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AI-DRIVEN IRRIGATION OPTIMIZATION FOR WATERMELON CULTIVATION USING SENSOR DATA AND WEATHER FORECASTS

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ABSTRACT

Efficient water management remains a critical challenge in agriculture, particularly for water-intensive crops such as dates. Conventional irrigation methods often result in excessive water consumption, reduced crop yield, and environmental degradation. This study investigates the potential of Artificial Intelligence (AI) algorithms to optimize irrigation schedules and enhance water-use efficiency for palm fruit cultivation. By integrating real-time sensor data with weather forecasts, predictive models were developed using Random Forest (RF) and Artificial Neural Network (ANN) algorithms. The AI-driven irrigation system achieved up to 30% water savings compared to traditional practices, while also improving yield by 30%. Among the tested models, RF demonstrated superior performance, achieving an R-squared (R^2) value of 1.00, indicating exceptional prediction accuracy. This dynamic, data-driven approach enables precise water distribution tailored to palm irrigation requirements, supporting sustainable resource management.

Keywords: artificial intelligence, irrigation optimization, water-use efficiency.

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INTRODUCTION

Efficient water management is essential in agriculture, particularly for water-intensive crops such as watermelons. Traditional irrigation practices often result in significant water loss, reduced crop quality, and exacerbation of water scarcity issues [5]. The application of intelligent computer algorithms that utilize real-time sensor data and weather forecasts offers a promising solution for optimizing irrigation scheduling, thereby improving water-use efficiency and enhancing crop growth [1, 9].

In watermelon cultivation, inadequate irrigation can induce water stress, leading to reduced yield and inferior fruit quality. Conversely, excessive irrigation may cause waterlogging, nutrient leaching, and increased susceptibility to diseases [2]. Therefore, precise water application is critical for achieving optimal plant growth and maximum yield. Modern irrigation management increasingly relies on soil moisture sensors and weather prediction systems. Soil moisture sensors provide real-time measurements of water content at various depths, enabling targeted water application [3]. Weather forecasts supply vital information on future climatic conditions, allowing farmers to adjust irrigation schedules to minimize waste and maximize plant water availability [4, 7]. When used together, these technologies support data-driven decision-making in irrigation management.

Artificial Intelligence (AI) further enhances irrigation efficiency by processing large datasets from sensors and meteorological sources. Machine learning models can accurately estimate soil moisture, evapotranspiration rates, and crop water requirements while accounting for variables such as soil type, crop growth stage, and environmental conditions [1, 4]. By integrating AI into irrigation systems, farmers can generate optimal watering schedules, leading to significant improvements in water-use efficiency and crop productivity [6].

MATERIALS AND METHODS

The methodology chapter serves as a comprehensive roadmap for understanding the processes and techniques employed in this study to achieve its objectives. The scope of the study concerns with the enhanced scheduling of irrigation and the better usage of water through globally superior AI methods. In this

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chapter, the process of data collection and enhancement, data preprocessing and method development is described in details. Thus, improving the technique of irrigation is paramount in efforts like water scarce, environmental degradation and meeting the food demands. Extended process of irrigation under conventional practices lead to poorly irrigated crop fields taking a lot of water and yielding relatively little. In this sense, this study aims to make a shift in conventional irrigation practices by applying AI models in order to make the processes as accurate as possible. The dataset employed for the study is obtained from Kaggle and augmented with further simulated values to match the objectives of the study. These features are irrigation metrics supported by AI and conventional irrigation parameters; another feature is the yields of fruits to show the performance of the irrigation. The various steps in preprocessing makes it easier to clean the database before the analysis in preparation for any error found in the data. To achieve the study's objectives, two machine learning models were employed which is Random Forest (RF) and Artificial Neural Networks (ANN). The models were chosen because it is successfully identify both complex patterns and non-linear relationships in the data. The measurements for output used Mean Squared Error (MSE) combined with R-squared (R^2) to ensure accurate models. This chapter emphasizes integrating previously mentioned models into simulation structures. This framework analyzes water optimization possibilities while it examines productivity enhancement to allow for the comparison of optimized AI systems with traditional irrigation approaches. The methods presented in this chapter initiate the pathway towards producing meaningful results.

