Comparative analysis of machine learning models for smart irrigation systems

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ABSTRACT

Intelligent irrigation systems play a crucial role in addressing the global issues of water scarcity, climate variability, and sustainable agricultural production. These systems can help identify the efficient time and the exact quantity of irrigation through the use of data-driven ideas, which ensures maximum crop yield with minimal use of water. This paper provides a thorough comparative analysis of the four most commonly used Machine Learning (ML) models: Support Vector Machines (SVM), Gradient Boosting (GB), K-Nearest Neighbors (KNN), and Logistic Regression (LR), to predict the need of irrigation based on critical environmental and agronomic variables. The dataset features include soil moisture, air temperature, relative humidity, solar radiation, and crop types, among other features, obtained using sensor networks installed on farmland. We trained and tested each model before comparing its performance using standard evaluation metrics, which include accuracy, precision, recall, F1 Score, and the Area Under the Curve. These findings indicate that GB and KNN models performed better than SVM and LR. For instance, GB and KNN achieved precisions of 95.6% and 92.4%, respectively, compared to SVM and LR, which achieved precisions of 86.2% and 72.8%, respectively. In both accuracy and generalization, the GB model performs overall best. This study contributes a fair investigation of the suitability of well-known ML models in irrigation forecasting for smart farming in the south-western region of Nigeria. This study makes use of a region-specific dataset that is gathered by sensor networks, involving 100,000 records in two farming seasons.

1. Introduction

One of the most critical issues that the 21st-century agricultural sector of the 21st century will have to address is the efficient management of water. In the face of growing pressure from climate change, urbanization, and population growth, the necessity of making sustainable food production and the preservation of water resources a global priority should be acknowledged. Approximately 70% of the world's water used in agriculture is lost due to poor irrigation practices (Dotaniya et al., 2023; Shemer et al., 2023). Even the conveyor irrigation systems tend to be based on set schedules or the subjective judgment of the farmer, resulting in either over- or under-irrigation. Not only do such inefficiencies result in water wastage, but crops and soil are also likely to suffer, and agricultural productivity in the long term cannot help but be adversely affected.

To overcome these challenges, the idea of intelligent irrigation systems has been presented as an innovative service, which helps to get accurate and real-time irrigation advice by using sensors (Devadiga et al., 2024), the Internet of Things (IoT) (Srikanthnaik, 2024), and artificial intelligence (Younes et al., 2024) in the process. Of them, Machine Learning (ML) models have emerged as a promising methodology of predicting irrigation requirements based on the dynamic variables of the environment and crop-related parameters, including soil moisture, air temperature, humidity, solar radiation, and crop type, among others.

This paper examines how machine learning models can be utilized to enhance irrigation decision-making in the agricultural sector. It gives a cross-sectional comparison of four of the more popular ML algorithms: Support Vector Machines (SVM), Gradient Boosting (GB), K-Nearest Neighbour (KNN), and Logistic Regression (LR). The effectiveness of each of the models is determined by taking key performance metrics when each of the models is tested. This study contributes to advancing the emerging field of precision agriculture, with a focus on the south-western part of Nigeria. The significant contribution of the study is assessing the applicability of the chosen machine learning models in predicting irrigation needs based on a region-specific dataset gathered through sensor networks in the south-western part of Nigeria. It provides a basis for deployment in a water-scarce and resource-limited context, enabling more water-efficient practices and improved crop productivity, which aligns with the broader agendas of climate resilience and sustainable agricultural development. The innovative aspect lies in the localization of model training and evaluation, making the outcomes deployable and practical for real-world innovative farming systems in similar regional and resource-constrained settings.

2. Related work

The use of Machine Learning (ML) in smart agriculture is one of the primary areas that has garnered significant attention, as it enables informed decisions based on data. In particular, ML-lookup innovative irrigation systems have promising potential to optimize water application and increase crop yields of predicting the ideal time and volume of irrigation to be used, considering environmental and agronomic conditions.

