whether there would be comparative analysis [19]. Gloria et al. introduced sustainable irrigation system based on real-time sensor data and smart analytics. This framework minimized the water consumption and enhanced the precision of monitoring, however there are issues regarding the efficiency of the decision-making and the ability to respond efficiently to it [20]. It is these holes that resulted in this research: the creation of an intelligent watering system which is scalable, flexible, and reliable.

III. Materials and Methods

The proposed system is based on the fact that, with two datasets, including a publicly available irrigation dataset created on Github and a synthetically generated dataset, which is built on core irrigation attributes, it is possible to make the process of agricultural irrigation more water efficient by predicting the optimal irrigation patterns and environmental conditions. The framework contains an ordered procedure which involves loading the data, transforming it, normalizing it, and splitting the data into portions to be used in activities such as classification and prediction. Some of the advanced ML methods used are ANN with optimized activation functions, LSTM networks and ensemble-based stacking classifiers to irrigation and best-time classification. Regression forecasting makes use of random forest, XGBoost, ADABoost, stacking, and voting regressors to render the predictions more stable. Model generalization is improved with the use of class balancing based on SMOTE and feature scaling based on StandardScaler. In the meantime, explainable AI techniques such as LIME and SHAP offer feature influence analysis which can be comprehended. An interface-based deployment system allows users to interact and obtain predictions in real time. The technique is intended to enhance the precision of predictions, the speed of the calculations, the easiness of comprehending the information, and credibility of the decisions. This will aid in the long run and proper irrigation control.

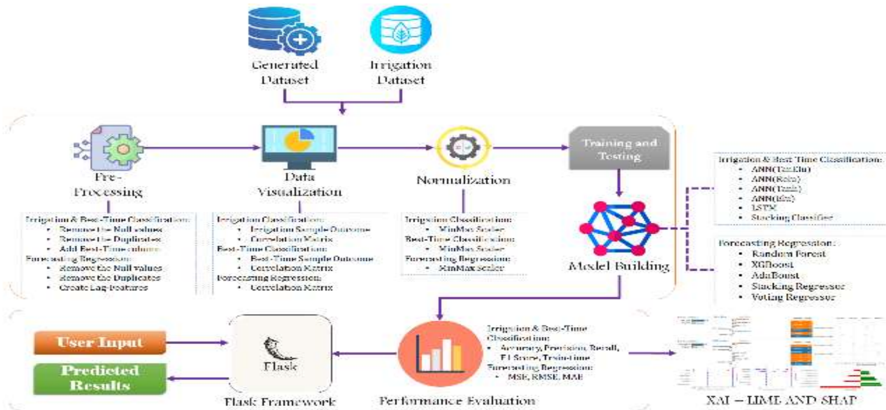

Fig. 1. Proposed Architecture

The proposed system design contains a structure of the irrigation data analysis during the start to finish, both fake and real data. It begins with such steps as the elimination of noise, handling of missing numbers, normalization, and data visualization. There are a number of machine learning and DL models intended to be trained and tested to classify the types of irrigation, and determine the amount of water they will require. Performance is measured by standard metrics and a Flask system allows a user to interact with the system and view the results. Models made easier to interpret and decisions more transparent using AI methods that can be explained like LIME and SHAP.

A. Dataset Collection

The data sample of this study is on irrigation. It is sourced out of a community GitHub repository and includes 3, 589 samples and nine characteristics. The dataset consists of both numeric information regarding the climate and the soil such as soil temperature, soil moisture, humidity, ambient temperature, type of crop, and time-related factors and some labels indicating what type of irrigation is required and when. The data set comprises of the temporal features as well as multi-feature environmental variability. This renders it handy in predictive modeling and it assists the developers in creating intelligent irrigation control systems that consume less water.