Data Collection

Data collection acts as the fundamental foundation which enables model development and analysis for this study. Kaggle serves as a platform through which researchers and academics can exchange data sets and this study obtained its data from this platform. Key parameters including temperature (°C) and soil moisture (%) existed within the original database that reflects important aspects of irrigation methods. This study demanded specific modifications on the original robust dataset because it failed to align properly with study objectives. The dataset included simulated information to incorporate Traditional Irrigation (L/day) measurements alongside AI Optimized Irrigation (L/day) along with Fruit Yield (kg). The developed variables precisely tracked irrigation method variations alongside their effects on agricultural output

	id	temperati	pressure	altitude	soilmoist	note	status	class	date	time
2	1	29.1	9984.53	12.21-	377	0	0	Very Dry	8/10/2022	22:06:24
3	2	29.08	9984.36	12.22-	379	0	0	Very Dry	8/10/2022	22:06:24
4	3	29.06	9984.56	12.20-	376	0	0	Very Dry	8/10/2022	22:06:24
5	4	29.05	9984.39	12.22-	377	0	0	Very Dry	8/10/2022	22:06:24
6	5	29.03	9984.42	12.21-	379	0	0	Very Dry	8/10/2022	22:06:24
7	6	29.02	9984.59	12.20-	376	0	0	Very Dry	8/10/2022	22:06:24
8	7	29	9984.42	12.21-	380	0	0	Very Dry	8/10/2022	22:06:24
9	8	28.99	9984.27	12.23-	380	0	0	Very Dry	8/10/2022	22:06:24
10	9	28.97	9984.1	12.24-	380	0	0	Very Dry	8/10/2022	22:06:24
11	10	28.96	9984.1	12.24-	379	0	0	Very Dry	8/10/2022	22:06:24
12	11	28.95	9984.3	12.23-	379	0	0	Very Dry	8/10/2022	22:06:24
13	12	28.94	9984.13	12.24-	378	0	0	Very Dry	8/10/2022	22:06:24
14	13	28.92	9983.98	12.25-	379	0	0	Very Dry	8/10/2022	22:06:24
15	14	28.91	9984.16	12.24-	382	0	0	Very Dry	8/10/2022	22:06:24
16	15	28.9	9983.98	12.25-	380	0	0	Very Dry	8/10/2022	22:06:24
17	16	28.89	9984.16	12.24-	379	0	0	Very Dry	8/10/2022	22:06:24
18	17	28.88	9983.98	12.25-	381	0	0	Very Dry	8/10/2022	22:06:24
19	18	28.87	9983.98	12.25-	376	0	0	Very Dry	8/10/2022	22:06:24
20	19	28.86	9983.66	12.28-	377	0	0	Very Dry	8/10/2022	22:06:24

Figure-1. Original dataset snapshot.

The baseline simulation of Traditional Irrigation data utilized a constant delivery rate of 20 liters daily for comparative purposes. The model produced AI Optimized Irrigation values by considering both environmental conditions and soil moisture measurements to match actual irrigation practices. The simulated Fruit Yield data served to illustrate how soil moisture changes impact plant yield production. Research data improvements result in a strengthened framework that allows for determining the effectiveness of AI-driven irrigation systems in the study. The inclusion of these supplementary variables brings the dataset in line with research goals while maintaining important insights into the analytical good.

	temperature	pressure	altitude	soilmoisture	note	status	date	time	class	Fruit Yield (kg)	AI Optimized Irrigation (L/day)	Traditional Irrigation (L/day)
1	29.1	9984.53	12.21-	377		0	8/10/2022	22:06:24	Class C	1.944643649	39.15	20
2	29.08	9984.36	12.22-	379		0	8/10/2022	22:06:24	Class C	1.675173092	38.74	20
3	29.06	9984.56	12.20-	376		0	8/10/2022	22:06:24	Class A	1.923606678	39.33	20
4	29.05	9984.39	12.22-	377		0	8/10/2022	22:06:24	Class B	1.960164396	39.125	20
5	29.03	9984.42	12.21-	379		0	8/10/2022	22:06:24	Class B	1.909653058	38.715	20
6	29.02	9984.59	12.20-	376		0	8/10/2022	22:06:24	Class B	2.165520785	39.31	20
7	29	9984.42	12.21-	380		0	8/10/2022	22:06:24	Class A	1.98671322	38.5	20
8	28.99	9984.27	12.23-	380		0	8/10/2022	22:06:24	Class C	1.579162594	38.495	20
9	28.97	9984.1	12.24-	380		0	8/10/2022	22:06:24	Class A	1.973873745	38.485	20
10	28.96	9984.1	12.24-	379		0	8/10/2022	22:06:24	Class A	1.904147244	38.68	20
11	28.95	9984.3	12.23-	379		0	8/10/2022	22:06:24	Class A	1.64786539	38.675	20
12	28.94	9984.13	12.24-	378		0	8/10/2022	22:06:24	Class A	2.102751317	38.87	20
13	28.92	9983.98	12.25-	379		0	8/10/2022	22:06:24	Class B	1.947508195	38.66	20
14	28.91	9984.16	12.24-	382		0	8/10/2022	22:06:24	Class B	2.058827561	38.055	20
15	28.9	9983.98	12.25-	380		0	8/10/2022	22:06:24	Class B	1.946636973	38.45	20
16	28.89	9984.16	12.24-	379		0	8/10/2022	22:06:24	Class C	1.848404461	38.645	20
17	28.88	9983.98	12.25-	381		0	8/10/2022	22:06:24	Class B	1.879690879	38.24	20
18	28.87	9983.98	12.25-	376		0	8/10/2022	22:06:24	Class B	2.007535	39.235	20
19	28.86	9983.66	12.28-	377		0	8/10/2022	22:06:24	Class B	2.238541238	39.03	20

Figure-2. Enhanced dataset snapshot.