Various authors have examined the application of ML analysis in irrigation prediction. For example, Teshome et al. (2024) utilized deep learning to predict soil moisture, while He et al. (2021) determined water allocation based on crop water requirements. Chlingaryan et al. (2018) reviewed the entire spectrum of precision agriculture technologies and discussed the use of ML in the analysis of sensor information toward making irrigation decisions. That is why Torres-Sanchez et al. (2020) introduced a decision support system based on supervised learning algorithms, Decision Trees, and SVM to automate irrigation scheduling, achieving a remarkable accuracy of decreasing water consumption.

Ponraj and Vigneswaran (2020) found that GB models have a better chance of predicting soil moisture conditions to determine when to irrigate than traditional linear classifiers. Among simple yet effective models, KNN was found to be effective in classifying irrigation needs among various types of crops used by Akshay and Ramesh (2020) and Jain et al. (2021). However, it struggles to work well on noisy and/or high-dimensional data.

The application of SVM has also not been spared since it is robust in classification tasks. In Shen et al. (2021) and Sumarudin et al. (2021), SVM was applied to a dataset on irrigation needs based on soil and climate information, achieving moderate success, albeit hindered by scalability problems due to the large dataset size. In the meantime, LR has been a benchmark in a lot of studies. Although its application, being interpretable and straightforward, may be beneficial, it often fails to represent the nonlinearity prevalent in agronomic settings (Aminuddin et al., 2021).

Nsoh et al. (2024) conducted a comprehensive review that demonstrated the effectiveness of IoT-driven solutions in combination with GB and SVM models of machine learning. What their work added was the emphasis on the fact that the real-time data collection capabilities of sensor network systems make a difference in providing adaptive irrigation treatments to maximize water savings and sustain crop health.

Likewise, Dong et al. (2024) discussed the practical implementation of an in-field IoT solution in precision irrigation, providing an example of an automated irrigation system that utilizes environmental sensors and predictive models in irrigation decision-making. Their findings validate the utility of ML-based systems in resource-limited real-world agriculture.

On a larger scale, a systematic literature review conducted by scholars in the year 2024 (Younes et al., 2024) found that the ML methods consistently outcast classic rule-based systems in accuracy, scalability, and applicability in any irrigation endeavour by synthesizing the results of more than 55 studies and establishing that the best ML methods (GB, KNN, and SVM) remain most reliable by far in all benchmarks in features of high precision and generalizable applicability. Yet another study, "Improving Soil Moisture Prediction with Deep Learning and Machine Learning Models" (Teshome et al., 2024), published empirical evidence that deep learning models and machine learning models based on GB-based outperformed KNN and neural network models in predicting soil moisture, a valuable indicator in irrigation planning.

In addition, an article in a journal published in 2024 in Sensors (Soussi et al., 2024) presented a cost-effective LoRaWAN-based innovative irrigation system suitable for small-scale agricultural fields. It devoted considerable attention to predictive analytics of irrigation valve control based on sensor signals; despite being mainly focused on hardware design, it highlights the importance of ML models in operating in real-time modes.

Irrespective of those contributions, there is a gap in the comprehension of the comparative functionality of these ML-based models with real-time sensors gathered intricately in various agronomic conditions. Additionally, there is a lack of literature on data-scarce areas, particularly with reference to sub-Saharan Africa. To fill this gap, this study tests and compares SVM, GB, KNN, and LR on a standard set of data gathered using sensor networks, thereby adding to the body of knowledge and increasing our understanding of the efficacy of ML-based innovative irrigation systems in resource-constrained environments.

