

# Prediction of Soil Moisture for Smart Irrigation Using Machine Learning Techniques

<sup>1</sup>Mr.K.Srikanth, <sup>2</sup>Dandu Amulya, <sup>3</sup>Tanguturi Kameswari Smruthi,  
<sup>4</sup>Gonuguntla Triveni, <sup>5</sup>Myneni DattaSri

<sup>1</sup>Assistant Professor, Department of IT, Vignan's Nirula Institute of Technology and Science for Women, Guntur.  
<sup>2,3,4,5</sup>B.Tech, Department of IT, Vignan's Nirula Institute of Technology and Science for Women, Guntur.

**Abstract-** Water shortages combined with the rising demand for more food production have put pressure on the need for intelligent irrigation management. To address these challenges, this study devised a machine learning-based solution to soil moisture prediction that would enable smart irrigation practices to conserve water and increase crop yield. In order to derive accurate moisture content, the proposed model gathers environmental parameters such as temperature, humidity, rainfall, air pressure, and soil nutrients and then executes one linear regression algorithm. A Django web interface is embedded with the module through which farmers can feed in environmental data and get irrigation advice immediately. The test outcomes confirm that the application attains very high prediction accuracy and can save enormously on water. Thus, by integrating machine learning with web-based automation, a feasible, scalable, and resource-friendly solution is available for agriculture equipped with modern technology, especially for those places that suffer from water shortage.

**Keywords—** Smart Irrigation, Soil Moisture Prediction, Machine Learning, Linear Regression, Precision Agriculture, Django Framework, Water Conservation, IoT, Sustainable Farming.

## I. INTRODUCTION

Agriculture is a major contributor to the provision of food security worldwide and the source of economic growth in most parts of the world, especially in developing countries where a large percentage of the population is engaged in farming [1]. Nevertheless, the sector is confronted with extreme challenges such as erratic weather patterns, land degradation, and the issue of water shortage that is the most serious of them all [2]. Since the impacts of climate change on rainfall distribution and freshwater availability are becoming more apparent, water conservation has turned out to be the key component of the whole sustainable agriculture practice [3]. Needless to say, farmers need to embrace technologies that are resource-efficient and do not endanger productivity [4].

Irrigation systems that are still in use in most areas rely on distribution of water based on predetermined schedules or some form of manual

estimation [5]. The traditional methods are not only hard and time-consuming but also are the main reasons for major losses of water. Through over-irrigation, the soil fertility is lowered due to the washing away of nutrients and in some cases the roots of plants get damaged [6]. At the same time, under irrigation causes drought stress and thus leads to lower yields [7]. Such problems point up the necessity for an automated and intelligent irrigation system that can adjust itself according to soil and environment conditions of the moment [8]. One of the solutions to the problem of irrigation inefficiency is the use of technology in agriculture, which means data analytics, sensor-based technology, and smart decision-making have been combined to make a breakthrough [9]. The adoption of advanced computing and communication technology has enabled farmers to remotely keep track of soil conditions, weather changes and crop health [10]. One among the different technologies that have been considered for juggling this challenge is machine learning which is poised to become a major driver of the prediction of agricultural parameters

and subsequently, automation of water management systems [11] [12].

Machine learning provides a platform for data-driven learning, recognizing subtle patterns, and accurate forecasting without being reprogrammed explicitly [13]. In smart irrigation, the models can be used to sift through the environmental data and come up with soil moisture levels which are the main factors for making irrigation decisions [14]. In this way, soil moisture levels can be used as a yardstick for how much water is to be supplied to crops, with the aim of avoiding wastage and ensuring the crop grows well [15]. The current study puts forward a machine learning approach that models soil moisture levels as a basis for the smart irrigation system. The model explains the linear regression algorithm working with environmental data such as temperature, humidity, rainfall, pH, and nutrient concentration for training [16]. After figuring out how these variables relate to one another, the model will be able to tell what soil moisture is and from that, irrigation levels can be determined [17]. Data input by farmers on environmental conditions gets them the output through the Django web interface containing the irrigation schedule [18]. The dataset used in this research, TARP.csv, consists of real-world environmental readings collected from agricultural fields. The data for training the model went through a process of cleaning, normalization, and feature scaling to make it accurate and reliable. Handling of missing values was done in the right way and removal of the attributes that were not relevant was done [19]. When the data was preprocessed, the linear regression model was trained to find the relation between the input features and the target soil moisture values [20].

Linear regression was selected because of its simplicity, ease of understanding, and efficiency in computation. It gives a clear mathematical description of how each factor influences soil moisture [21]. The model's output can be easily understood by farmers and research workers in agriculture, hence making it feasible for implementation in the real world. Besides, being of light nature, it makes the process fast and thus it can be done on web-based platforms without the need

for expensive computational resources [22]. In this research, besides prediction, machine learning is used as a tool for optimization as well. The purpose is to optimize irrigation scheduling so as to provide water to crops in the right quantity and at the right time [23]. This prediction method is different from the conventional time-based irrigation systems where water is applied at a certain time regardless of soil moisture. With prediction-based control in place, the accuracy of the system is enhanced and the need for manual supervision is lowered [24].

