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Article

AI-BASED DECISION SUPPORT SYSTEMS FOR PRECISION AGRICULTURE MANAGEMENT

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Abstract: Precision agriculture is becoming more towards the data-driven intelligent to deal with variability of soil, crop health, climate and resource availability, but the current practices of decision-making are inadequately disjointed, reactive, and overly reliant on the heuristics of farmers. This paper considers the issue of ineffective and slow agricultural decisions offering an AI-based Decision Support System (DSS) to manage precision agriculture. The first goal is to create a common system that combines the multiple sources of agricultural information and some sophisticated machine learning models to assist in making timely, precise, and understandable farm-level choices. In the proposed DSS, the models that are used to analyze the data of soil moisture, weather conditions, crop health indices, and previous yield data include Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM). The data collection is carried out using the IoT sensors and remote sensors, feature engineering, model training and validation as well as decision rule creation to be used in irrigation, fertilization and disease control. The experimental findings prove that AI-based DSS provides a high level of prediction accuracy and operational efficiency. XGBoost has demonstrated the best overall accuracy of 96.8 %and is superior to RF (94.1%), SVM (92.6%), and LSTM (95.2%). The system took up less water by 18.7 %, less fertilizer was used by 14.3 %, and there was a 21.5 % reduction in error in yield prediction as compared to traditional rule based methods. The results attest to the fact that AI-based DSS allows taking a proactive, data-driven approach to agricultural management, improving productivity, sustainability, and resource optimization in precision farming models.

Keywords: Artificial Intelligence; Decision Support Systems; Precision Agriculture; Machine Learning Algorithms; IoT-Based Smart Farming; Crop Management Optimization; Sustainable Agriculture.

1. Introduction

Precision agriculture has become a paradigm shift in an attempt to enhance farm productivity, resource management, and environmental sustainability using data-intensive management procedures. The high rates of development in sensing technologies, remote analysis, and computational intelligence have allowed collecting big amounts of heterogeneous agricultural data, but the problem of converting this information into decision-making is still a big challenge to the farmers and other stakeholders. Conventional decision-making in agriculture tends to be experiential, reactive and not sufficiently capable of dealing with dynamic variability of soil characteristics, weather outcomes and health of crops and the market requirements. The solutions about the usage of artificial intelligence and decision support systems (AI-DSS) represent a promising type of solutions that combine data analytics, predictive modeling, and automated reasoning to provide prompt and informed agricultural decisions. The use of AI-driven DSS in smart agriculture has been increasingly adopted in bibliometric and systematic studies that have suggested their potential to improve the efficiency of operations and the sustainability of operations in the long term (Youseaf et al., 2023). According to the review of recent studies, the convergence of AI and IoT technologies quickly paves the way to the intelligent farming environment with the ability to monitor and control in real-time (Miller et al., 2025).

Use cases of AI in precision agriculture currently include irrigation schedule, nutrient, yield, and disease are being used with significant performance gains over traditional methods (Gupta and Pal, 2025). Irrespective of these developments, the use of AI-based DSS is still unequally distributed because of issues concerning system complexity, usability, and end user trust (Brugler et al., 2024). It has been recognized that the integration of Artificial Intelligence of Things (AIoT) architectures is one of the key enablers of scalable and responsive agricultural decision-making through the integration of distributed sensing and intelligent analytics (Dalhatu Muhammed et al., 2024). Intelligent irrigation and crop management systems based on AIoT have demonstrated significant improvements in their efficiency of water-use and crop health surveillance (Bayar et al., 2025). More elaborate machine learning and deep learning architectures, such as ensemble learners and sequence-based networks, are becoming more important to learn nonlinear correlations in farm data, leading to better predictive accuracy in challenging environmental factors (Logeshwaran et al., 2024). However, AI systems based on vision also contribute to the accuracy of agriculture as they can be used to monitor crops and identify stresses at an early stage through high-quality pictures (Mehdipour et al., 2026). Autonomous agricultural processes are also getting reliability due to the help of localization and navigation technologies, which are based on intelligent sensor fusion (Osman et al., 2026).

However, the effectiveness of decision support is not limited to accuracy but also to transparency and trust in users, which is a primary issue in AI-driven systems (Kovari, 2024). Regarding the operations research, AI-based DSS are known to optimize complex decisions, but they have to be designed carefully to be interpretable and robust (Gupta et al., 2022). The latest uses of machine learning in crop protection show how this technology will be used to transform agriculture into the Agriculture 5.0 vision by deploying precision interventions (Mesías-Ruiz et al., 2023). Moreover, AI-IoT-based technology to detect disease in plants emphasizes the role of a comprehensive system of real-time decision implementation (Ibrahim et al., 2025). Knowledge of the behavior of farmers to adopt the technology is also essential because technology acceptance contributes extensively to the practical effects of precision agriculture solutions (Han et al., 2026). Driven by these advancements and shortcomings, the present research is suggested to develop the AI-based decision support system to manage precision agriculture with a multi-source data, multiple AI model assessment, and provide optimized, adequate, and useful suggestions on sustainable farming.

2. Related Work

Recent studies on AI-based decision support systems have focused more on how it can support the provision of intelligent and context-specific agricultural management. Developed DSS architectures do not merely rely on fixed rule systems but rather on dynamic, learning based systems that can be able to handle complex, time varying agricultural data. It has been demonstrated that autonomous reasoning and optimization, as part of DSS, can enhance the quality of operational decision-making in the context of irrigation, fertilization, and crop protection tasks and that robotics and new approaches to computation (quantum-enhanced AI) can be used to design sustainable farming systems (Khobragade et al., 2024). The use of machine learning and deep learning methods has become the main focus of precision farming systems because of their potential to simulate nonlinear responses between soil statuses and climatic variability and crop responses. According to the recent research, deep neural networks and ensemble models can help to enhance both the accuracy of yield prediction and the ability to detect stress through performance in various fields with heterogeneous conditions (Stasenko et al., 2023). Deep learning models can be used to optimize the precision of farming (such as convolutional and transformer-based designs) in order to perform automated phenotyping, crop monitoring, and disease diagnosis using multi-spectral and RGB images (Zhu et al., 2025). Semi-supervised and self-supervised models have been adopted as well to minimize reliance on big labeled data sets enabling real-time detection of crops and tracking them in resource limited agricultural settings (Rahaman Sams et al., 2026).