	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

The irrigation data employed in this paper would be provided in a GitHub repository that can be viewed by anybody. It contains 3,589 records bearing nine attributes. It contains figures concerning the weather and the soil such as the temperature, moisture and humidity of the soil, the ambient temperature, the nature of crop and time in hours. It also contains labels that indicate the extent to which irrigation should be done and at what time. The data set consists of transformation of various environmental factors and characteristics which evolve with time. This would be beneficial in predictive modeling and to assist in developing smart, data-oriented, 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

During the planning phase, real and artificial irrigation data is also ready to ensure that the data is correct and that the modeling is performing well. Initially, noise and errors are removed by removing missing numbers and records. Derived Best-Time attribute is incorporated into such jobs as best-time classification and irrigation so that the information helpful in decision making can be improved. In regression prediction, lag features are presented to indicate the change in things over time and patterns in development. All these steps prior to processing the data make it more consistent, reflect features better, and contribute to sorting and guessing errors in all learning activities associated with irrigation.

C. Data Visualization

In the data visualization step, real and artificial irrigation datasets are examined in order to make intelligent modeling decisions. The sample outcome visualizations indicate the distribution of the classes in terms of the tasks such as irrigation and best-time prediction and highlight trends and potential imbalances. All the classification and forecasting cases are correlated to create correlation matrices, in which the relationship and dependence between features may be examined. Such visual analyses can be useful to know the structure of the data better, to help you assess the relevance of features as well as help you locate important factors. It simplifies this model, makes it more credible, and more overall predictive.

D. Normalization

Normalization of the real and fake data is applied in tasks such as irrigation classification, best-time classification and forecasting regression to ensure that the scaling of the features is identical. With the help of a MinMax scaling technique, all numerical features are transformed to a common range. This prevents features of larger values to dominate the learning process. The step stabilizes the numbers by making the models converge a lot faster and also, comparing learning between features becomes easier. Regular normalization is useful in ensuring that training models are fair, they are more inclined to generalize, and their outcomes are more reliable in classification and regression.

E. Training and Testing

In testing and training the model, the performance and generalization capability of the model is tested on both real and fake data sets. Splitting the preprocessed and normalized data into training and testing groups is done to ensure that the evaluation is fair. The training data is used to train models that underlie patterns and the testing data is used to test the extent to which the models are able to make predictions about samples they have not seen yet. Such a separation ensures that information does not leak out, performance can be accurately measured and that classification and predicting models are practical in the real world.

F. Algorithms

Classification Models

ANN with TanELU Activation: With bound and unbound activation characteristics, TanELU activation ANN enhance the learning of nonlinear representations. This composite action allows gradient flow to be enhanced, and it aids to maintain a stable convergence and enhance generalization of a model. It is thus possible to have reliable performance of classification in input patterns that are highly variable and complicated.

ANN with ReLU Activation: ANN with ReLU activity are more efficient in calculating and train faster by avoiding disappearing gradient issues. The piecewise linear activation promotes sparse responses of neurons and therefore is able to detect hierarchical features and enhance the classification performance with high-dimensional and nonlinear datasets.

ANN with Tanh Activation: Symmetric distribution of outputs produced by ANN because of tanh activation facilitates gradient transmission and stable learning. The activation increases sensitivity of the model to minor variation in features and also aids in nonlinear mapping of patterns. This results in improved model stability and stable classification.
ANN with ELU Activation: The ELU-activated ANNs reduce the stability of the training process and allow controlled negative responses to occur reducing changes in bias in neuron activations. The gradient flow is enhanced and convergence accelerated. This facilitates the system to learn nonlinear relationships in a better and faster way even when the information is modified.
Long Short-Term Memory (LSTM): LSTM networks also store the time relationships with the memory cells and gating systems, which retain only the most significant historical data. With this sequential learning, the prediction is more accurate, it can detect long distance patterns and enhance the accuracy of classification in data environments that evolve with time.
Stacking Classifier: The stacking classifier is a mixture of various base models which compiles a meta-learning framework which unites all the predictions into one output. This ensemble strategy takes the best of the models that are well-integrated to reduce variance, increase generalization and produce more precise classifications and decision-making globally.