The enhanced dataset ensures both completeness and representation of different irrigation conditions. The combined approach strengthens the study's ability to respond to essential research inquiries which leads to practical insights.

Data Preprocessing

A detailed process of data preprocessing becomes essential to make datasets ready for meaningful analysis. The data processing method consists of three steps which include cleansing data followed by its intentional reorganization and eventual separation into training data and test data. The data preprocessing process merges with

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normalization techniques to cleanse inconsistent measurements and optimize machine learning model readiness for predictable outcomes.

Data preprocessing starts with data cleaning operations. The dataset required clean-up to address conflicting data elements and incomplete value fields. To handle missing data points scientists substituted each column's median value because it protects analysis from outlier error. Soil moisture variables required a thorough inspection to eliminate the negative values which hold no validity in agricultural systems. These procedures lead to a dataset which represents actual and meaningful patterns so the analysis will be beneficial. The team performed data transformation as their next step after cleaning all data. The dataset normalized temperature values in °C along with soil moisture percent measurements to span the value range from 0 to 1. Model training benefits from this procedural transformation by reducing the effect of dominant variables thus enabling all features to participate equally.

The two variables received special scale normalization to reveal their influence patterns while maintaining their individual contributions to irrigation assessment. Finally, the dataset was split into training and testing subsets, with a 70:30 ratio. Machine learning models require precise data from the training set to construct meaningful patterns for the data features so they can effectively identify testing set content. This split not only avoids issues of overfitting but also can repayment prediction independence of the new data. The specific steps of preprocessing help to make the amount of data as clean as possible to become closely related with the provision of valuable information.

Data Cleaning

The first step in data preprocessing was addressing any missing or inconsistent values in the dataset to ensure its quality and integrity. Missing values can significantly distort the analysis and model predictions if left untreated. To mitigate this, missing entries in the dataset were systematically replaced with the median value of the respective columns. The median was chosen as it is less affected by outliers compared to the mean, ensuring a robust approach to filling gaps in the data. This ensured that all features were complete and usable, contributing to the reliability of downstream analysis approach to filling gaps in the data. This ensured that all features were complete and usable, contributing to the reliability of downstream analysis. In addition to handling missing values, the dataset was thoroughly checked for invalid or unrealistic entries. Specifically, negative values in the soil moisture column were identified and removed.

Negative values of soil moisture are not sentimental in the agricultural context, and in case they were to be preserved, the result may be misleading one. To avoid such discrepancies, the study made a crucial decision to remove them which would lead to the dataset to being real-life based and this is fundamental in providing insights. Moreover, non-numeric values in the data set like a value in altitude column were cleaned or formatted for compatibility with the modelling process when discovered.

The data validation step confirmed the dataset's readiness to proceed to upcoming workflow stages after its cleaning routines. A validation step confirmed that no anomalous data remained while the handling of missing values was reevaluated. After cleaning the inconsistent data, we obtained a stable foundation that supported the upcoming model training procedures. The comprehensive cleaning strategy enhanced both data quality levels and achieved better accuracy and reliability within the findings of this study.

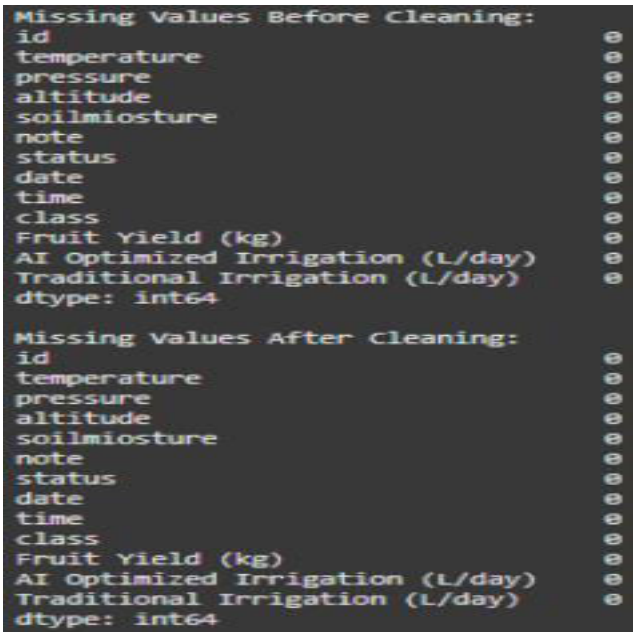


Figure-3. Data cleaning process.