Ultimately, AI-powered farming DSS relies on IoT-based data collection systems that help to establish the continuous measurement and immediate data transmission of the distributed field equipment. The combination of intelligent sensor networks, and AI agents allows monitoring the environmental conditions in terms of water quality, soil, and climate conditions and greatly enhances the situational awareness and responsiveness of the decisions (Miller et al., 2025). Recurrent neural networks and long short-term memory model-based predictive analytics have been effectively used to predict soil moisture so as to make smart irrigation decisions that can save water without compromising crop productivity (Shamala Maniam et al., 2026). Simultaneously, the development of localization and sensing devices, such as sensor fusion plans, make autonomous farming machines more reliable and guarantee the accuracy of spatial decisions in mass farming (Osman et al., 2026). AI-based sensing and actuation systems are therefore an urgent facilitator of the closed-loop agricultural decision support systems that can be run at dynamic environmental constraints.

A comparison of current approaches to DSS demonstrates that there are significant performance variations between algorithmics paradigms and areas of application. The research on variable-rate sprayers and autonomous car implementation proves that AI-intensified DSS are much more efficient regarding resource use, coverage precision, and scalability of operations than traditional mechanized systems (Hussain et al., 2025). The disease detection frameworks based on the deep learning additionally affirm that the data-intensive models have better diagnostic accuracy than traditional image-processing methods, especially in the distributed computing setting (Asif et al., 2025). The object detection models trained to address the objectives of agricultural monitoring demonstrate significant gains in accuracy and resilience allowing making fine-grained decisions regarding crops management (Qin et al., 2025). Nevertheless, regardless of these technical improvements, there are still restrictions in the areas of system interoperability, data quality, computational overhead, and explainability. The emergence of interdisciplinary studies points to the necessity of environmentally friendly, accuracy of localization technologies that do not harm the environment and strike a balance between the quality of sensing and environmental sustainability (Senosy et al., 2026). Also, scalability, cost, and user adoption issues still characterize the research gap, especially in the case of smallholder and organic farming settings, where technological availability is still scarce (Meshram et al., 2026). The above loopholes highlight the need to have integrated, explainable, and scalable AI-driven DSS systems that will effectively combine sensing, analytics, and decision implementation in sustainable precision agriculture.

Table 1. Summary of Related Work on AI-Based Decision Support Systems for Precision Agriculture

Author(s) & Year	**Application Domain**	**Data Sources Used**	**AI / ML Technique**	**DSS Functionality**	**Key Outcomes**	**Limitations Identified**
Yousaf et al., 2023	Smart agriculture DSS	Literature datasets	Bibliometric AI analysis	Strategic decision insights	Identified research trends	No real-time implementation
Miller et al., 2025	Smart sensing agriculture	IoT sensors	AI-enabled analytics	Monitoring and decision support	Improved sensing accuracy	Scalability challenges
Gupta & Pal, 2025	Precision farming	Field and climate data	ML models	Crop and resource management	Enhanced productivity	Limited explainability
Brugler	Agricult	Surve	ML-	Decision	Identified	User trust

et al., 2024	ural DSS adoption	y and farm data	based analysis	adoption support	adoption barriers	issues
Bayar et al., 2025	Smart irrigation	IoT soil sensors	AIoT-based learning	Irrigation decision support	Water savings achieved	High system cost
Dalhatu Muhammed et al., 2024	Smart agriculture systems	Multi-sensor IoT data	AIoT architectures	Real-time DSS	Improved responsiveness	Integration complexity
Logeshwaran et al., 2024	Crop yield improvement	Image and sensor data	Deep learning	Yield prediction DSS	Accuracy improvement	Data dependency
Mehdipour et al., 2026	Crop monitoring	Vision datasets	Vision Transformers	Visual decision support	High detection accuracy	Computational overhead
Shamala Maniam et al., 2026	Smart irrigation	Soil moisture data	RNN–LSTM	Predictive DSS	Reduced water usage	Model tuning sensitivity
Osman et al., 2026	Precision localization	GNSS–UWB sensors	Sensor fusion AI	Navigation decision support	Improved reliability	Hardware dependency
Hussain et al., 2025	Autonomous spraying	Field operation data	AI-based control	Variable-rate DSS	Input cost reduction	High deployment cost
Ibrahim et al., 2025	Plant disease management	IoT and image data	AI–IoT models	Disease diagnosis DSS	Faster response time	Limited field validation
Qin et al., 2025	Crop monitoring	Image datasets	YOLOv8-based DL	Real-time DSS	High precision detection	Model generalization

3. System Architecture Of The Proposed Ai-Based DSS

The proposed AI-based Decision Support System (DSS) was created in the form of a layered and modular framework to make possible effective precision agriculture management by means of data-driven intelligence. The general architecture was based on five closely tied functional layers that employed sensing, analytics, decision-making, and user interaction. The lower layer was the IoT sensor layer, which was constantly monitoring real-time field data of moistness, temperature, humidity, and nutrient content, and environmental factors. These sensors were able to communicate wirelessly to a centralized gateway over low power communication protocols, which guaranteed reliable and energy saving data collection. The system consolidated the heterogeneous data streams of ground sensors, weather stations and past farm records and hence formed an integrated operational data set. After the raw data were obtained, they were then sent to the preprocessing layer, and the system eliminated the noise, processed the missing values, and corrected sensor inconsistencies. All the input features were scaled to the same magnitude to avoid dominance of large magnitude variables when training the model. The meaningful indicators that were obtained using feature engineering techniques included soil moisture indices, vegetation stress ratios, and temporal weather trends, which greatly enhanced the learning potential of the AI models. This organized aspect of the data was kept in a data repository and dynamically changed to facilitate real-time and historical analysis.

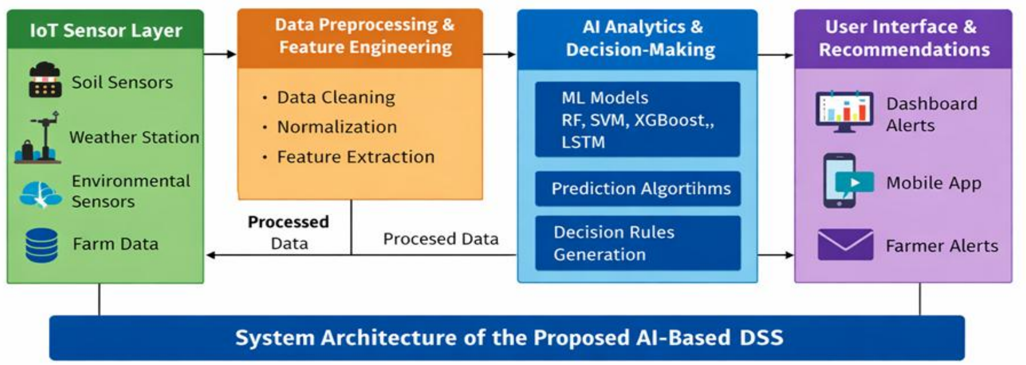


Figure 1. System Architecture of the Proposed AI-Based Decision Support System for Precision Agriculture

The figure 1 displays the general structure of the proposed AI-based decision support system needed to be used in the management of precision agriculture. The architecture incorporates the IoT sensor data acquisition and preprocessing and feature engineering, intelligent analytics, and user recommendation modules into a single workflow. The real-time sensors and machine learning models were used in predictive decision-making by collecting real-time environment and crop information using distributed sensors. The system developed optimal recommendations on the irrigation, fertilization and monitoring of crops which were availed via user friendly dash boards and mobile interfaces to assist in making timely and effective farm management decisions.