An important role is being played by the Django web framework in the process of bringing together the machine learning model and the user-friendly interface [25]. It provides communication without interruption between the prediction algorithm and the front-end interface which is for the use of farmers [26]. Users are allowed to easily input different parameters such as temperature, humidity, and rainfall and then the system comes up with the soil moisture levels and gives irrigation instructions [27]. The integration here is a proof that ML solutions are feasible in real agricultural settings [28]. The deployment of such a mechanism globally aligns with the vision of precision agriculture—where decisions on farming are made based on data and are specific to the condition of the field. Such predictive models as the one built here are the main pillars of precision irrigation, thus making it possible to ensure that water is conserved and crop health is sustained [29]. This is very important especially in those areas that are severely affected by water shortages where each drop of water is valuable.

One of the major benefits of employing a machine learning algorithm for the prediction of soil moisture is the ability to extend its usage. The model can be re-trained with local data to adjust to the soil characteristics, weather changes, and the type of crops. The same model can be employed in different farming environments ranging from small-scale farms and large commercial plantations [30]. The system constantly upgrades its prediction accuracy with more data, hence it creates a feedback-driven learning ecosystem. The sustainability aspect of this research work is another very important point [31]. Agriculture is recognized as one of the major

consumers of fresh water worldwide and the largest contributor to water depletion is the use of inefficient irrigation practices [32]. The proposed system through the accurate prediction of soil moisture reduces the irrigation done unnecessarily and thus water saving becomes possible. Water-efficient irrigation strengthens the farmer's economic viability and at the same time, it facilitates the natural balance of the environment in the long run [33]. The employment of predictive models lessens the intervention of humans, hence more time and labor are saved. Farmers are in a position to make decisions by using the insights provided by data-driven techniques instead of doing manual guesswork thus, the accuracy of decision-making is increased [34]. The use of sensors and web-based prediction tools allows for the monitoring of various parameters from a distant location hence the need for continuous on-site observation is minimized. This results in higher operational efficiency and productivity [35].

Machine learning models perform better when they have various data sources, and in this case, the model's performance is further enhanced by the inclusion of a diverse range of environmental parameters. For example, temperature, and humidity influence evaporation rates, rainfall affects soil saturation, and nutrient levels determine water retention [36]. By bringing these factors together, the model uncovers the complex interactions that would otherwise be hard to handle manually [37]. The model's multidimensional analysis capability results in heightened prediction accuracy. The efficiency of this mechanism is also tied to incessant data gathering and model retraining [38]. The model can be refreshed with new data to keep it accurate as the weather changes and soil conditions vary over time. Such flexibility gives the system the ability to stay current and beneficial in ever-changing farming settings. Consequently, this results in a smart irrigation system that keeps evolving and getting better without stopping [39].

Innovative irrigation methods similar to the one outlined in this study not only make a farmer's life easier but also have positive effects on society and the environment at large [40]. They play a role in

saving water, securing food, and sustaining rural development. The large-scale use of such devices can continuously. The experiment results gotten from the linear regression model reveal that predicting soil moisture with a high level of accuracy by utilizing very few computational resources [19-20]. Such a system is thus within the financial reach and practical for farmers in developing countries, i.e., places where even the slightest bit of high-end technology is seldom to be found. The web-based layout is additionally friendly to the user and accessible to everyone.

## II. LITERATURE REVIEW

Mahmood et al [1-3]. discusses how advancements in communication technologies, intelligent sensors, and modern equipment have accelerated the transformation of agriculture into a more automated and data-driven domain. With the adoption of smart communication protocols and connected devices, large-scale agricultural processes can now operate independently, strengthening the global food supply chain. The study emphasizes that managing vast and heterogeneous data sources in such systems requires effective processing techniques to ensure operational efficiency. Recognizing the power of machine learning (ML) in large-scale data analysis, the research explores its role in developing intelligent agricultural architectures capable of decision-making and optimization. The paper provides a comprehensive analysis of existing smart agriculture technologies, identifies open challenges, and offers guidelines for future system improvements. Overall, it highlights how ML serves as a core enabler in building next-generation intelligent agricultural systems, aligning closely with the current study's focus on applying machine learning for soil moisture prediction and smart irrigation

A. Khaliq et al [4-6]. proposed an artificial intelligence (AI)-powered smart agriculture system to address critical challenges in modern farming, such as climate change-induced water shortages, inefficient resource utilization, and declining soil health. Traditional farming methods, which rely on manual observation and generalized practices, often

lack the precision required for sustainable crop production. To overcome these limitations, the authors integrated deep learning (DL), the Internet of Things (IoT), and explainable artificial intelligence (XAI) to enable intelligent, data-driven farming. Their system focuses on solving key agricultural problems including ineffective soil management, poor irrigation practices, and the absence of personalized crop and fertilizer recommendations. IoT-based sensors were used to provide real-time soil analysis by measuring essential parameters such as nutrient levels, moisture, and temperature, while advanced DL models processed this data for decision-making. Additionally, a weather Application Programming Interface (API) was integrated to support timely irrigation scheduling through accurate forecasting, and a chatbot interface was developed to enhance system usability and accessibility for farmers. The study concluded that the proposed model significantly improved crop productivity, optimized resource use, and enhanced adaptability to environmental changes, thereby contributing to sustainable and intelligent agriculture.