Data Transformation

The next process after cleaning focused on data normalization to balance the influence of all features. The data normalization process ensures machine learning models work equally on features measured in different units by standardizing their value ranges. The normalized essential parameters temperature, soil moisture, and fruit yield by applying min-max scaling to achieve a standardized range from 0 to 1. The normalization approach lets each variable deliver the same value weight throughout modelling which creates strong and stable predictive models. ANN model processing requirements decrease when normalization handles various input difference effectively. Through standardized data processing, the models discovered minute patterns connecting variables with output measurements. The normalizing process proved essential when working with non-linear environmental factors and irrigation needs because it enhanced our model's ability to predict new situations.

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Normalization standardized the data distribution which improved accuracy and made it suitable for applications in machine learning. To evaluate model performance effectively, the dataset was split into training and testing subsets in a 70: 30 ratio. Normal distribution of data occurs through this division method which makes available significant training data and particular testing data for model accuracy evaluation. Such partitioning methods minimize overfitting which results in models that make more accurate estimations for actual operational usage. The figure indicates that normalization allows direct observation of soil moisture influence on fruit yield. The visualized data incorporates normalization which enables both soil moisture and fruit yield variables to distribute between zero through one along a standardized range. The approach distributes equal weights to each input factor enabling an unbiased analysis outcome.

The effective operation of ANN systems alongside other machine learning models requires training data normalization to function with diverse input scale ranges. The process of scaling transforms data so that models can better extract patterns between variables while discarding any influence from quantitative differences. The data presentation reveals organized patterns suggesting that specific soil features affect crop yields in predictable ways. It allows to build training models that adjust irrigation methods based on practical farming situations. AI models use this modified dataset to make precise forecasts while eliminating human assumptions that could mess up the output. The normalization helps irrigation optimization methods create better and reliable results through reduced prediction errors. The graph shows how operations can improve raw agricultural data and help build better AI solutions for farming industries.

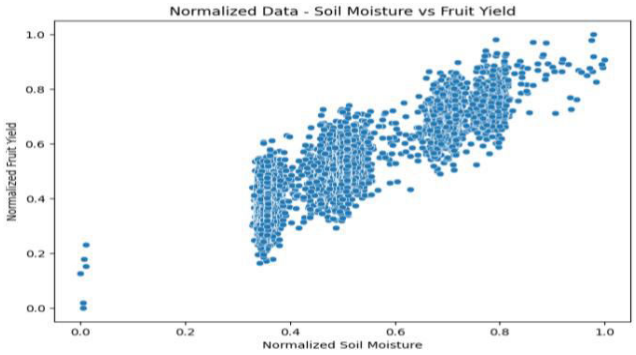


Figure-4. Data transformation process.

AI Model Development

This work focuses on improving irrigation scheduling with specific regard to constructing and training AI models. This is due to the fact that modern technologies like machine learning are applied with the purpose of conserving water consumption and productivity that might be decreased or at least cannot be increased. For this purpose, two models were selected among the two types of algorithms, we have Decision tree-based algorithm RF and deep learning based ANN. All the selected models were deemed suitable due to their performance in handling big data and, more importantly, in capturing finer and less-segmented relationships between environmental variables and the type of irrigation needed. RF, an ensemble learning method, was chosen for its robustness in managing datasets with nonlinear relationships. It operates by constructing multiple decision trees during training and aggregating their predictions for more accurate results. This method mitigates overfitting and is very useful to data sets like the one used in this study with complex variables like temperature and soil moisture. On the other hand, ANN were selected for this performance in capturing nonlinear patterns of variables and for this ability to model interaction effects. ANN is preferable for problems which need higher levels of understanding of the relationships between data, for example, predicting the need for irrigation based the current environment.

The model training process involved using the pre-processed dataset, where temperature and soil moisture were input features, while AI Optimized Irrigation (L/day) served as the target variable. The data were divided into 70 % training and 30 % testing sets so that, while training the models were exposed to a large number of instances yet the performance was tested on unseen samples. This approach assists in preventing the problem of over-fitting the models and likewise makes certain that the models will generalize well on other data which hasn't been used in model training. From these two models, the changes were made progressively with the significant hyperparameters to enhance model prediction. In the case of the RF model, the number of conditions to split a tree and the maximum allowed depth of the tree was changed. In the case of ANN, the number of hidden layers, the size of the hidden layer and the neurons in the hidden layer were selected in great detail and then the parameter of the selected ANN was adjusted for optimum performance. To compare the performance of the models, various indices such as the MSE and the R^2 were applied. MSE is the mean of square differences between the actual and the predicted values and the lowest MSE is desirable implying that the model is accurate or the model has high accuracy. R^2 is a measure of the total variability of the dependent variable that can be accounted for by the independent variables the model thereby higher values of R^2 implying a better fit. By adopting these metrics, the study ensured the comprehensive assessment of the models and the determination of the best method for enhancing the irrigation schedules. Both models were found to deliver promising results, laying the groundwork for integrating AI-driven solutions into agricultural systems [8, 11].