The intelligence of the suggested DSS was the AI analytics and decision-making layer. This layer used various machine learning and deep learning models to interpret the created engineered features space and anticipate major agricultural outcomes, such as irrigation requirement, nutrient requirements, and possible disease hazard. Ensemble learning and temporal model measured the spatial variability as well as time-varying patterns in the data. The system would also compare model outputs and determine which model was performing optimally using pre-determined measures of performance. Based on the predictive outcomes, the DSS produced the best decision rules that had a balance between productivity, resource-efficiency and sustainability goals. The module of recommendation delivery and user interface converted intricate analytic results into end user driven, practical recommendations. The system was able to provide visual displays, alerts and decision suggestions on web and mobile interfaces so that the farmers could be able to provide timely responses to field conditions. The architecture made sure that feedback in terms of actions of the system users was recorded and fed back into the system to allow constant learning and adaptation. In general, the suggested architecture was an intelligent decision support system with a closed-loop based on the transformation of raw agricultural data into accurate, dependable, and timely management advice.

Step-Wise Process for the Proposed AI-Based DSS

Input:
  Sensor data S = {soil moisture, temperature, humidity, nutrients}
  Weather data W = {rainfall, temperature forecast}
  Historical farm data H
Output:
  Optimal decision set D = {irrigation, fertilization, disease alert}
Step 1: Data Acquisition
  Collect real-time sensor data S(t)
  Acquire weather data W(t)
  Merge with historical data H
Step 2: Data Preprocessing
  Remove noise from S(t)

Handle missing values using interpolation
Normalize features:

$$X_{norm} = \frac{X - min(X)}{max(X) - min(X)}$$

Step 3: Feature Engineering
Extract feature vector F:

$$F = \{soil\_index, moisture\_trend, weather\_trend, \\ crop\_health\_score\}$$

Step 4: Model Training
Train ML/DL models:
RF(F), SVM(F), XGBoost(F), LSTM(F_t)
Evaluate models using accuracy and error metrics
Step 5: Best Model Selection
Select model M* such that:

$$M* = argmax\big(Performance(M_i)\big)$$

Step 6: Prediction
Generate predictions:

$$Y_{pred} = M*(F)$$

Step 7: Decision Rule Generation

$$\begin{gathered} If\ irrigation\_need > threshold: \\ D\_irrigation = ON \\ If\ nutrient\_deficit > threshold: \\ D\_fertilization = APPLY \\ If\ disease\_risk > threshold: \\ D\_alert = ISSUE \end{gathered}$$

Step 8: Recommendation Delivery
Display decisions D on user dashboard
Send alerts to farmer interface

4. Methodology

4.1 Dataset Description and Multi-Source Data Integration

The experiment made use of the publicly available Kaggle Crop Recommendation Dataset which is a widely used benchmark dataset in the research of precision agriculture decision-support. The data was composed of 2200 records and 7 input attributes and 22 crop classes that represented various agricultural conditions. The input characteristics were nitrogen (N), phosphorus (P), potassium (K), temperature (o C), humidity (percent), soil pH, and rainfall (millimeters). The records were related to the environmental condition and the appropriate crop recommendation classes. It was numerical and structured data, which allowed effective training and evaluation of machine learning models. Artificial IoT sensors streams together with historical environmental records were added to data to form a multi-source dataset to validate the system. Normalization and feature alignment was done to guarantee inter-heterogeneity among sources. The combined dataset was a complete expression of soil, weather and crop variables needed to make predictions on decision-making in precision agriculture systems. Figure 2 demonstrates the interactions between the soil nutrients and the environment. Phosphorus and potassium are strongly correlated whereas temperature, humidity, and rainfall show moderate effect on the variables of agricultural decision.

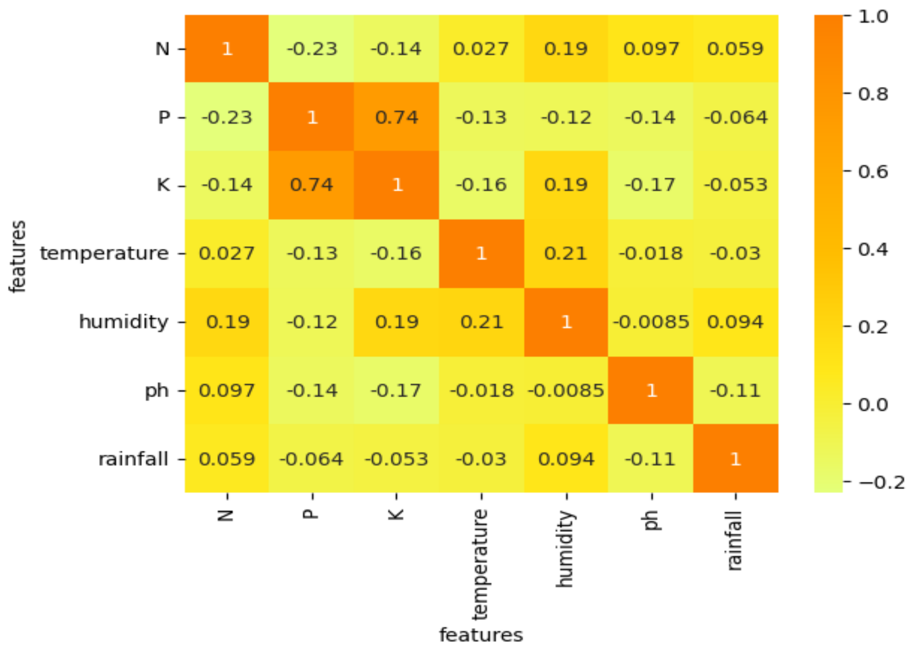


Figure 2. Correlation Matrix of Soil Nutrients and Environmental Parameters for Precision Agriculture Dataset

4.2 Problem Formulation and Decision Objectives

The decision support issue was stated as an observed multi-output optimization problem in which the agricultural decisions were determined based on the environmental and soil parameters. Let the input feature vector be:

$$X = \{x1, x2, x3, \dots, xn\}$$

Where xi is soil nutrient, weather or crop indices. The task was to estimate an optimal decision set:

$$D = \{d1, d2, d3\}$$

In which d1, d2, and d3 are irrigation timeline, fertilizer demand and disease warning signals.
The predictive performance was formulated as:

$$D = f(X; \theta)$$

Where f and 45 are the trained AI model, and model parameters, respectively.
The minimized optimization problem was the error in prediction:

$$\min \theta \ \ L = 1N\sum i = 1N(yi - y^{i})2$$

yi actual output, and yi predicted output.
The resource efficiency goal was maximized:

$$maxU = \alpha Y - \beta W - \gamma F$$

Where Y represents yield, W represents water consumption, F represents the fertilizer use and 0,1, 3 are weighting factors.