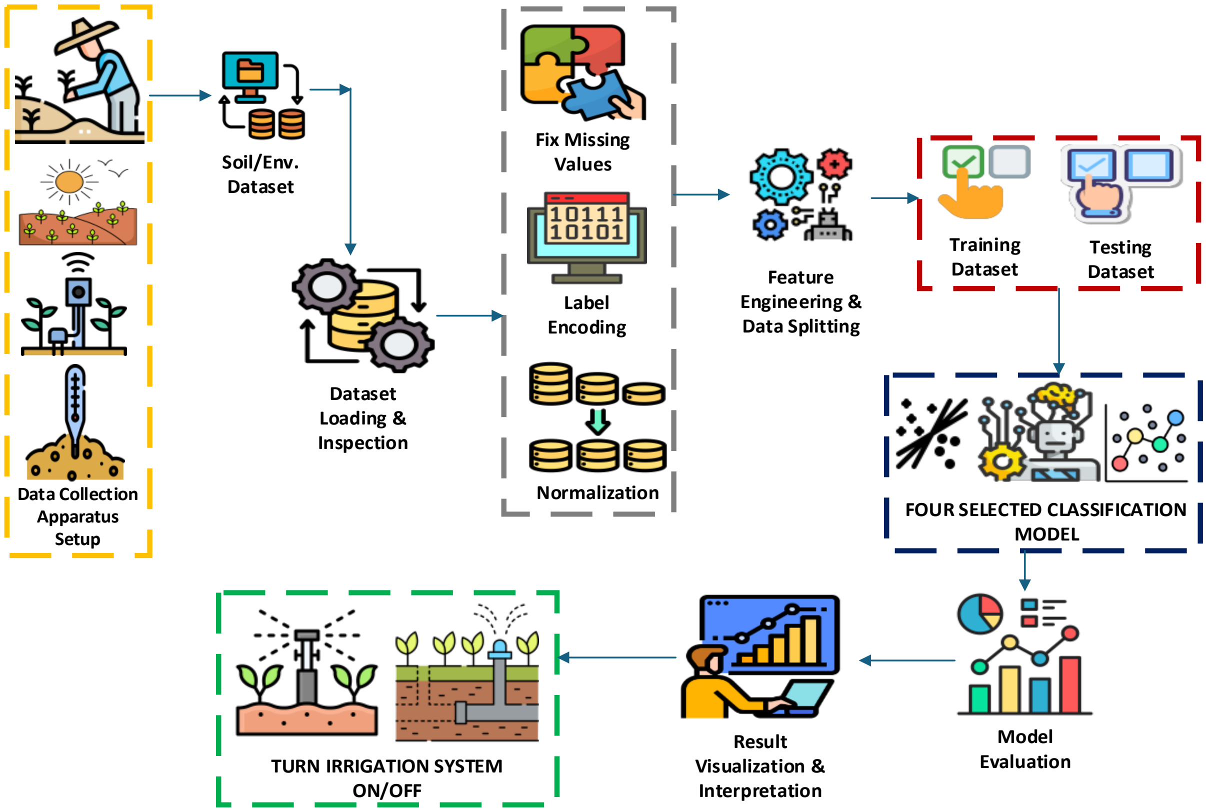
3. Methodology

3.1. Research design

The research design employed in this study is an experimental research design (as shown in Figure 1), which takes a quantitative approach to compare and assess four machine learning algorithms in predicting irrigation needs. The objective is to determine which model yields the most accurate results and generalizes effectively when applied to environmental and agronomic data.

Figure 1

Architectural Design of The Study



Note. Data analysis results of the research

3.2. Dataset description

This study obtained the dataset to be used, based on sensors deployed in the fields (as shown in Figure 1), with the assistance of the Department of Soil Science at the Federal University of Agriculture, Abeokuta (FUNAB). The dataset is a set of environment and agronomic factors as shown in Table 1 which contains: Soil moisture (Volumetric water content, m^3/m^3), Air temperature (°C), Relative humidity (%), Solar radiation (W/m^2), Rainfall (mm), Crop type (categorical), Soil type (categorical), irrigation needed (binary: 0 = No, 1 = Yes). The dataset consisted of 100,000 records collected during two growing seasons with varying climate and soil conditions.