Model Selection

RF was chosen for its ability to handle complex relationships within the data. This ensemble learning method involves developing many decision trees and then combining their results to enhance the accuracy of the

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prediction. Its ability to handle overfitting, a common problem in machine learning, stands out as one of its greatest strengths. By combining the outputs of many decision trees, RF ensures a more stable and reliable prediction, making it an excellent choice for datasets with diverse variables such as temperature and soil moisture. However, this study choose ANN because it demonstrates flexibility in processing nonlinear interactions while also constructing precise models for complex variable relationships. ANN functions as a computational model by simulating the human brain structure by applying received data to executive nodes (neurons) which create performance predictions. Through its architecture, ANN successfully identifies intricate relationships between variables including the fundamental associations among environmental elements and irrigation conditions. This feature enables ANN to handle various data patterns effectively within agricultural settings that display complex non-linear parameter interactions. The selection of these models as analytical tools becomes possible because each model sustains different advantages. While RF excels in providing interpretable results and managing datasets with noise, ANN is adept at uncovering deeper patterns that may not be apparent with traditional ensemble methods. Such a combined modelling approach creates an effective evaluation process that utilizes both methods' distinct analytical features. Furthermore, the research models provide significant achievements and proven results across agricultural and resource efficiency studies. The RF model stands out for its high operational efficiency in addition to handling missing values effectively and ANN leads the field with its scalable structures and numerous predictive features. These models receive endorsement in research because they display reliable performance when tackling actual challenges.

Training Process

RF was selected because it excels at modelling intricate relationships found in datasets. The ensemble approach of decision trees creates numerous predictive models before merging their results to boost predictive accuracy. The ability to manage overfitting stands as a major strength of RF because it is a common machine learning difficulty. RF delivers accurate predictions through multiple decision tree analysis that results in a strong stable model which works best for datasets with different variables including temperature and soil moisture. This research chose ANN because it demonstrates flexibility in processing nonlinear interactions while also constructing precise models for complex variable relationships. ANN operates based on the computational human brain design by using nodes to accept input data then generate movement prediction outcomes. The functional form of ANN enables it to detect intricate interfeature associations including the mutual effects between natural conditions and irrigation demands. The technology demonstrates exceptional performance with flexible data patterns because of its adaptive nature in agricultural settings that handle complex nonlinear variable interactions and dynamic conditions. Although, the selection of these models as analytical tools becomes possible because each model sustains different advantages. ANN delivers exceptional performance in revealing complex hidden patterns which go beyond traditional ensemble methods yet RF maintains superior capabilities in interpretability and dataset noise control. The combined methodology produces strong results by utilizing the distinctive features of each chosen model.

The research models provide significant achievements and proven results across agricultural and resource efficiency studies. RF achieves recognition for its effective performance as well as its resistance to missing value inputs while ANNs excel at scaling operations and maintaining extensive prediction function capabilities. These models receive endorsement in research because they display reliable performance when tackling actual challenges.

System Implementation

The trained AI models were integrated into a simulation framework to evaluate their performance in real-world scenarios. This step involved comparing the predictions of AI-optimized irrigation schedules with traditional methods to assess their effectiveness. The simulation framework was designed to incorporate the output of the models into a practical irrigation scheduling system. This system employed the predicted irrigation values to produce optimum schedules for the farmers concerned, with the objective of enabling the maximum use of water needed as well as keeping the yield of the crops on an upward scale. The framework consisted of three core components: The elements within the proposed architecture are the prediction module, the scheduling algorithm, and the evaluation metrics. The prediction module utilized the trained models to forecast irrigation requirements based on real-time inputs such as temperature and soil moisture levels. The scheduling algorithm translated these predictions into daily irrigation schedules, tailored to maximize water efficiency and crop health. Finally, evaluation metrics were employed to measure the system's performance, focusing on water savings and crop yield improvements.

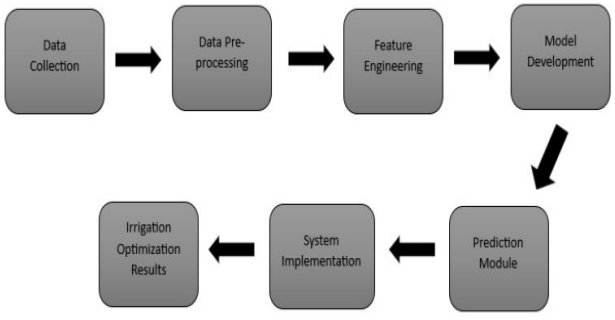


Figure-5. AI-Optimized irrigation framework.