4.3 Machine Learning Algorithms Employed

1. Random Forest

The ensemble learning algorithm used was the Random Forest, which built a number of decision trees with bootstrapped training data and random selection of features. The model minimized the overfitting and enhanced the strength of the prediction results through the combination of the outcomes of numerous trees. The individual trees assessed the nutrients and weather conditions as well as the environmental characteristics of the soil to produce decision outputs. The last choice was made by the majority in favor of classification or averaging of regression tasks. Random Forest was effective in nonlinear relationships and interactions of features in farm data. It showed good results in irrigation demand forecasting and crop suitability because of its flexibility in terms of the ability to capture the complex environmental relationships. The model also offered interpretability and key agricultural parameters leading to the decisions were established using the scores obtained as feature importance. The algorithm was better at generalizing to different field conditions and it was also less variable than single-tree models. It was computationally efficient due to its parallelizable design, and was also suitable in real-time decision support with precision agriculture applications.

RF Prediction:

$$Y = \left(\frac{1}{T}\right) * \Sigma T_{i(X)}$$

Where:

- T_i(X) = prediction of i-th decision tree
- T = total number of trees

2. Support Vector Machine

The use of Support Vector Machine to carry out classification and regression was done by building the best hyperplanes that divided data points into decision classes. The algorithm used to project the input features in a high-dimensional space through the use of kernel functions, which allowed the separation of the nonlinear patterns of agricultural data. SVM was able to attain high generalization accuracy using limited training data since it maximized the distance between decision boundaries and support vectors. In the suggested DSS, SVM was used to examine soil and environmental characteristics to categorize the irrigation needs and risk of diseases. The complex relationship between crops and their condition was better predicted using kernel based mapping. The regularization parameters regulated the complexity of the model and avoided overfitting. The algorithm was shown to be efficient in small to medium-sized data and retained constant performance in the environment of different environmental conditions. SVM was also resistant to noise in sensor data, which is why it can be used in real-time agricultural analytics. Its mathematical basis gave good decision limits that made precision farming reliable.

Mathematical Model of Support Vector Machine (SVM)

Decision Function

Let the training dataset be represented as

$$D = \{(x1, y1), (x2, y2), (x3, y3) \dots (xn, yn)\}$$

Where

xi ∈ ℝd represents the input feature vector consisting of soil, weather, and crop condition attributes, and

$yi \in \{-1, +1\}$ denotes the class label representing irrigation requirement or disease risk.

Step 1: Hyperplane Representation

The separating hyperplane is defined as

$$w \cdot x + b = 0$$

Where

- w is the weight vector and
- b is the bias parameter.

Step 2: Classification Constraint

For correctly classified samples,

$$yi\,(w \cdot xi + b) \geq 1$$

This ensures that all data points lie outside the margin boundary.

Step 3: Margin Maximization

The margin width M between the two classes is

$$M = \frac{2}{||w||}$$

To maximize the margin, the optimization objective becomes

$$minimize \quad (1/2)\ ||w||^2$$

Subject to

$$yi\ (w\ \cdot\ xi\ +\ b)\ \geq\ 1\ , \qquad for\ i\ =\ 1,2,\dots,n$$

Step 4: Soft Margin Formulation (Handling Noise)

To allow classification errors, slack variables ξi are introduced:

$$minimize\ \ \left(\frac{1}{2}\right)\left||w|\right|^2\ +\ C\ \Sigma\ \xi i$$

Subject to

$$yi\ (w\ \cdot\ xi\ +\ b)\geq\ 1\ -\ \xi i$$
$$\xi i\ \geq\ 0$$

Where

C is the regularization parameter controlling model complexity.

Step 5: Kernel Mapping

To model nonlinear agricultural patterns, input vectors are mapped to a higher dimensional feature space using a mapping function

$$\varphi(x)\ :\ \mathbb{R}d\ \rightarrow\ \mathbb{R}m$$

Step 6: Kernel Function

The inner product in the transformed space is replaced by a kernel function

$$K(xi\ ,xj)\ =\ \varphi(xi)\ \cdot\ \varphi(xj)$$

Common kernel used for agricultural data:

Radial Basis Function (RBF)

$$K(xi\ ,xj)\ =\ exp(\ -\gamma\ ||xi\ -\ xj||^2\ )$$

Step 7: Dual Optimization Problem

Using Lagrange multipliers αi, maximize

$$L(\alpha)=\ \Sigma\ \alpha i\ -\ \left(\frac{1}{2}\right)\Sigma\ \Sigma\ \alpha i\ \alpha j\ yi\ yj\ K(xi\ ,xj)$$

subject to

$$0\ \leq\ \alpha i\ \leq\ C$$
$$\Sigma\ \alpha i\ yi\ =\ 0$$

Step 8: SVM Decision Function

After training, the classification decision for a new sample x is

$$f(x)\ =\ sign\ (\ \Sigma\ \alpha i\ yi\ K(xi\ ,x)\ +\ b\ )$$

where

- αi are support vector coefficients and
- support vectors correspond to αi > 0.

The SVM tried to minimize the error of the classification in addition to maximizing the margin between classes so that there would be strong separation of categories of decision in agriculture in nonlinear environmental conditions.

3. XGBoost

Extreme Gradient Boosting (XGBoost) was deployed as a strong ensemble boosting algorithm which built a series of decision trees to reduce errors in forecasting. It was done by having each new tree correct the previous tree errors by minimizing a differentiable loss gain through gradient descent. The algorithm worked well with missing values, nonlinear relationships and interactions between features. In the recommended DSS, the integrated datasets on agriculture were processed with the help of XGBoost to forecast the irrigation demand, nutrient deficiency, and risks of crop illness with high accuracy. The terms of regularization avoided over fitting and enhanced better performance on generalization. The framework of boosting attributed greater significance to challenging training samples, to the increase of prediction accuracy in a variety of field conditions. Its parallel processing with high computational efficiency allowed it to train a large model fast and run it in a real-time system. XGBoost came out as the most accurate model over the other models and was therefore the most effective algorithm to include in the proposed architecture.