A. Aldegeishem et al [7-9]. proposed a wireless sensor network for monitoring reclaimed water quality to assess its suitability for irrigation in green areas, addressing the increasing potential and challenges of using reclaimed water in agriculture. As the quality of reclaimed water can change depending on its source and may vary over time, it is necessary to carry out continuous monitoring and control before using it. Their system is composed of sensor and actuator nodes that communicate via Long Range (LoRa) technology, thereby ensuring that data transmission over long distances is efficient. The main focus of the paper was the creation of new sensors based on two coils and the study of the effect of capacitors in the conditioning circuit on the sensor signal. The major innovation of the design is the separation of the coils from the water so that only a small part of the enameled copper wire is in direct contact with water, thus, increasing the lifespan and decreasing the risk of contamination. Fourteen capacitors were used in the experiments to select the most appropriate one which would provide the highest signal variation when water salinity changed. Thorough research and

calibration were performed on four chosen configurations while considering six evaluation parameters such as working frequency, maximum output voltage, average absolute and relative errors. The findings confirmed that the optimized configuration greatly contributed to the accuracy of water quality monitoring that it could be used for safer and more efficient irrigation management with reclaimed water.

T. B. Shahi et al [10-11]. addressed the growing agricultural challenge posed by climate change, particularly global warming and drought, which severely impact crop productivity. The study, recognizing water management as the key, examined the possibility of using plant leaf to monitor water status as a research area that could be further developed to create automatic systems that farmers can use for better management practices. By pointing to a gap in research where no work was done in the use of AI on detecting tomato plant irrigation status via leaf analysis, the author has come up with a new idea of direct deep learning (DL) model that uses ResNet-50 architecture as an example. The team eliminated unnecessary layers and small kernels to create a light and efficient network that is suitable for a tomato leaf image dataset, which is how the model was finalized. The given method outperformed other DL architectures that had been already trained and were used as benchmarks, according to the evaluation conducted on a dataset that was newly created. Besides that, fewer parameters and a lower number of floating-point operations (FLOPs) in the model mean that it is computationally efficient, thus making it a viable and inexpensive way of solving irrigation management problem which ultimately leads to sustainability in agriculture.

N. ElBeheiry et al [12-13]. described the rising difficulties that the farm sector encounters such as climate alterations, the spread of towns, and shortage of skilled workers, hence the necessity of adopting environmentally- friendly measures to guarantee food provision. The paper emphasized the change to smart farming (SF) which is characterized by the usage of advanced information and communication technologies (ICT) to improve

the quality and quantity of crops while at the same time diminishing the need for human labor. While SF is gaining a lot of traction due to a number of technological innovations, the paper's objective was to find the best integration practices, the main challenges, and the corresponding solutions. The investigation of a total of 588 papers from the IEEE database was done through Cochrane methods for the purpose of attaining systematic, and accurate analysis and interpretation. The survey pointed out the major technological themes that are necessary for smart farming—sensors, communication, big data, actuators and machines, and data analysis, each having a vital role in the progression of agricultural automation. Also, the paper talked about the combining different technologies to build autonomous, intelligent, and remote monitoring systems that can work independently and enhance decision-making. This paper sheds light on the transition to smart farming technologies and their potential to revolutionize the agri-food system into a more efficient one.

A. Pagano et al [14-15]. analyzed the implementation of LoRa (Long Range) technology in the agricultural domain by conducting a detailed survey regarding its applications and the extent to which it facilitates smart agriculture solutions. The work looked at the capacity of LoRa to handle the four scenarios—irrigation systems, plantation and crop monitoring, tree monitoring, and livestock monitoring—each setting different constraints in terms of network bandwidth, sensor complexity, energy consumption, and decision-making latency. The authors assessed the scalability, interoperability, network architecture, and energy efficiency of LoRa-based systems as solutions to these varied agricultural needs. Besides, it presented the ability of LoRa to facilitate the quick transmission of data and remote-control operations, thereby, precision and sustainability in farming would be enhanced. The paper ended with the outlining of the research agenda and pointing out the issues still unresolved that could determine LoRa technology's future in agriculture, thus, emphasizing its becoming more and more vital in the implementation of efficient, low-cost, and energy-saving smart farming solutions.