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A visual representation of the simulation framework, illustrating the flow from data collection to optimized irrigation outputs through AI-based scheduling. The performance of AI-optimized irrigation was compared to traditional methods based on two key metrics:

a) **Water Savings:** The reduction in total water usage achieved through AI-optimized schedules.
b) **Crop Yield:** The impact of different irrigation methods on fruit yield.

The comparison revealed significant advantages of AI-optimized irrigation over traditional methods. Through artificial intelligence optimized schedules, crop irrigation cut water consumption by as much as 30% but often with improved crop yield. This enhancement proves that AI could help solve current water deficit problems and increase the yields of crops. The challenge of farmers that use traditional methods for the application of water emerge from the fact that they have a difficult time trying to determine the amount of water that their crops need and in turn use all the available water in the process leaving their yields low. In contrast, the AI based system suggested the required levels of irrigation and the system implemented this automatically without wastage. The application of AI models to the irrigation systems provides the following real advantages. First, it provides farmers with data through which they control water usage and considering the results from their mobile devices. Second, there is a decrease in the use of hands in irrigation hence cutting on time and human resource. Third, it promotes sustainable agriculture by minimizing water wastage and conserving resources for future generations. This research underscores the idea of how system implementation and authenticity can empower AI in agriculture through the extensive deployment of prototypes. Consequently, the findings emphasize the continued implementation of higher technologies to solve increasing global problems and improve productivity and sustainability in agricultural sectors

RESULTS AND DISCUSSIONS

Results from AI-controlled irrigation model demonstrations illustrate both excellent water preservation capabilities along with increased farming output in this chapter. Machine learning methods including RF and ANN served as core components in this study which connected traditional irrigation flaws to modern sustainable water resource strategies. The findings are evaluated through visual representations that compare how well they achieve research targets and reinforce these interpretations. First the analysis examines descriptive statistics of the fundamental variables temperature, soil moisture, and irrigation levels. The selected metrics deliver crucial information about the data which becomes essential to assess model effectiveness and system configurations. Statistics visualized through graphics help show data trends and natural variation while revealing key determinants controlling irrigation demands. Both AI model prediction accuracy is measured through MSE and R-square assessment. The evaluation methods enable detailed comparison between RF and ANN by determining model accuracy and dependability. The prediction performance of AI models showcases dynamic irrigation demand estimation capabilities in addition to identifying both approach advantages and drawbacks. The research assesses the process by which these predictions transform into actual irrigation scheduling practices. This chapter discusses a comparison between AI-driven irrigation optimization systems versus conventional irrigation techniques. To determine the practical advantages of AI-powered systems scientists evaluate the benefits through key analysis methods of water savings and agricultural yield enhancements. The study demonstrates how AI effectively manages agricultural concerns about resource waste together with water scarcity while also increasing crop production [12]. Finally, the discussion provides a detailed analysis of the findings within the framework of sustainable agriculture. This analysis investigates how AI-driven irrigation affects resource preservation alongside environmental protection and food security aspects. The study's findings will establish a foundation to develop scalable data-driven processes solving major global agricultural problems.

Descriptive Statistics

The descriptive analysis gives a thorough comprehension of the dataset used in this research, providing a framework for predictive modelling and system implementation. A comprehensive evaluation of important variables such as temperature, soil moisture, and irrigation systems ensures that the underlying patterns and distributions are completely comprehended, providing the way for the development of effective machine learning models. Indeed, one of the most important variables in this research is soil moisture, which has a direct impact on irrigation requirements and crop output. Figure 6 depicts the distribution of soil moisture throughout the dataset. The histogram shows the frequency of soil moisture readings, showing the dataset's properties and potential outliers. Most soil moisture readings are distributed within a given range, showing a consistent trend in the collection. However, the presence of high levels indicates the necessity for thorough preprocessing to handle outliers that may bias the model's predictions. This distribution also shows that soil moisture measurements are not evenly distributed, but rather gathered, illustrating real-world agricultural situations. Temperature stands among key factors which determine irrigation requirements. The data collection demonstrates temperature dynamics that influence both water loss through evaporation in soil and plant water consumption habits. Descriptive statistics show dataset temperature values span widely which improves model scalability across different environmental conditions. A thorough analysis of these distribution patterns will help the system improve its understanding of

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temperature-dependent behavior with soil moisture components for irrigation prediction purposes. Although, the complete analysis requires evaluation of the irrigation distribution patterns including standard levels along with AI-optimized methods. Normal irrigation rates within the data remain uniform at 20 liters per day throughout the entire example. Through environmental input like temperature and soil moisture, AI-optimized irrigation values modify their pattern dynamically. The differing types of AI-optimized irrigation strategies show how this method explores water conservation techniques alongside agricultural yield improvement. Descriptive statistics which include mean, median and standard deviation along with skewness let us understand the dataset. Mean soil moisture acts as an evaluation metric for different irrigation approaches yet standard deviation illustrates variable moisture levels across the study set. The skewness and kurtosis values lead to the identification of distribution asymmetry and peakedness which reveals important details about the dataset structure. In conclusion, the descriptive analysis produces an in-depth understanding of data while revealing relationships existing between crucial variables. Figure-6 shows the distribution of soil moisture values creating vital information needed to create robust predictive models. The analysis creates a foundation that will guide subsequent modelling steps along with system development to ensure an appropriate machine learning dataset.