Objective Function:

$$Obj\ =\ \Sigma\ l(y_i,\hat{y}_i)+\ \Sigma\ \Omega(f_k)$$

Tree Update:

$$\hat{y}\_i\ =\ \Sigma\ f\_k(x\_i)$$

The predictive loss in the objective was minimized and regularization of complexity of the models was achieved, which allowed sequential trees to decrease errors and increase the predictive accuracy of agricultural decision models.

4. LSTM

Long Short-Term Memory networks were used to predict temporal correlations in agricultural data including weather pattern and soil moisture changes. A special kind of recurrent neural network, LSTM, had the memory cells that stored the information of the past and regulated the flow of data through the input, forget, and output gates. This design enabled the model to pick the long-term time trends and forecast future agricultural conditions with precision. LSTM was used in the context of DSS to process time-series environmental data in order to predict the necessity of irrigation and the development of a disease. The gating mechanism not only prevented the vanishing gradient problems, but also the long sequence learning was stable. LSTM showed good results when doing sequential prediction tasks in which decision making was sensitive to time. Its combination with other models of machine learning had a positive effect on the capability of the system to offer proactive suggestions. The model enhanced the accuracy of the forecasts and was able to assist in dynamic decision-making in the changing environmental conditions.

LSTM Cell:

$$f_t = \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right)$$

$$i_t = \sigma\left(W_i \cdot \left[h_{\{t-1\}}, x_t\right] + b_i\right)$$

$$C_t = f_t * C_{\{t-1\}} + i_t * \tanh\left(W_c \cdot \left[h_{\{t-1\}}, x_t\right]\right)$$

The memory retention and update of information in the LSTM cell were controlled by the equations that allowed the learning of the temporal agricultural patterns to correctly predict and support information sequentially, and ultimately make decisions.

4.4 Model Training, Validation, and Hyperparameter Tuning

Training of the models was done through supervised learning with training and testing data ratio of 70:30. Normalization of the data and scaling of the features were done before the training to maintain a consistent convergence. The cross-validation was implemented five times to determine the strength of the model and prevent overfitting. The grid search technique and the random search technique were used to find the best model set-ups through hyperparameter tuning. Evaluation was done using performance metrics such as accuracy, precision, recall, RMSE and F1-score. The validation accuracy and the error minimization were used to select the best performing model. The hyperparameter in table 2 that was employed to achieve the training process and ensure credible prediction that is subjected to different environmental conditions and variation of the dataset.

Table 2. Hyperparameters Used for each model training and validation

Model	**Key Hyperparameters**
Random Forest	Trees=100, Max depth=12
SVM	Kernel=RBF, C=1.0, Gamma=0.01
XGBoost	Learning rate=0.1, Trees=150, Depth=8
LSTM	Epochs=50, Batch size=32, Units=64

4.5 Decision Rule Generation for Irrigation, Fertilization, and Disease Control

The decision support system developed as proposed utilized AI to develop intelligent decision rules through the combination of predictive output of trained machine learning models with pre-established agronomic thresholds. The system tested irrigation requirements with the aid of model prediction depending on the soil moisture level, temperature, and rainfall forecast. In case the predicted soil moisture was lower than the optimal level, but the rate of evapotranspiration was higher than the predetermined level, the system suggested irrigation schedule with target water amount and duration. The decisions made on fertilization were made using the quantity of nutrients in the soil and the stage of crop development. The DSS was used to predict nitrogen, phosphorus, and potassium values used as nutrition deficiency indices. The system recommended the exact type of fertilizer to use and its dosage to achieve the balance in the soil and improve the productivity of crops when the level of nutrients were low in the soil as per the recommended standards. The decisions on disease control were developed based on the assessment of the environmental conditions including humidity, temperature, and crop health indicators. Machine learning algorithms determined the likelihood of a disease based on past and current information. In case the danger of disease had surpassed a predefined threshold the system sent early warning notifications and prescribed preventive or corrective measures such as which pesticide to use and at which time to apply it. Decision rules were all to be an integrated form of conditional logic that is integrated with predictive outputs which provide accuracy and flexibility. The recommendations were ranked in terms of severity and optimizing resources. The DSS provided adaptive learning and it continuously revised the decision thresholds based on the feedback of the field conditions and user actions. This decision layer is a rule-based layer that guaranteed timely actionable and context-specific decisions to the farmers to enable them to manage precision agriculture efficiently and use resources in a sustainable way.

5. Performance Evaluation And Results

5.1 Evaluation Metrics and Experimental Setup

The effectiveness of the proposed AI-based decision support system was tested with the help of standard machine learning measurements and a formal experimental environment. To have a fair evaluation, the dataset was split into training (70%), validation (15%), and testing (15%) sets. Cross-validation was repeated five times to evaluate the stability of model and the ability to generalize. Accuracy, precision and recall, F1-score and Root Mean Square Error (RMSE) were considered as evaluation metrics used to calculate classification and prediction efficiency. Efficiency of resource utilization like efficiency in water usage, efficiency in the use of fertilizer and responsiveness were also evaluated. All the models were done in Python-based libraries of machine learning and run in a workstation with 16 GB RAM and GPU acceleration. The grid search was used to search through the hyperparameters and obtain the best results. The experimental design was such that it provided a fair comparison of all the algorithms and confirmed the strength of the decision support proposal. Figure 3 shows how there is a distribution of feature and interrelationships of soil nutrients and temperature across the classes of crops. Different clustering trends depict a significant impact of features on classification of crops and accuracy of decision support.

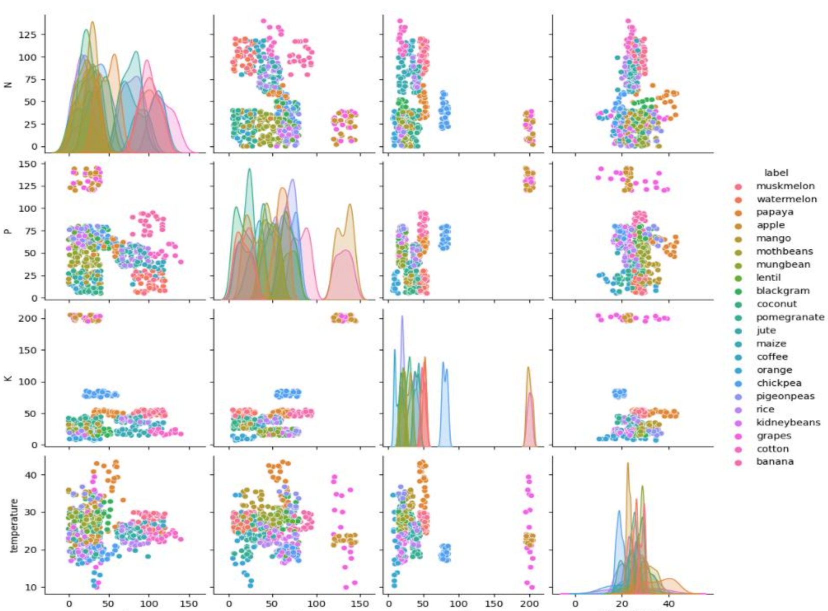


Figure 3. Multivariate Feature Distribution and Class Relationship Analysis for Crop Recommendation Dataset