Regression Prognostic Model
Forecasting Regression Models
Random Forest Regressor: RF regression involves the use of numerous decision trees which are constructed randomly by selecting features and assembling data. Combining predictions with other trees of the system increases its strength and reduces the overfitting and enables the nonlinear associations of the model and hence constant and accurate forecasting.
XGBoost Regressor: XGBoost regression trains more accurate predictions by iteratively boosting its previous predictions by correcting the remaining errors. Due to its regularized learning structure, it is more accurate in predictions, more accurate in capturing interactions between features and more successful in generalizing, and has been very successful in challenging forecasting condition.
ADABoost Regressor: ADABoost regression is an effective method to combine weak learners with more weight to the instances having larger prediction errors in the course of training. This slowing down of the improvement process makes the model more receptive to challenging patterns, reduces bias, and the model is more precise and consistent in environments having varied kinds of data.
Stacking Regressor: The stacking regressor relies on a meta-learner to determine how the outcomes of different regressions models should be combined. This stratified ensemble approach identifies various patterns of data, reduces weakness of each model and enhances the precision and extrapolation properties of results in challenging regressions.
Voting Regressor: The voting regressor involves averaging techniques that are employed in aggregateing the forecast of various regression models to obtain the final results. This group method balances the various types of models, reduces the variance, flattens fluctuations in predictions, and the prediction of fluctuations to dynamic environmental factors is easier.

IV. Experimental Results

Accuracy: The extent to which a test can discriminate between a sick and a healthy person is referred to as its accuracy. In order to have an idea of the accuracy of a test, we should determine the percentage of true positives and true negatives. In math terms this can be expressed as.

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

Precision: Precision refers to the proportion of the accurately diagnosed cases or samples with reference to the accuracy of the diagnosis as positives. Thus, here is the way to compute the accuracy:

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

Recall: In ML, recall is a measure of a model which indicates its ability to find all the significant instances of a particular class. It reveals the level of modeling that a model captures the instances of a given class. It is calculated as the number of correct positive predictions/the number of actual positives.

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

F1-Score: It is possible to measure ML model accuracy by the F1 score. It sums up the accuracy and recall scores of a model. The measure of accuracy is the number of times that a model in the entire dataset gave the correct guess.

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

MSE: MSE is a method of determining the inaccuracy of statistical models. It examines the formulated mean squared deviation between observed and supposed. When no error in the model is made, the MSE is equal to zero. The increase in its value is proportional to the increase in model mistake. The mean squared error is also written MSD in order to spell it out.

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

RMSE: RMSE is one method of determining the average difference between what a statistical model would have predicted would have occurred and what actually occurred. It is the standard deviation of the residues with math terminology. The residuals indicate the distance between a regression line and the points of the data.

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

MAE: Absolute Error is the error that is there in measuring something. It is the discrepancy between what was documented and what was the truth.
I will give you an example, where the scale shows the weight to be 90 pounds yet you know that you actually weigh 89 pounds, then the scale is 1 pound off.

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

TABLE I. 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

The results of the comparison of the performance results presented in Table 1 indicate that the Extension Stacking and Extension LSTM models perform better than ANN models in accuracy, precision, memory, and F1-scores, and the Extension Stacking is more efficient and faster to train.

TABLE II: 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 summary of the model performance is provided in Table 2, where it can be seen that Extension Stacking performed the most and has the highest accuracy and F1-score and the shortest training time. ANN and Extension LSTM, however, achieve comparable results but not as good ones.

TABLE III: 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

Table 3 indicates the effectiveness of various regression. Extension Stacking and Extension Voting possess the least MSE, RMSE and MAE and predicts more accurately than the Random Forest, XGBoost and AdaBoost.

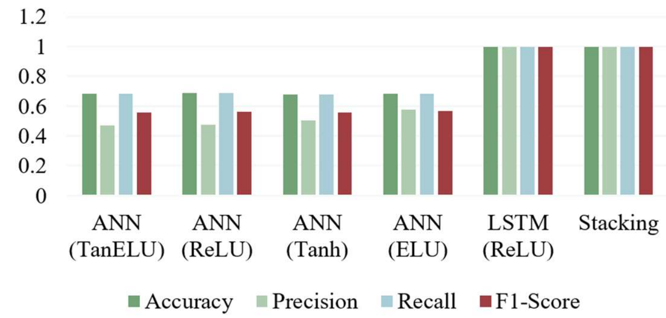

Fig. 4. Comparison Graph - Best-Time Classification

Graph.1 compares accuracy, precision, recall, F1-score and training time of ANN versions and extension models. It demonstrates that Extension LSTM performs well, but requires many times greater training.