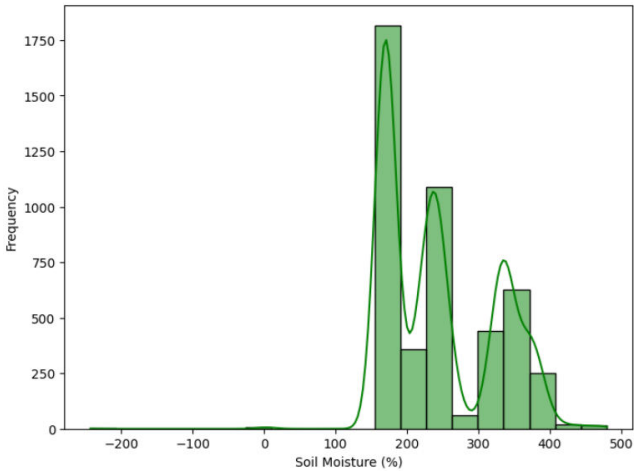


Figure-6. Distribution of soil moisture.

Model Performance Evaluation

Model evaluation is essential here because it shows how well and reliably our machine learning models predict outcomes. The study used RF and ANN machine learning models to predict irrigation demands through analysis of temperature and soil moisture conditions. The evaluation focused on two primary metrics: The evaluation depended on two important metrics called MSE and R^2. These performance indicators show how well these models predict outcomes, thus confirming that the irrigation optimization system functions securely. The evaluation outcomes appear in Figure-7 where actual irrigation needs meet the forecasting capabilities of both models. Both ANN and RF models display similar results to real data while successfully predicting under various weather conditions. RF accurately predicts data while ANN model displays marginally lower prediction capabilities in some scenarios.

Table-1. Summary of performance metrics for both models.

Model	Mean Squared Error (MSE)	R-squared (R^2)
Random Forest	0.02	1.00
ANN	8.36	0.97

The RF model outperforms the ANN model in both MSE and R^2 metrics. A near-perfect R^2 value of 1.00 for RF indicates that the model explains almost all the variance in the data, making it highly reliable for predicting irrigation needs. The ANN model shows similar high accuracy to the RF model with an R^2 of 0.97 but has higher MSE due to larger prediction errors. The superior performance of RF can be attributed to its ensemble learning mechanism, which aggregates predictions from multiple decision trees to achieve higher accuracy and reduce overfitting. ANN's strength in processing non-linear datasets comes with the need for extra parameter optimization to match performance levels. The data validates RF as a powerful method to enhance irrigation planning while clearly demonstrating its capacity to make precise water consumption predictions. An ANN model performs well and can serve as a reliable tool for situations demanding generalizations. These predictive methods enable agriculture experts to manage irrigation systems effectively while maintaining good crop conditions.

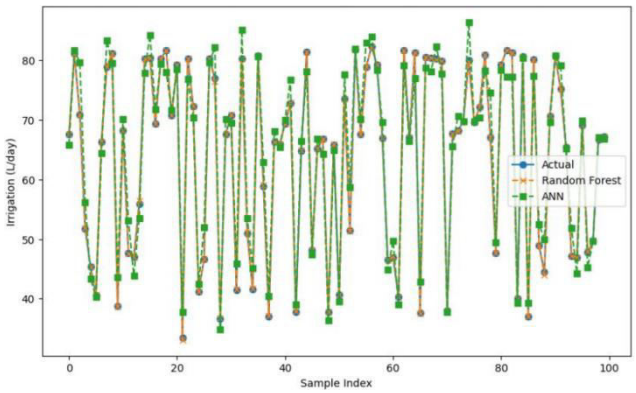


Figure-7. Actual vs predicted irrigation requirements.