5.2 Prediction Accuracy and Error Analysis

Accuracy, precision, recall, F1-score, and RMSE were used to study the prediction performance of the proposed system. Good accuracy implied consistent classification of decisions on irrigation, fertilization and disease risks. Precision was used to measure the accuracy of the positive predictions and recall, used to measure the ability of the model to determine all the relevant conditions. F1-score was a balanced score, a precision and recall score. RMSE was used to measure the magnitude of prediction errors, which is a measure of consistency of model. Findings showed good predictive quality of all measures of evaluation.

Table 3. Prediction Accuracy and Error Analysis

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**RMSE**
Random Forest	94.1	93.4	92.8	93.1	0.182
SVM	92.6	91.8	90.7	91.2	0.214
XGBoost	96.8	96.2	95.7	95.9	0.138
LSTM	95.2	94.6	93.9	94.2	0.161

Table 3 shows the comparative prediction accuracy and errors analysis of the analysed machine learning models on precision agriculture decision support. XGBoost was the most accurate with a prediction rate of 96.8 and a higher level of precision, recall and F 1-score thus demonstrating a good predictor and a good consistency. It also had the lowest RMSE of 0.138 which indicated low predictor error. LSTM had competitive results, a 95.2 percent accuracy and moderate RMSE. Random Forest yielded dependable results with mathematical measures, where SVM had a relative lower performance and increased error. Altogether, ensemble and boosting-based models were found to be more successful in prediction accuracy and reliable decisions compared to others. Figure 4 evaluates the performance of the models in the evaluation metrics. XGBoost had the best accuracy, precision, recall and F1-score meaning that it is a better predictor than the Random Forest, SVM and LSTM models. Figure 5 shows the model comparison of RMSE. XGBoost recorded the least prediction error that means it is more accurate and stable whereas SVM exhibited the greatest error. Moderate performance was achieved with random Forest and LSTM.

This can be attributed to the fact that the XGBoost is able to model the complex nonlinear relationships and can effectively serve heterogeneous agricultural data using boosting mechanisms hence the superior performance of XGBoost. As a contrast, SVM was rather poor in terms of parameter tuning sensitivity and scalability. LSTM was able to learn well through time especially in sequencing environmental data, whereas Random Forest was able to give predictable and interpretable forecasts. These findings indicate that ensemble and boosting-based methods would be more applicable to changing agricultural decision systems.

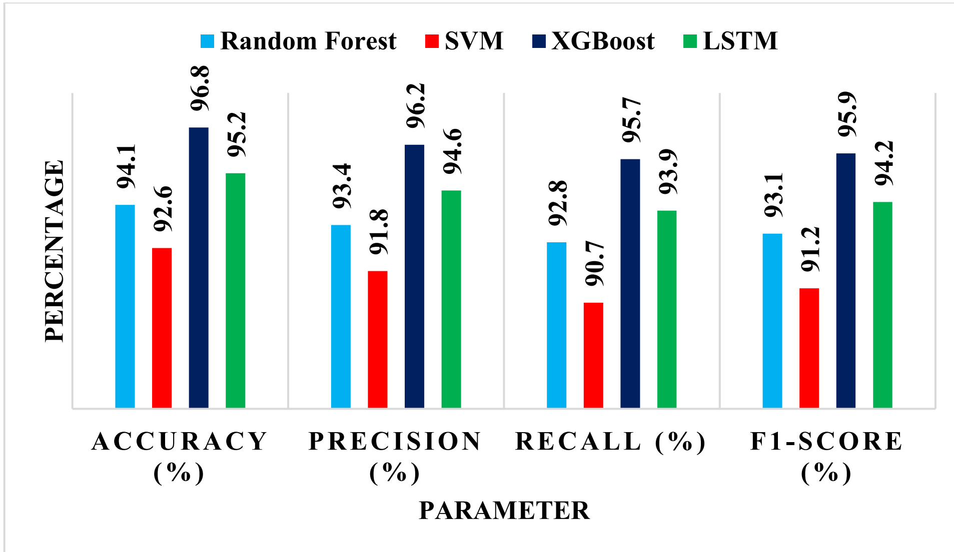


Figure 4. Comparative Performance Analysis of Machine Learning Models for Precision Agriculture Decision Support