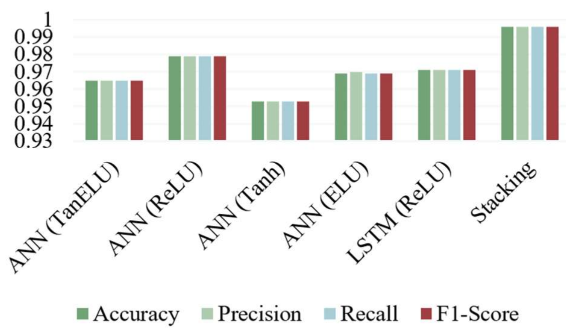

Fig 5. Comparison Graph – Irrigation Classification

In Graph.2, accuracy, precision, recall, F1-score, and time for training these ANN activation functions and extension models are used to compare. The results show that both types of models work similarly, but at different computational costs.

Fig 6. Comparison Graph – Forecasting Regression

Graph.3 compares RF, XGBoost, ADA, Extension Stacking and Extension Voting with the measures of MSE, RMSE and MAE. ensemble extension models have shown more stable and balanced performances in terms of errors.

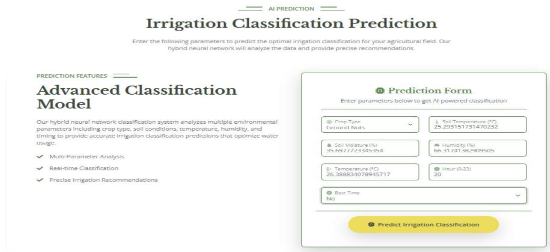

Fig.7 Enter the input data

The image depicts an irrigation classification prediction interface where users enter information on crop type, soil moisture, temperature, humidity and growth stage to get real-time irrigation recommendations by the use of an advanced classification model.

Fig.8 Predicted Result

The system predicts No Irrigation with a confidence level of 91.7% which means the current environmental and soil moisture conditions are sufficient for crop growth. It suggests monitoring the moisture level while suggesting appropriate crops depending on current conditions in the field.

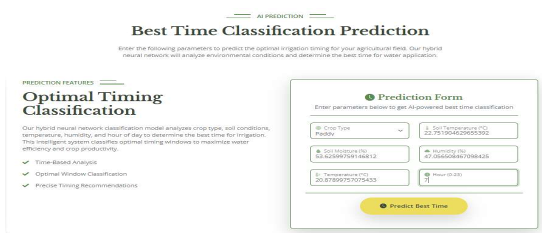

Fig. 9 Enter the input data

The interface displays an AI-based best time classification input form where the users can enter the type of crop, the temperature, the wetness, the humidity, and the PH of the soil in order to quickly find the best time to water it.

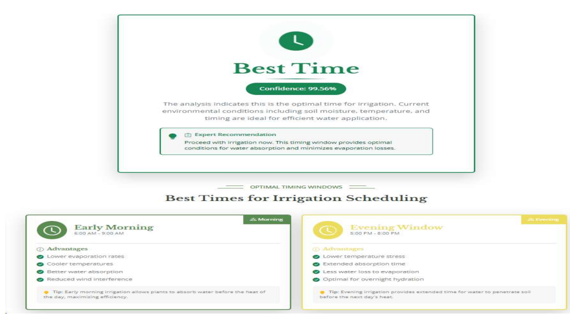

Fig. 10 Predicted Result

With 99.56% accuracy, the system lets you know when the best time to water your plants is, whether it is early in the morning or late at night, where the weather is at its best. This way the plants will be able to absorb water better, they will lose less and grow bigger.