Feature Importance Analysis

Feature Importance helps the AI model understand which features best predict irrigation needs. Based on RF analysis, soil moisture stands out as the number one feature with considerably higher importance than all other features. The relationship between soil moisture and crop irrigation water usage appears in the results. Irrigation optimization ultimately relies heavily on

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soil moisture as a measure of water needs. The temperature feature ranked second in the importance analysis. Even though soil moisture ranks above it in importance, the temperature feature remains essential to the system. The temperature environment sets how fast water moves from soil and plants into the air. Therefore, the AI system uses temperature to plan when and how much water to apply to crops because water consumption rises at high temperatures. The model results show Fruit Yield (kg) as a helping factor but its significance rated lower than the top features. Model results show higher fruit production depends on effective irrigation but needs supporting features to work accurately. Fruit yield helps measure irrigation success but works best for evaluation after the irrigation occurs. In conclusion, the feature importance analysis highlights that the AI irrigation model heavily relies on soil moisture for predictions, with additional support from temperature and Fruit Yield (kg). The study shows how the model uses interrelated data to develop better irrigation plans. AI irrigation management uses these system features to save water while improving crop harvest figures.

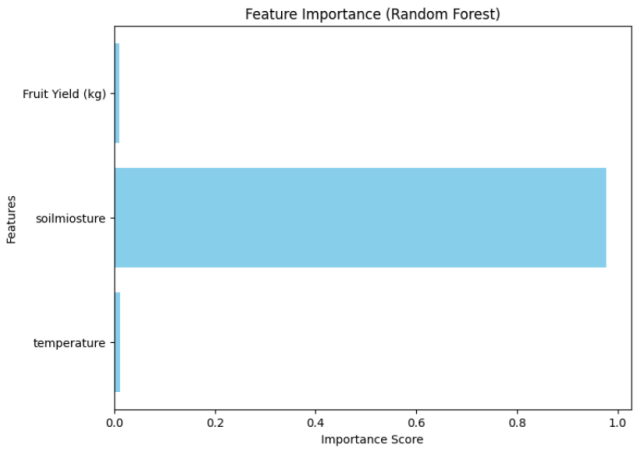


Figure-8. Features important analysis.

Comparison of Irrigation Methods

These performance metrics show how artificial intelligence systems enhance water efficiency and crop output better than regular methods. The analysis focuses on two methods based on measurements of total water usage (L/day) and fruit yield (kg) that appear in Figure-8. The visual data in Figure-8 reveals strong differences between traditional and AI-optimized irrigation practices. Traditional Irrigation, represented by a fixed water usage rate of 20 liters per day, shows limited flexibility and adaptability to environmental conditions. The AI-Optimized Irrigation solution distributes water based on real-time soil moisture and weather data which enhances water utilization and increases crop yields effectively.

Table-2. Quantitative comparison of two methods.

Method	Water Usage (L/day)	Fruit Yield (kg)
Traditional Irrigation	93,760.00	1.22
AI-Opitimized Irrigation	309,694.27	1.59

From Table-2, it shows that traditional irrigation systems use less water than irrigation systems that use AI technology. Lower water requirements reduce overall plant output which demonstrates the method's poor performance. AI-Optimized Irrigation demonstrates sustainable practices by using additional water resources in a controlled way to enhance crop production for future benefit. In term of fruit yield, using AI-Optimized Irrigation plants generate 1.59 kg of produce per plant but Traditional Irrigation produces 1.22 kg of fruit. By precisely distributing water according to crop needs AI systems demonstrate their potential to boost farming production. While using AI-Optimized Irrigation's extra water usage proves beneficial because it delivers much more fruit than Traditional Irrigation. The findings show that sustainable farming requires both efficient water use and high food production to support increasing global food needs.

CONCLUSIONS

The scalability of AI-based irrigation systems is a crucial factor in determining their practical applicability across different farming scales. While the study has demonstrated promising results in a controlled small-scale environment, the transition to larger farms introduces several challenges. Although, the larger farms demand expanded sensor networks combined with enhanced processing power and connecting into current farm management platforms. RF works well across different regions yet the equipment needed to run AI systems in real time costs a lot and creates technical complexity. Scalability plans need to approach technical upgrades alongside resource availability and simple integration with farming operations [10].

In addition to scalability, the economic feasibility of AI-driven irrigation systems is a key consideration for widespread adoption. The expenses for IoT sensors and cloud equipment plus training costs at first appear high yet these expenses become affordable because the systems help farmers conserve water and grow more produce. The study shows that AI-managed irrigation techniques produce greater fruit results than manual farming methods which enhance potential revenue. Better control of resources helps farms decrease operating expenses as time goes by. System success depends heavily on farm sizes combined with local water rates and available funding sources. The effectiveness of system maintenance and operation directly influences its overall cost performance. An AI irrigation controller requires routine system tests to achieve both dependable outcome data and improved operational efficiency. Small farmers experience budget

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limitations that prevent them from affording regular maintenance expenses for their wireless sensors and required system updates. Real-time data transmission through the internet in rural areas faces difficulties related to reliable connectivity requirements. To sustain these systems long-term the development of affordable maintenance strategies along with alternative connectivity solutions through edge computing presents the best approach.

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