Table 1

Description of Dataset Features

Dataset Feature	Description	Data Type
Soil Moisture	Volumetric water content in the soil (m^3/m^3) indicates soil hydration level.	float
Air Temperature	Ambient temperature around the crop area (°C) affects evapotranspiration.	float
Relative Humidity	Atmospheric moisture content (%); this influences the evaporation rate.	float
Solar Radiation	Amount of sunlight received (W/m^2); this impacts plant transpiration.	float
Rainfall	Measured precipitation (mm); this contributes to natural soil water replenishment.	float
Crop Type	Type of crop planted (categorical); different crops have varying water needs.	string (categorical)
Soil Type	Texture and composition of the soil (categorical); these factors affect water retention.	string (categorical)
Irrigation Needed	Target variable (binary: 0 = No, 1 = Yes); indicates whether irrigation is required based on environmental conditions.	int (binary: 0 or 1)

Note. Data analysis results of the research

Rule-based logic, validated by a soil scientist familiar with local farming practices, was applied to the sensor data to derive the target variable, "Irrigation Needed," as depicted in the pseudocode in Figure 2. The irrigation was tagged as not needed (0) and needed (1) when soil moisture was above a critical level (< 0.30 m^3/m^3), air temperatures were above 32°C, relative humidity was below 40%, and recent Rainfall was minimal (< 05mm). Moreover, irrigation in sensitive crops such as maize and vegetables was ineffective when soil moisture was slightly adverse and solar radiation was high, despite other factors not being too adverse. This method ensures that the target label accurately reflects the realistic agronomic needs in the local context.

Figure 2

Pseudocode For Derivation of Target Variable

```
Pseudocode for Derivation of Target Variable
for each record in dataset:
    # Set initial irrigation flag to 0 (no irrigation needed)
    irrigation_needed = 0
    # Rule-based thresholds (based on expert input and local context)
    if soil_moisture < 0.30:  # Volumetric water content threshold
        if air_temperature > 32 or relative_humidity < 40:
            if rainfall < 5:#Recent rainfall(e.g. in past 24-48hours)
                irrigation_needed = 1
    elif crop_type in ["maize", "tomato", "vegetable"]:
        if soil_moisture < 0.35 and solar_radiation > 500:
            irrigation_needed = 1
    # Assign the derived label
    record["irrigation_needed"] = irrigation_needed
```

Note. Data analysis results of the research

3.3. Data preprocessing

To provide quality and uniformity of data, the following preprocessing was done:

i. Missing Value Treatment: The missing values of records were imputed with mean/mode (in case of numerical/categorical values, respectively) or discarded, when sparsity was greater than 30%.

ii. Label encoding: These categorical features, like the type of soil and crop type, were numerically coded as numerical forms through label encoding.

iii. Scaling: Scale numerical features were scaled using Min-Max scaling to move into a similar range [0,1], which increased model performance.

iv. Data Splitting: We divided the data into training (70 percent) and testing (30 percent) data through stratified sampling to keep the classes proportional.

3.4. Selected machine learning models

The popularity and proven performance in classification tasks were used to select four machine learning models for a comparative analysis. All the selected models were trained using the Scikit-learn framework in Python. The chosen models are:

i. Support Vector Machine: It was trained by an RBF kernel, and regularization parameters (C) and gamma were optimized by the grid-based method.

ii. K-Nearest Neighbours: Applied with different values of *k* (3 - 15) and the distance measure being the Euclidean distance measure.

iii. Gradient Boosting: In 100 estimators and 0.1 learning rate are applied with the tuning by cross-validation.

iv. Logistic Regression: Logistic Regression with regularization of L2 and balanced class weights to manage any form of class imbalance.

3.5. Model evaluation metrics

To assess the accuracy and stability of the machine-learning models used in the innovative irrigation system, a set of universal measures was employed. These measures determine how effectively each algorithm forecasts irrigation needs using environmental and agronomic data. Accuracy, Precision, Recall, F1-score, and AUC were the primary metrics used.

Accuracy: Accuracy is a measure of a model's overall performance, indicating the percentage of correctly predicted observations in relation to the total number of observations. Intuitively, the metric seems reasonable; however, it draws incorrect conclusions when classes are not uniformly distributed in the datasets.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}} \tag{1}$$

Precision: Precision determines the ratio of correctly identified positive instances to the total number of predicted positive examples. This measure is handy when the cost of false positives is significantly higher than the cost of false negatives.