V. Conclusion

In conclusion, the proposed method addresses an important problem, namely, how to best use water in agricultural irrigation to meet the world's growing food needs, while protecting limited freshwater supplies. The method uses two datasets: one irrigation dataset, which is open to the public on Github and a dataset that was made up from base irrigation features. A lot of preprocessing steps were used such as removing null values and duplicates by adding more features and normalizing the data using MinMax Scaler. Especially, SMote and StandardScaler were used for LSTMs and stacking classifiers models in best-time classification. ANN using TanELU, ReLU, Tanh and ELU activation function and LSTM network and stacking classifiers for irrigation and Best Time classification. For the purpose of forecasting regression task following algorithms were used: RF, XGBoost, ADaboost, Stacking Regressor, and Voting Regressor. The system is even better now that it is based on explainable AI techniques such as LIME and SHAP, and has a Flask based interface that allows users to enter and make predictions in real-time. It did much better job than the other classifiers; it got 99.9% correct for best time classifier, 99.6% correct for irrigation classifier and RMSE of 0.288 for predicting regression. Overall, the method that was created is a solid, easy-to-understand and useful framework in making automated, data-driven decisions about how to best use water for irrigation in agriculture.

In the future, the technology will be able to incorporate more factors of the environment and the crops themselves that will result in even more accurate scheduling of irrigation. In order to make generalization improve for a broader scope of agricultural areas, researchers can explore advanced hybrid models that combine DL and ensemble methods. When real-time sensors are in combination with IoT devices, dynamic, automated irrigation control can be made possible. This reduces the amount of human work and wastage of water. Cloud-based deployment and mobile app interfaces might be helpful to make it easier for farmers to access and grow their systems. Using advanced AI techniques that can be explained can also provide you with more information on how various features affect one another. This can help you make better decisions and use water in a more sustainable way, which will help lead to increased crop yields and resource protection.

References

[1] Morchid, A., Elbasri, A., Oughannou, Z., Qjidaa, H., El Alami, R., Bossoufi, B., ... & Skruch, P. (2025). An Innovative Smart Irrigation Using Embedded and Regression-Based Machine Learning Technologies for Improving Water Security and Sustainability. IEEE Access.

[2] Lephondo, I., Telukdarie, A., Munien, I., Onkonkwo, U., & Vermeulen, A. (2024). The outcomes of smart irrigation system using machine learning to minimize water usage within the agriculture sector. Procedia Computer Science, 237, 525-532.

[3] Laouz, H., Ayad, S., Labib Terrissa, S., Nabila Benharkat, A., & Merdaci, S. (2024). Performance and robustness analysis of advanced machine learning models for predicting the required irrigation water amount. International Journal of Computing and Digital Systems, 16(1), 1399-1412.

[4] Preite, L., & Vignali, G. (2024). Artificial intelligence to optimize water consumption in agriculture: A predictive algorithm-based irrigation management system. Computers and Electronics in Agriculture, 223, 109126.

[5] Pandi, V. S., Kura, P., Kumar, K. S., Nirmala, D., & Kumar, S. R. (2025, February). Artificial intelligence for irrigation system optimization: leveraging predictive analytics to enhance water management and decrease agricultural resource consumption. In 2025 International Conference on Computational, Communication and Information Technology (ICCCIT) (pp. 299-304). IEEE.

[6] FAO, The Future of Food and Agriculture: Alternative Pathways to 2050. Rome, Italy: Food and Agriculture Organization of the United Nations, 2018.

[7] L. He, Y. Du, M. Yu, H. Wen, H. Ma, and Y. Xu, “A stochastic simulation-based method for predicting the carrying capacity of agricultural water resources,” Agricultural Water Management, vol. 291, Art. no. 108630, Feb. 2024.

[8] I. A. Lakhiar et al., “A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints,” Agriculture, vol. 14, no. 7, p. 1141, Jul. 2024.

[9] Z. Gu, Z. Qi, R. Burghate, S. Yuan, X. Jiao, and J. Xu, “Irrigation scheduling approaches and applications: A review,” J. Irrigation and Drainage Engineering, vol. 146, no. 6, Art. no. 04020007, 2020.

[10] R. Kondaveti, A. Reddy, and S. Palabtla, “Smart irrigation system using machine learning and IoT,” in Proc. Int. Conf. Vis. Towards Emerging Trends Commun. Netw. (ViTECoN), Mar. 2019, pp. 1–11.

[11] V. J. Baruah et al., “Precision irrigation management: A step toward sustainable agriculture,” in Remote Sensing in Precision Agriculture. Amsterdam, The Netherlands: Elsevier, 2024, pp. 189–215.