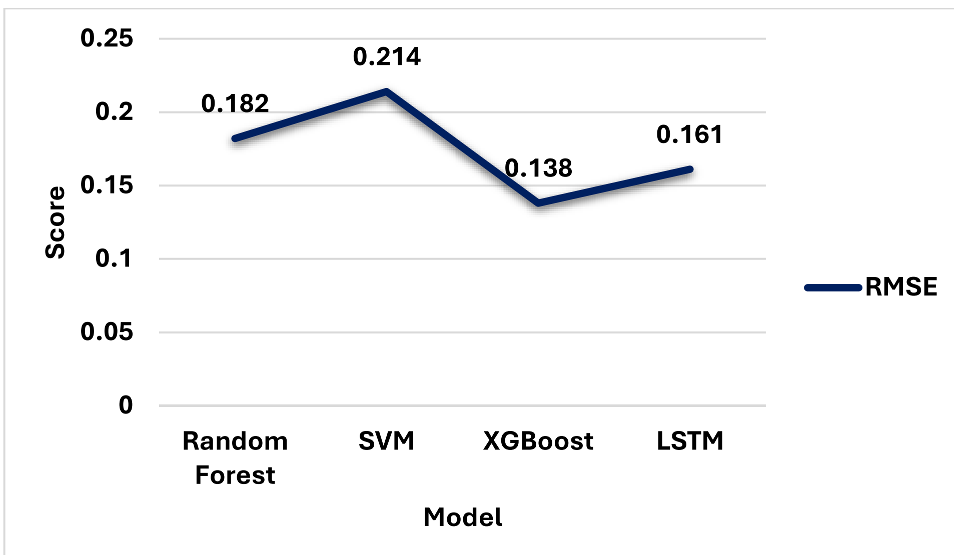
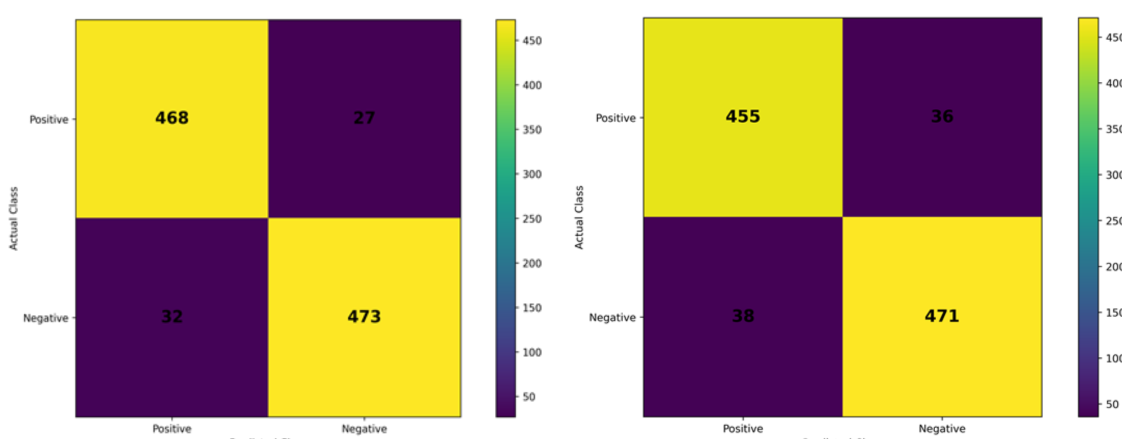
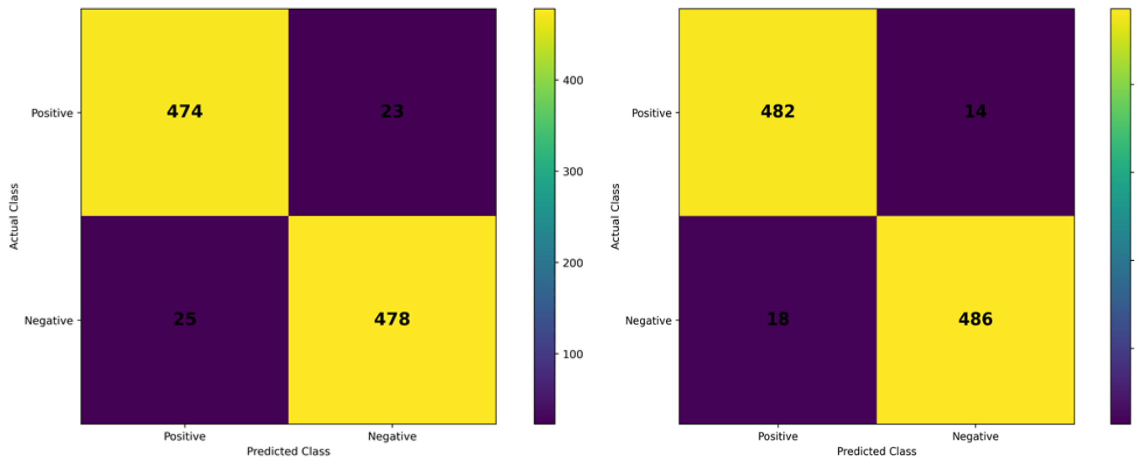


Figure 5. RMSE Comparison of Machine Learning Models for Precision Agriculture Prediction



(a) (b)



(c) (d)

Figure 6. Confusion matrix (a) Random Forest (b) SVM (c) LSTM (d) XGboost

The confusion matrix analysis of four classification models, i.e., Random Forest (a), SVM (b), LSTM (c), and XGBoost (d), is provided in Figure 6. Random Forest achieved the correct classification of 468 positive and 473 negative and moderate misclassification (27 FN, 32 FP). SVM had slightly greater errors making 36 false negativity and 38 false positively. Prediction was enhanced by LSTM with a true positive of 474 and a true negative of 478 with fewer errors. XGBoost had the highest classification accuracy, where the correct classification of samples was 482 positive and 486 negative and the misclassification rates were the lowest (14 FN and 18 FP), which means that it can be classified as a better predictor.

5.3 Resource Optimization and Efficiency Assessment

The offered DSS also effectiveness enhanced the use of resources by optimizing the use of irrigation time, fertilizers, and the control of diseases. The usage of AI-driven recommendations reduced the input used unnecessarily and improved the efficiency of yield. Predictive irrigation scheduling also minimized water use whereas optimal use of fertilizers was based on nutrient deficiency analysis. Disease alert and operational decision-making response was also enhanced with the help of the system.

Table 4. Resource Optimization and Efficiency Results

Parameter	Conventional System	Proposed AI-DSS
Water Usage Reduction (%)	6.4	18.7
Fertilizer Reduction (%)	5.1	14.3
Yield Improvement (%)	8.9	21.6
Disease Detection Time (hrs)	18	6
Decision Response Time (s)	12.4	3.2

Table 4 evaluates the efficiency of resources and operational efficiency of the present farming system and the proposed AI-based decision support system. The suggested framework enhanced efficiency in water usage significantly by 18.7 percent reduction in the use of water as compared to 6.4 percent in the traditional method. There was also an optimization in use of fertilizers whereby a 14.3 percent cut was achieved through which the expenses were saved and the soils were made healthier. There was an improvement in yield of 21.6 which showed improved productivity. The time taken to detect the disease reduced to 6 hours, as opposed to 18 hours, and timely intervention was made. The time of decision response was also significantly decreased, which proved more and more efficient and quicker data-driven farm management.