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

Recall refers to the ratio of correctly identified actual positive cases to the total number of positive cases, also known as sensitivity. The high recall facilitates the identification of all pertinent events, while the low recall hinders their identification.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (3)$$

F1-Score: F1-Score is a harmonic mean between the precision and the recall, thus a combination of the criterion-based considerations. It is a commonly used composite measure, as it drops comparatively gradually with reductions in precision or recall.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

AUC (Area Under the Curve): A receiver-operating-characteristic curve-based AUC is an aggregate measure of the overall discriminating power of a classifier over all conceivable cut-offs.

$$\text{AUC} \in [0,1], \text{ with 1 being a perfect classifier} \quad (5)$$

3.6. Experimental procedure

In Figure 3, this study presents the flowchart of the experimental process for comparing the selected classification model for predicting the need for irrigation. Figure 3 shows that the activities involved in the experiment are:

i. Inspect the dataset to determine structure and quality by loading and exploring.

ii. Carry out preprocessing of data to handle missing values, name encoding, feature scaling, and division into training and test sets.

iii. Apply the four ML models with suitable hyperparameter tuning.

iv. Perform model training, where each model is trained on the training set and tested on the unseen data (that is, the testing set).

v. Obtain and compare the evaluation parameters.

vi. Make a visualization of the results in terms of confusion matrices and ROC curves.

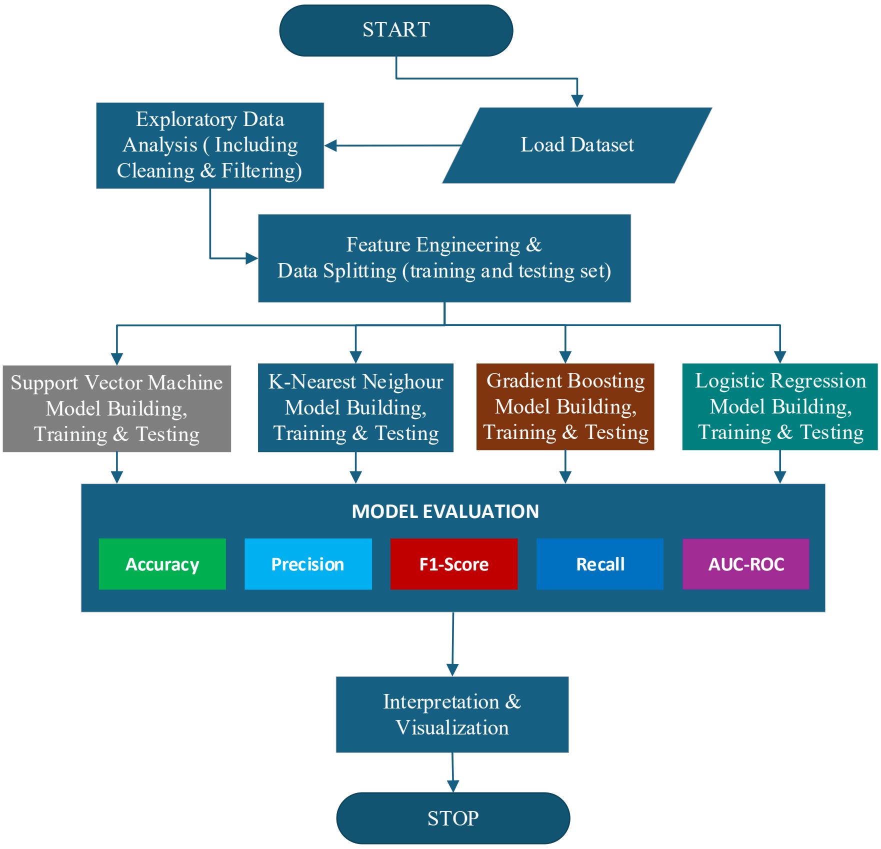
vii. Conduct statistical tests to verify whether there are significant differences in observed performance.

The employed tools and environment include Python 3.10 and libraries such as Scikit-learn, Pandas, NumPy, Matplotlib, and Seaborn, all within Google Colab.