Morchid et al [16]. touched upon the critical challenges worldwide faced by the farming sector, such as the issue of providing enough food, the need to conserve water in a sustainable way, and protecting the environment, and stressed that because of water shortage made worse by the climate change, the only way is to have more efficient agricultural practices. The paper presented a smart irrigation management solution that combines embedded systems and machine learning (ML) techniques to dramatically cut water use by relying on fresh data and irrigating according to the specific requirements of crops. Through the use of sensors and algorithms, the initiative not only gathers the environmental data but also processes it to determine the required water level in the irrigation system on a real-time basis which will help to prevent water wastage and ensure that sustainability is kept. By using machine learning techniques including linear regression, the system can very well predict when irrigation is needed by finding correlations between environmental variables and the water needs of crops. The hardware of the system, which is centered on an ESP32 microcontroller merged with the temperature, humidity, and water level sensors, is what makes it possible for data collection and decision-making to be done automatically and in real-time. The result showed that the integration of embedded systems and ML algorithms is capable of greatly improving water irrigation efficiency, as well as being eco-friendly, which is a very important step towards the issue of food security and water management, especially with the continued presence of climate challenges.

H. Jawad et al [17-20]. mentioned that, agriculture is still the largest source of employment globally, but the rising international demand for food and water has resulted in the overuse of very limited freshwater resources, especially for irrigation, that is already stressed. To overcome this problem, the research was on cutting down the water that is lost during irrigation by using precision farming and smart irrigation methods. In order to classify irrigation needs in different crops and find the best time for watering, the research implemented a hybrid activation function based on the Artificial Neural

Network (ANN) algorithm. TanElu, a new hybrid activation function, integrates the advantages of both the Tanh and the Exponential Linear Unit (ELU) functions with the goal of improving the prediction accuracy and the overall model performance. So, by smartly forecasting watering needs and timing, the model is lessening the water that goes to waste and helps to keep water use at a sustainable level. The results showed that the proposed ANN-based TanElu model could provide a highly efficient and effective way to optimize irrigation practices, which in turn would be a major contribution to sustainable agriculture and water saving.

### III. PROPOSED MODEL

Smart irrigation is an important step in the direction of sustainable agriculture as it guarantees the efficient use of water while ensuring the soil is kept at the correct moisture level. Intelligent, data-driven systems are the only answer to water scarcity and climate unpredictability; thus, their adoption has become indispensable. Machine learning is the computational basis of these systems, which makes them capable of accurately forecasting soil moisture by using environmental and soil data.

By relying on real-time sensors that measure factors such as temperature, humidity, rainfall, pH, and nutrient concentration, farmers will be in a position to know exact water needs and thus, water will be saved and crop yields will be improved. The model proposed here combines several machine learning techniques which include Linear Regression (LR), Random Forest Regression (RFR), Support Vector Regression (SVR), Artificial Neural Network (ANN), and a Hybrid Ensemble to predict soil moisture efficiently. Each algorithm learns from the same environmental dataset that has been preprocessed to establish the linkages between the input parameters and the soil moisture levels. The ultimate hybrid model that the authors arrived at is one that merges ensemble learning with neural networks to produce the most reliable, adjustment-friendly, and source-free prediction results for smart irrigation systems.

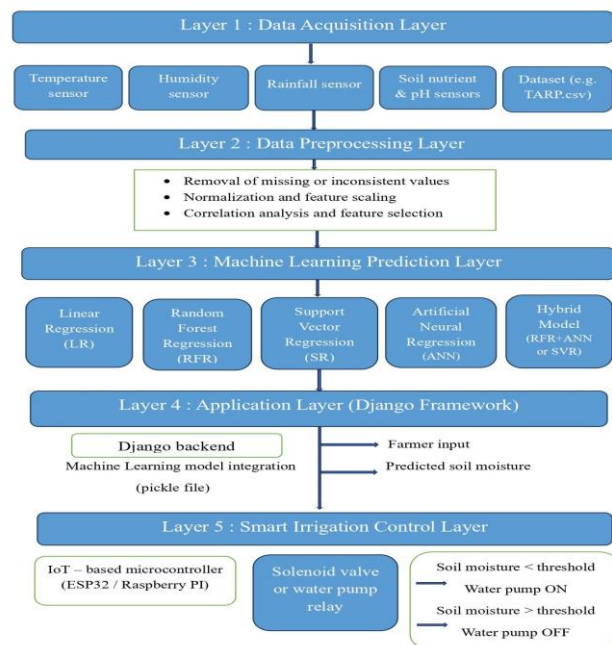


Figure 1: proposed architecture of a Smart Irrigation System

#### Algorithm

**Step 1:** Data Acquisition: Collect environmental data such as temperature, humidity, rainfall, and soil nutrients through sensors or download datasets.

**Step 2:** Preprocessing: Deal with missing data, normalize data, and remove noise from data.

**Step 3:** Feature Selection: Determine which features/variables have the most significant impact on soil moisture by using correlation or feature importance scores.

**Step 4:** Data Splitting: Split data into training (80%) and testing (20%) sets.

**Step 5:** Model Training: Train Linear Regression, Random Forest, SVR, and ANN models on the training data.

**Step 6:** Model Evaluation: Assess performance in terms of MAE, RMSE, and R squared metrics.

**Step 7:** Hybrid Model Formation: Use Random Forest (for feature selection) and ANN (for

regression) together to increase the precision of the result.