[12] R. Gómez-Chabla, K. Real-Avilés, C. Morán, P. Grijalva, and T. Recalde, “IoT applications in agriculture: A systematic literature review,” in ICT for Agriculture and Environment, vol. 901. Cham, Switzerland: Springer, 2019, pp. 68–76.
[13] E. Wang et al., “Development of a closed-loop irrigation system for sugarcane farms using the Internet of Things,” Computers and Electronics in Agriculture, vol. 172, Art. no. 105376, May 2020.
[14] R. K. Mishra, “Fresh water availability and its global challenge,” Brit. J. Multidisciplinary Adv. Stud., vol. 4, no. 3, pp. 1–78, May 2023.
[15] E. A. Abioye et al., “Precision irrigation management using machine learning and digital farming solutions,” AgriEngineering, vol. 4, no. 1, pp. 70–103, Feb. 2022.
[16] A. Bhoi et al., “IoT-IIRS: Internet of Things based intelligent-irrigation recommendation system using machine learning approach for efficient water usage,” PeerJ Computer Science, vol. 7, p. e578, Jun. 2021.
[17] A. Vij et al., “IoT and machine learning approaches for automation of farm irrigation system,” Procedia Computer Science, vol. 167, pp. 1250–1257, Jan. 2020.
[18] A. Raghuvanshi et al., “Intrusion detection using machine learning for risk mitigation in IoT-enabled smart irrigation,” Journal of Food Quality, vol. 2022, Art. no. 3955514, 2022.
[19] M. S. Munir et al., “Intelligent and smart irrigation system using edge computing and IoT,” Complexity, vol. 2021, Art. no. 6691571, Jan. 2021.
[20] A. Glória, J. Cardoso, and P. Sebastião, “Sustainable irrigation system for farming supported by machine learning and real-time sensor data,” Sensors, vol. 21, no. 9, p. 3079, Apr. 2021.
[21] R. Bhavani and A. Thambi, “Managing irrigation needs based on smart decisions using machine learning,” ICTACT Journal on Soft Computing, vol. 12, no. 2, pp. 2540–2544, Jan. 2022.
[22] Y. Tace et al., “Smart irrigation system based on IoT and machine learning,” Energy Reports, vol. 8, pp. 1025–1036, Nov. 2022.
[23] F. Rustam et al., “An artificial neural network model for water quality and water consumption prediction,” Water, vol. 14, no. 21, p. 3359, Oct. 2022.
[24] Z. Gu, T. Zhu, X. Jiao, J. Xu, and Z. Qi, “Evaluating the neural network ensemble method in predicting soil moisture in agricultural fields,” Agronomy, vol. 11, no. 8, p. 1521, Jul. 2021.
[25] P. K. Kashyap et al., “Towards precision agriculture: IoT-enabled intelligent irrigation systems using deep learning neural network,” IEEE Sensors Journal, vol. 21, no. 16, pp. 17479–17491, Aug. 2021.
[26] I. M. Pires et al., “Homogeneous data normalization and deep learning: A case study in human activity classification,” Future Internet, vol. 12, no. 11, p. 194, Nov. 2020.
[27] N. Al-Ansari, S. A. Abed, and S. H. Ewaid, “Agriculture in Iraq,” Journal of Earth Science and Geotechnical Engineering, vol. 11, no. 2, pp. 223–241, 2021.
[28] F. Doshi-Velez and B. Kim, “Considerations for evaluation and generalization in interpretable machine learning,” in Explainable and Interpretable Models in Computer Vision and Machine Learning. Cham, Switzerland: Springer, 2018, pp. 3–17.
[29] R. Patil and S. Tamane, “A comparative analysis on the evaluation of classification algorithms,” Int. J. Electrical and Computer Engineering, vol. 8, no. 5, pp. 3966–3975, 2018.
[30] M. Oosthuizen, The Quest for Safe Irrigation Water: Investigating UV Irradiation Treatment of River Water to Reduce Microbial Loads, M.S. thesis, Stellenbosch Univ., Stellenbosch, South Africa, 2022.