The models in this research predict irrigation need based on eight input variables (as presented in section 3.2) obtained through sensor measurements. The result or target variable is a simple binary product of 0 and 1, which denotes ‘No’ and ‘Yes’ (meaning ‘No irrigation required’ and ‘Yes irrigation required’) respectively, derived based on a rule-based threshold and validated by an expert. Each of the machine learning models (SVM, GB, KNN, LR) was trained to predict whether irrigation is needed based on these inputs. The actual labels were used to interpret model predictions, and their effectiveness was evaluated through relevant metrics, including accuracy, precision, recall, F1-score, and AUC (as presented in Section 3.5), to determine whether the models were effective in predicting irrigation needs in relation to different environmental and agronomic factors. This strategy facilitates intelligent irrigation by allowing the timely and region-specific data-driven irrigation decisions.

Figure 3

Flowchart of The Comparative Study



Note. Data analysis results of the research

4. Result and discussion

In this section, we present the results of implementing and testing the four machine learning models - SVM, KNN, GB, and LR - in predicting irrigation needs. The preprocessed dataset was used to train and test the models, and their performance was measured in terms of five standard metrics, namely accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC). Table 2 and Figure 3 present the performance metrics for each model on the test dataset.

Table 2

Performance of Selected Classification Models

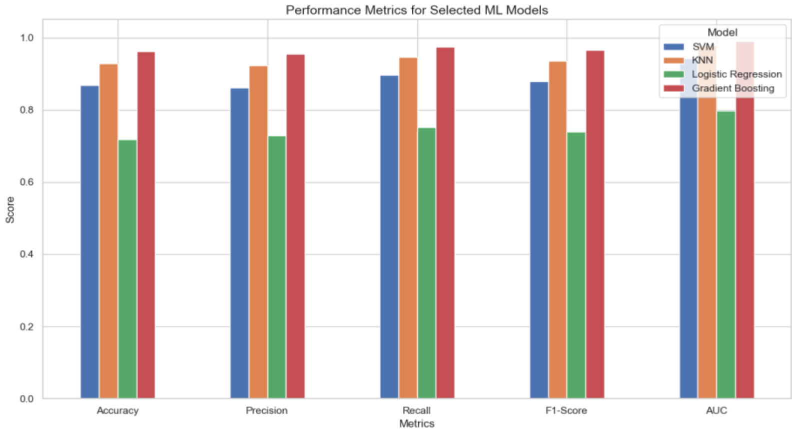
Model	Accuracy	Precision	Recall	F1-Score	AUC
SVM	0.8678	0.8622	0.8959	0.8787	0.9428
KNN	0.9294	0.9235	0.9463	0.9348	0.9781

GB	0.9624	0.9555	0.9751	0.9652	0.9903
LR	0.7176	0.7284	0.7524	0.7402	0.7984

Note. Data analysis results of the research

Figure 4

Performance Visualization of Selected Metrics



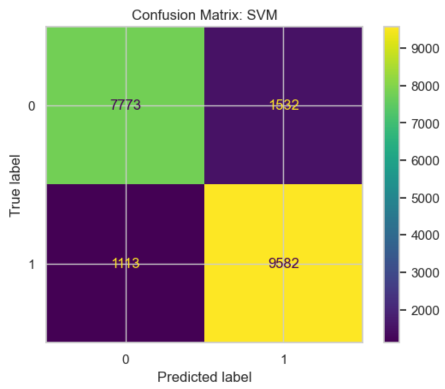
Note. Data analysis results of the research

Table 2 indicates that the GB model produced the best results in all performance measures, as it had the strongest predictive capacity, with an approximate accuracy rate of 0.96, an F1-score of approximately 0.97, and an AUC measure of 0.99. The KNN model was next, with approximate values of 0.93, 0.92, 0.95, 0.93, and 0.98 for accuracy, precision, recall, F1-score, and AUC, respectively. This option can be suggested in situations when the necessary computational capacity is lower. The SVM achieved a moderate accuracy of 0.87; however, it indicated that it would suffer from reduced generalization levels when applied to unseen data or a testing dataset. LR had the lowest accuracy of 0.72, meaning it was not very applicable to the complex and non-linear prediction of irrigation. This performance is graphically presented in Figure 4 as a complementary visualization for Table 2.