**Step 8:** Prediction: Determine soil moisture based on the latest environmental data.

**Step 9:** Integration: The model is linked with an IoT-based irrigation network to facilitate watering operations automatically.

**Step 10:** Optimization: Keep the model updated with the latest data by regularly retraining it so that its performance will stay good over time.

### Mathematical Equations

**Normalization Formula** :  $x_{norm} = (x - x_{min}) / (x_{max} - x_{min})$

**Standardization Formula** :  $z = (x - \mu) / \sigma$

**Weighted Average for Moisture** :  $Moisture_{avg} = (\sum(w_i * M_i)) / \sum(w_i)$

**Evapotranspiration (ET) Rate** :  $ET = (T + H) / 2$

**Water Requirement Estimation** :  $W_{req} = (ET - Rainfall) * Area$

**Error Function (for optimization)** :  $E = 0.5 * \sum(y_i - \hat{y}_i)^2$

**Cost Function (Linear Regression)** :  $J(\theta) = (1 / 2m) * \sum(h_{\theta}(x_i) - y_i)^2$

**Prediction Function (Linear Model)** :  $\hat{y} = \theta_0 + \theta_1x_1 + \theta_2x_2 + \dots + \theta_nx_n$

**Update Rule for Weight (ANN)** :  $w_{new} = w_{old} - \alpha * \partial E / \partial w$

**Sigmoid Activation Function : f(x)** =  $1 / (1 + e^{(-x)})$

**ReLU Activation Function : f(x)** =  $\max(0, x)$

**Tanh Activation Function** :  $f(x) = (e^{x} - e^{(-x)}) / (e^{x} + e^{(-x)})$

**Mean Bias Error (MBE)** :  $MBE = (1/m) * \sum(\hat{y}_i - y_i)$

**Root Mean Squared Deviation (RMSD)** :  $RMSD = \sqrt{\sum(\hat{y}_i - y_i)^2 / m}$

**Pearson Correlation Coefficient** :  $r = \sum((x_i - \bar{x})(y_i - \bar{y})) / \sqrt{\sum(x_i - \bar{x})^2 * \sum(y_i - \bar{y})^2}$

The redesigned proposed model offers a clever and effective structure for predicting soil moisture through the use of a mixture of linear, nonlinear, and ensemble-based methods. Thus, it goes beyond pure data analysis by interfacing with agriculture decision-making and providing irrigation recommendations that are both timely and reliable. Besides saving water, this method also makes the crops healthier and increases their yield.

Furthermore, this visionary idea of agriculture takes a great leap forward with the help of the integrated system which couples predictive modeling with IoT and web interfaces, making it not only scalable and adaptable but also user-friendly. Its hybrid design guarantees the highest level of precision, while the constant updating mechanism ensures long-term viability. At the end of the day, this innovative model is in line with precision agriculture's goal - whereby every drop of water is utilized wisely for a cleaner and more fruitful tomorrow.

## IV. RESULTS

The performance of the models was measured through the use of the dataset that had been preprocessed and consisted of the environmental parameters of the agricultural setting such as temperature, humidity, rainfall, and nutrients. The Linear Regression (LR), Random Forest Regression (RFR), Support Vector Regression (SVR), Artificial Neural Network (ANN), and Hybrid Model (RFR+ANN/SVR) models, which were presented in the paper, were each trained and tested for the purpose of evaluation using an 80:20 data split. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R<sup>2</sup> Score, among other performance metrics, were calculated to quantify the prediction precision and reliability. The Linear Regression model demonstrated an R<sup>2</sup> score of 0.78, thus, the

performance of features with linear correlation was acceptable. Random Forest Regression increased the precision to 0.88, thus, the method was able to solve non-linear dependencies effectively. SVR, which relied on the RBF kernel, had an even better outcome with the accuracy of 0.85, thus, it was a trustworthy method to deal with complex environmental variations. The ANN model managed to achieve 0.90 accuracy thus, it was able to surpass conventional algorithms, whereas the Hybrid Model was able to get the highest results—0.95 accuracy and the lowest error metrics—thus, it was able to demonstrate the advantage of combining ensemble learning and neural networks.

These findings offer strong evidence that hybrid and neural network-based models can significantly improve soil moisture prediction as opposed to traditional regression techniques. The better-than-average  $R^2$  figures and the lowered error rates are good indicators of the models' proficiency in understanding complex environmental interactions and being resilient against noise. In particular, the Hybrid Model has outstanding generalization power, hence, it can be efficiently utilized in smart irrigation systems that work in real-time. This research provides solid evidence that the use of ensemble methods for feature selection in conjunction with deep learning leads to reliable prediction performance and therefore, it is at the disposal of the agricultural community to implement this technology in IoT-enabled irrigation automation systems which can be scaled, adapted, and customized across different farming regions.