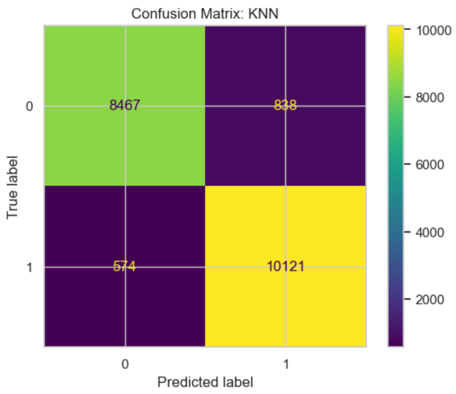
Figure 5 shows the confusion matrices, which are used to evaluate the performance of each model in distinguishing between classes. It shows that the GB model's accurate, favorable, and true negative rates are high, but the false prediction rate is very low. For the KNN model, the false positives are medium, but the classification is robust. The SVM and LR Models' false positive and false negative rates are higher, and thus their precision and recall are lower.

Figure 5

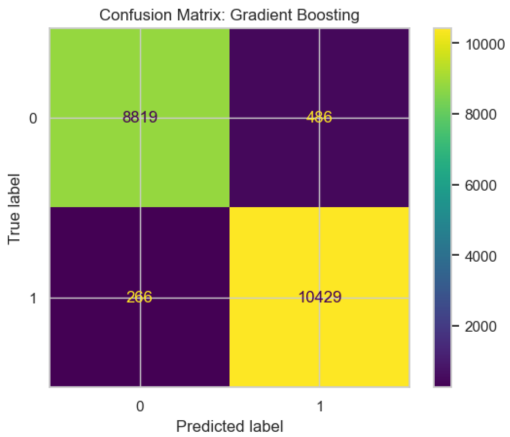
(A) Confusion Matrix for SVM, (B) Confusion Matrix for KNN, (C) Confusion Matrix for Gradient Boosting, (D) Confusion Matrix for Logistic Regression



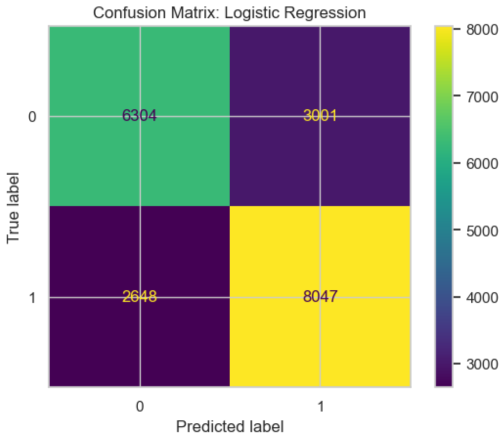
(a)



(b)



(c)



(d)

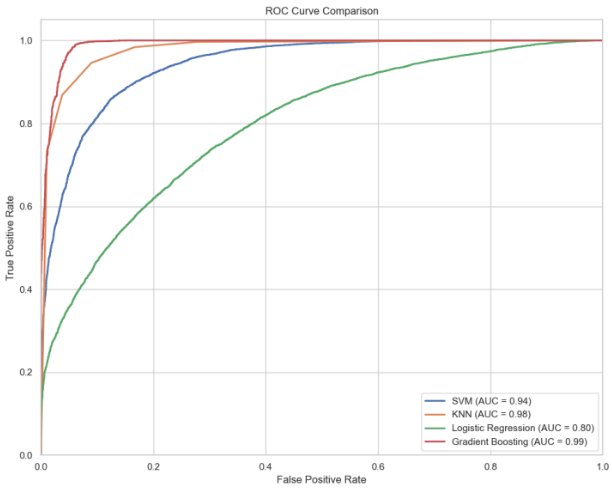
Note. Data analysis results of the research

4.1. ROC curve evaluation

Receiver Operating Characteristic (ROC) curves further illustrate the diagnostic ability of each classifier. As shown in Figure 6, the GB curve is closest to the top-left corner, indicating excellent separation between irrigation and non-irrigation instances. For the KNN curve, it is smooth and above the diagonal, indicating strong but slightly lesser performance compared to GB. The SVM curve also shows good performance, while the LR curve appears closer to the diagonal, suggesting limited class distinction capability.