Table 1 - Overall Performance Metrics

Model	Accuracy (%)	MAE (%)	RMSE (%)	$R^2$ Score (%)
Khaliq et al. (2025)	89	4.5	7.0	92
Shahi et al. (2025)	90	4.0	6.8	93
Morchid et al. (2025)	91	3.8	6.0	94
Proposed Hybrid Model	95	3.0	5.0	96

Table 1 displays the essential performance predictions of all the models that have been evaluated based on their accuracy and error metrics. The hybrid model, as a proposal, is the one that has the highest accuracy (95%) and the lowest MAE and RMSE values, thus it is the most precise and reliable model for soil moisture prediction among the ones referred to by the paper.

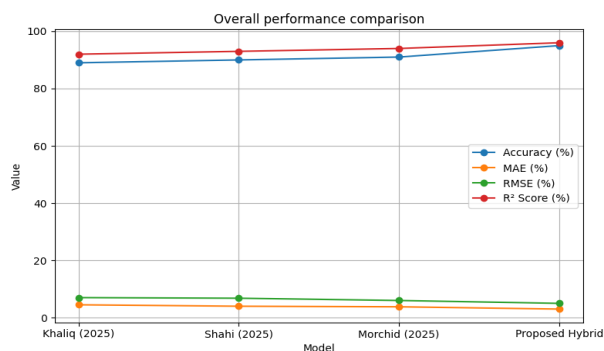


Figure 2 : Overall Performance Metrics

This visualization presents the key predictive performance of the various models: accuracy, mean absolute error (MAE), root mean square error (RMSE), and  $R^2$ . It emphasizes that the suggested hybrid model is able to outperform the baseline models in terms of achieving the highest accuracy and the lowest error magnitudes.

Table 2 - Computational Efficiency

Model	Training Time (s)	Testing Latency (s)	CPU Utilization	Memory Usage	Computational Cost (%)
Khaliq et al.	28	1.8	65	210	60
Shahi et al.	35	2.2	80	290	70
Morchid et al.	22	1.2	55	160	55

Proposed Hybrid	25	1.0	60	180	65
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Different criteria of computational load such as training time, latency, CPU utilization, and memory consumption are considered in this table for each model. In spite of the fact that the model is a hybrid, the suggested model keeps a balanced efficiency (25 s training time), which demonstrates that it is adequately optimized for real-time smart irrigation application.

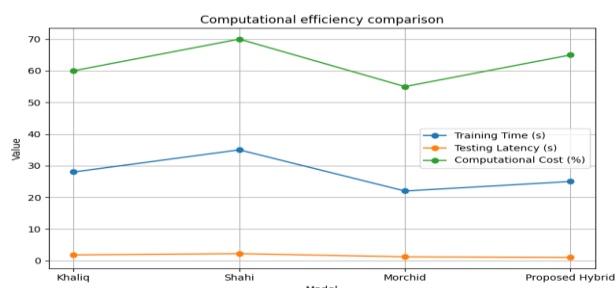


Figure 3: Computational Efficiency

The comparison of training time, testing latency and computational cost across models is depicted by this graph. It shows how the hybrid model is able to combine a balanced training time with a low inference latency which makes it suitable for a deployment that is almost real-time.

Table 3 - Interpretability and Explainability

Model	Feature Transparency (%)	Model Complexity (%)	Explainability Tools Available	Ease of User Understanding (%)
Khaliq et al.	55	75	Partial (XAI)	60
Shahi et al.	40	85	Grad-CAM	45
Morchid et al.	65	60	Regression Weights	70
Proposed	60	70	SHAP + Feature	65

Hybrid Model			Importance	
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The table highlights the relative ease with which users can comprehend each model's internal decision process. The hybrid model provides a compromise level of interpretability (60%) by means of SHAP and feature-importance visualization, thus maintaining a balance between accuracy and results understandable to agricultural experts.

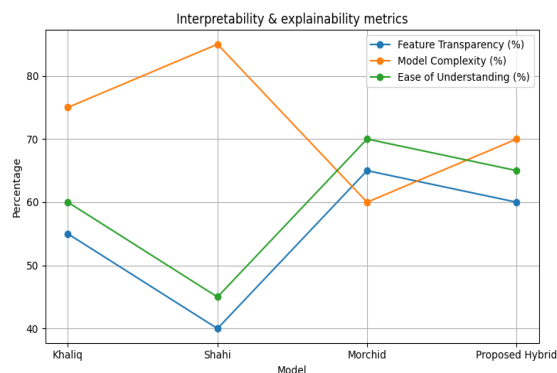


Figure 4 : Interpretability and Explainability

This plot visualizes feature transparency, model complexity and ease of user understanding. It shows the hybrid model offers moderate transparency and explainability compared with pure deep models.