Figure 6

The Selected Model AUC ROC Curves Depicting Each Model's Performance



Note. Data analysis results of the research

4.2. Discussion

The experiment results presented in this paper provide evidence of the increasing capabilities of Machine Learning (ML) in optimizing irrigation activities, as demonstrated by improved predictive accuracy and timeliness. Among the four models measured - SVM, KNN, GB, and LR - Gradient Boosting was the most effective in predicting irrigation needs, closely followed by KNN. This is because GB has an ensemble-based mechanism of correlating weak learners to create a good predictive model, thereby increasing generalization and minimizing overfitting.

KNN also outperforms SVM and LR, further confirming that instance-based learning is appropriate in spatially heterogeneous agricultural settings, where specific conditions, such as soil moisture and humidity, may differ across locations. Nonetheless, since KNN is unable to scale well with large datasets, it is another factor that affects its effectiveness in being introduced into real-world applications, such as large-scale farm monitoring systems.

Although SVM and Logistic Regression are basic and computationally effective, they were not significantly effective in dealing with complex, non-linear patterns of nature. In a similar study, Shen et al., (2021) and Sumarudin et al., (2021) reported that SVM achieved moderate success but was limited by the large dataset size, especially when applied to irrigation-based soil and climatic datasets, due to scalability issues. The poorer performance measures of the SVM and LR models among the selected models indicate that these models may not be well-suited for practical innovative irrigation systems, especially in conditions where interacting forces influence irrigation choices.

In general, the findings are consistent with the latest pertinent research of the years 2023 and 2024, which stress the efficiency of ensemble and neighbourhood-based models in precision agriculture operations. The results validate that, when properly utilized, the machine learning approach can play a crucial role in intelligent water management in resource-limited and information-limited environments.

5. Conclusion

In this research, a comparative study of four popular machine learning models was carried out to find out the capabilities of each of them to demonstrate their predictive capabilities in determining irrigation requirements using environmental and agronomic data.

The Gradient Boosting model achieved the best accuracy, precision, recall, F1-score, and AUC; therefore, it was the most suitable candidate for an innovative irrigation application among the other models tested. KNN also demonstrated potential, whereas a fair margin beat SVM and Logistic Regression.

Excellent results with GB and KNN models reveal the potential of machine learning in sustainable agriculture, as they offer the possibility of providing efficient irrigation scheduling. The implications of these findings are particularly significant for regions facing water supply shortages, climatic fluctuations, and yield optimization requirements.

6. Limitations and future work

Despite the promising results achieved in this study, some limitations were identified that present opportunities for future research and system enhancement. In terms of complexity and deployment of the model, Gradient Boosting has the best performance; however, it is also computationally expensive and cannot work on limited edge devices without prior groundwork. There is also an absence of a real-time application. The models were offline-trained and tested. Software applications and integration with intelligent irrigation equipment (such as solenoid valves, wireless sensors) are beyond the scope of this study and were not developed in real-time.

To expand on the findings of this study, several key areas are identified for future research. (1) Data Expansion and Real-time Gathering: Distributing field sensors IoT into many locations and environmental conditions will assist in generating bigger and more heterogeneous datasets, which enhance models' robustness and responsiveness. (2) Edge Deployment and Model Optimization: In the future, the model could be compressed or pruned, or a lightweight model such as XGBoost-Lite or TinyML could be used to create a deployment model that could run on hardware with limited capacities. (3) Hybrid and Deep Learning Methods: Exploiting the recent advances in the techniques of deep learning (e.g., LSTM, CNN) by considering them combined with the conventional ML approach might add a higher value in the ability to reveal complex relationships to the time-dependent environmental variables. (4). Decision Support System Integration: The prediction will be turned into a practical course of action with the models embedded into an easy-to-use Decision Support System (DSS) for the farmers.

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NO CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflict of interest.

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