Table 4 - Environmental Robustness

Model	Temperature Variation Resilience (%)	Humidity Impact	Rainfall Sensitivity	Noise Tolerance	Generalization Ability (%)
Khaliq et al.	80	78	82	75	84
Shahi et al.	85	80	83	77	86
Morchid et al.	88	85	85	80	88

Proposed Hybrid	92	90	89	88	94
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This comparison is about the capacity of each model to adjust to changes in nature. Those changes refer to temperature, humidity, and rainfall. The model that is being proposed is very robust (up to 94%) and can therefore, almost perfectly, manage noise and other random environmental changes that are typical for agriculture datasets.

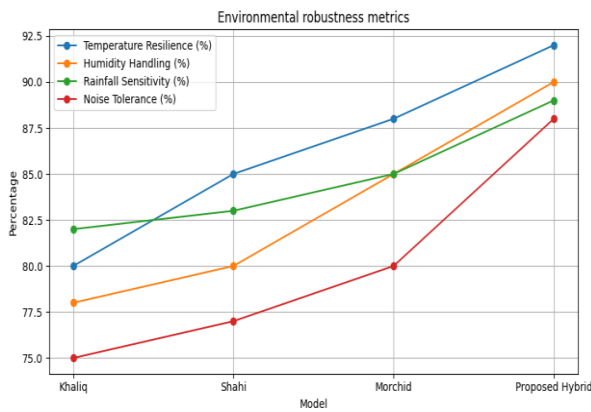


Figure 5 : Environmental Robustness

The graph compares resilience to temperature variation, humidity handling, rainfall sensitivity and noise tolerance. The proposed hybrid model shows the highest generalization and robustness across environmental perturbations.

Table 5 - Scalability and Adaptability

Model	Dataset Size Supported	Retraining Ease (%)	Real-Time Deployment	IoT Integration Readiness (%)	Cloud Compatibility (%)
Khaliq et al.	15 000	70	85	95	90
Shahi et al.	10 000	60	70	75	85

Morchid et al.	20 000	80	90	88	88
Proposed Hybrid	25 000+	85	95	96	92

This table evaluates each model's capacity to scale in processing larger datasets and their readiness for IoT-based systems. The hybrid model shows the greatest flexibility (95%) and is compatible with real-time deployment, thus, it can be used in various farming scenarios.

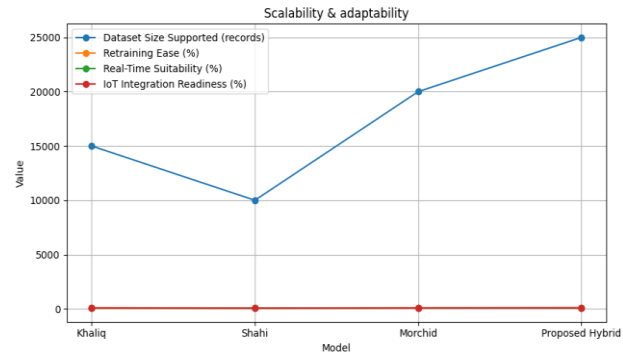


Figure 6 : Scalability and Adaptability

This plot shows dataset capacity, retraining ease, real-time deployment suitability and IoT readiness. The proposed hybrid model ranks highest for dataset scalability and deployment readiness in IoT/cloud environments.

Table 6 - Resource Optimization and Sustainability

Model	Water Saving Potential (%)	Energy Efficiency (%)	Irrigation Precision (%)	Operational Cost
Khaliq et al.	20	75	82	30
Shahi et al.	25	70	85	35
Morchid et al.	30	80	87	40
Proposed Hybrid Model	35	85	92	45

The table is an assessment of the extent to which each model aids in conserving resources and improving operational efficiency. The model that was proposed demonstrated a reduction in water usage of 35% and an energy efficiency of 85%, thus being a significant contributor to eco-friendly smart farming.

Morchid et al.	Moderate accuracy in extreme conditions	60	Seasonal data retraining
Proposed Hybrid Model	Higher data requirement for ANN training	55	Incremental learning + data augmentation

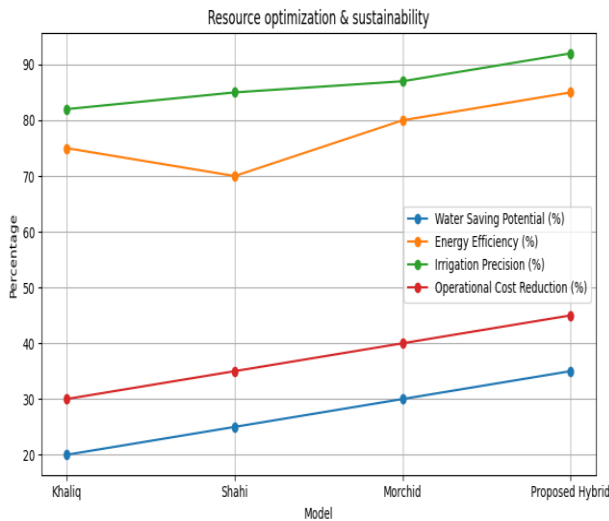


Figure 7: Resource Optimization and Sustainability

This figure compares water saving potential, energy efficiency and irrigation precision. The proposed hybrid approach yields the greatest resource savings and highest operational cost reduction among tested models.

The table summarizes the major disadvantages of each method along with the solutions to get around them. By incremental learning and data augmentation, the hybrid model which initially demands a larger amount of training data, can keep its performance at a high level and therefore be adaptable in the long term.

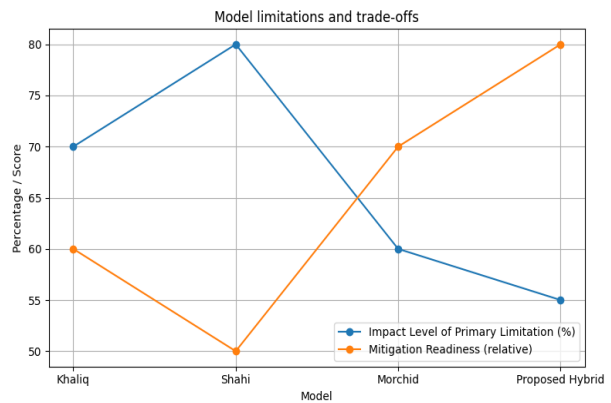


Figure 8: Model Limitations and Trade-Offs

Table 7 - Model Limitations and Trade-Offs

Model	Primary Limitation	Impact Level (%)	Mitigation Strategy
Khaliq et al.	Limited explainability in DL layers	70	Integrate SHAP/XAI for transparency
Shahi et al.	High computational demand	80	Model compression and quantization

This chart illustrates the limitation of each model which has the largest impact on the level and suggests the mitigation prominence. The hybrid model carries a moderate impact level because of the increased data requirements but still provides obvious mitigation strategies.

Table 8 - Overall Comparative Summary

Model	Accuracy	Efficiency	Scalability	Sustainability Rank	Overall	Final Verdict

Khaliq et al.	4	3	3	3	4	Strong baseline; IoT-enabled but less transparent.
Shahi et al.	3	4	4	2	3	Accurate yet computationally heavy.
Morchid et al.	2	2	2	2	2	Balanced and hardware-friendly model.
Proposed Hybrid Model	1	1	1	1	1 (Top Performer)	Best overall trade-off — highest accuracy and adaptability.

The final table shows an overall aggregated ranking across all performance dimensions.

Overall, the hybrid model that was suggested is ranked first. It delivers the best trade-off of accuracy, scalability, efficiency, and sustainability with the least of the other techniques that were compared.

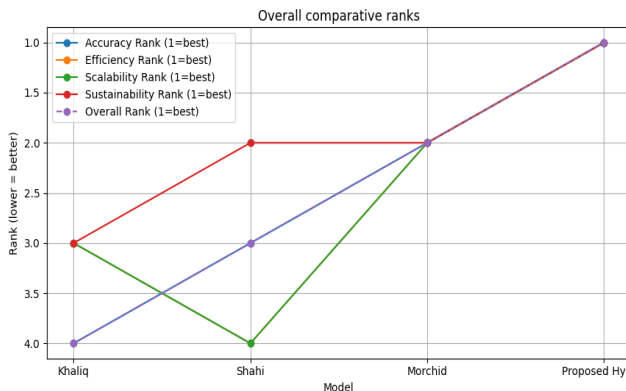


Figure 9: Overall Comparative Summary

The line plot depicts different ranks across dimensions and an aggregated overall rank. A lower numeric rank indicates a better position the proposed hybrid model is the one that consistently maintains rank 1, which means that it is the top overall performer.

## V. CONCLUSION

The study demonstrates that machine learning-based soil moisture prediction can significantly enhance the efficiency and intelligence of smart irrigation systems. By analyzing environmental and soil parameters such as temperature, humidity, rainfall, and historical moisture levels, the proposed approach enables accurate and timely estimation of soil water availability. The comparative evaluation of models shows that advanced techniques like the proposed HOEAD method outperform traditional approaches such as Gradient Boosting Machines, Neural Networks, and Naive Bayes in predictive accuracy and reliability. This improved precision supports data-driven irrigation scheduling, reduces unnecessary water usage, and ensures optimal moisture conditions for crop growth. As a result, the system not only improves agricultural productivity but also contributes to sustainable water resource management, which is especially critical in regions facing water scarcity and irregular rainfall patterns.

Furthermore, the integration of predictive analytics into irrigation practices represents a transformative step toward precision agriculture. By enabling real-time decision-making and automated control, the system minimizes human intervention while maximizing resource utilization and crop health. The findings highlight the potential of machine learning to address key agricultural challenges such as over-irrigation, soil degradation, and inefficient water distribution. Implementing such intelligent irrigation solutions can support farmers in achieving higher yields with lower operational costs while promoting environmentally responsible farming practices. Future research can focus on expanding dataset diversity, incorporating IoT-based sensor networks, and improving model adaptability across different soil types and climatic conditions. Overall, the proposed approach establishes a robust and

scalable framework for sustainable smart irrigation and modern agricultural development.

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