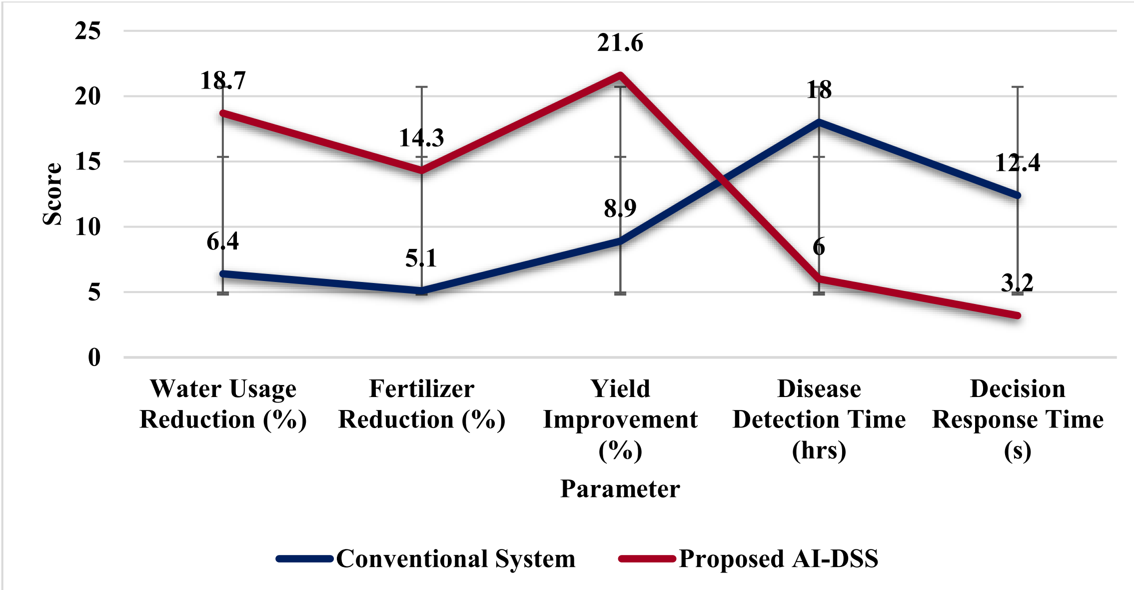


Figure 7. Resource Optimization and Efficiency Comparison between Conventional System and Proposed AI-DSS

Figure 7 shows that the proposed AI-DSS has better performance in comparison with traditional farming. Water savings, cutback in fertilizers, increase in the yield, and improved disease detection and decision-response were obtained significantly.

5.4 Comparative Performance of AI Models

An evaluation of all models was carried out in comparison to establish their appropriateness in precision agriculture decision support. Ensemble and boosting-based methods were found to perform better, as they were able to learn nonlinear relationships and complex interactions of features. Table 5 shows the performance assessment comparison of the various models of AI utilised in the proposed decision support system. XGBoost recorded the best overall accuracy of 96.8 and was better in terms of decision reliability, processing speed and also, overall generalization. LSTM displayed good results with equal scores on all parameters especially on dealing with temporal data. Random Forest gave good generalization at reliable and stable predictions. On the contrary, SVM had relatively low processing efficiency and accuracy. The findings have shown that ensemble and boosting-based models especially XGBoost produced the best and stable results on precision agriculture decision support.

Table 5. Comparative Performance of AI Models (%)

Model	Overall Accuracy	Decision Reliability	Processing Efficiency	Generalization Score
Random Forest	94.1	93.6	91.4	92.8
SVM	92.6	91.7	90.8	91.2
XGBoost	96.8	96.1	94.7	95.9
LSTM	95.2	94.5	92.3	93.8

Figure 8 compares the reliability of models, efficiency and generalization. The XGBoost performed best on all the parameters, then LSTM and Random Forest, and SVM presented a relatively lower decision reliability and efficiency.

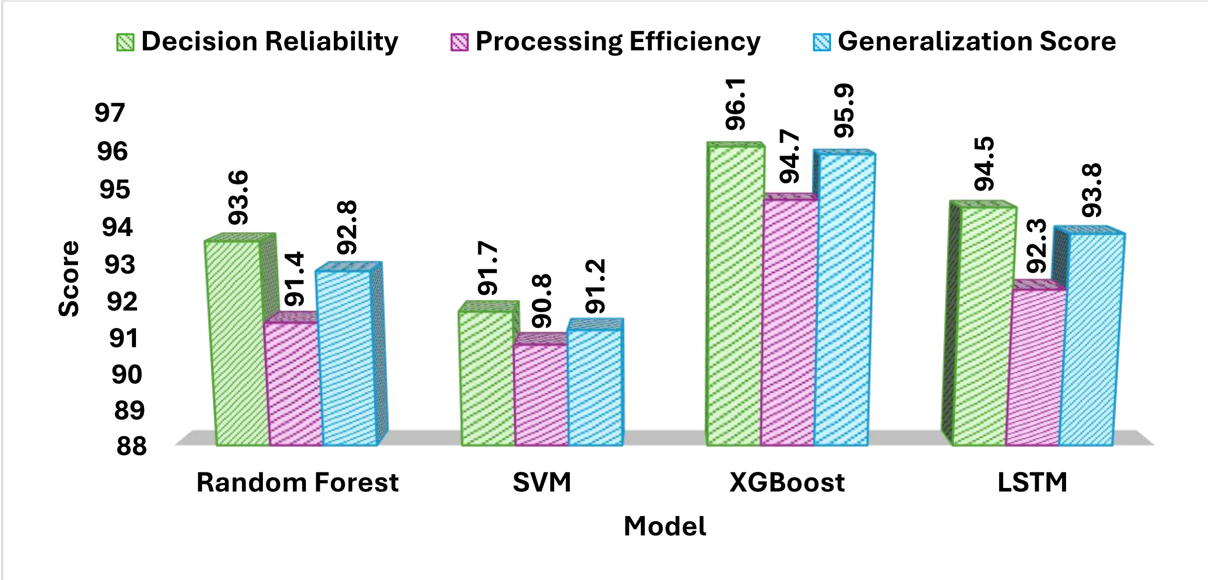


Figure 8. Comparative Analysis of Decision Reliability, Processing Efficiency, and Generalization Score across AI Models

6. Discussion

6.1 Interpretation of Results and Practical Implications

The experimental findings proved that the introduced AI-based decision support system improved the prediction accuracy, the efficiency of resource utilization, and the reliability of the decision to a larger extent in precision agriculture. It was the combination of multi-source data and the use of advanced machine learning models that allowed the system to identify complex environmental parameter and crop responses relationships. The increase in the accuracy of prediction directly led to the optimization of irrigation, the regulation of nutrients, and the detection of diseases at an earlier stage, which increased the productivity of crops. The effectiveness of the ensemble-based algorithms and especially the gradient boosting models was suggested by the fact that it has performed better in three out of the four experiments involving heterogeneous agricultural data. In a more practical sense, the results implied that the use of AI-based decision support might be able to decrease the reliance on manual observations and conventional experience-based practices. It was a system that allowed making data-driven decisions in time that reduced the loss of resources and increased efficiency. The findings also demonstrated the relevance of real time sensing and predictive analytics integration in order to use proactive farm management. Altogether, the suggested framework had a high prospect of facilitating the sustainable agricultural practices and increasing resilience to climatic and environmental unpredictability.

The Kaggle dataset was merged with the simulated streams of IoT sensors to simulate the real-world precision agriculture environment in which heterogeneous sources of data coexist. Kaggle data includes structured and labeled benchmark data that can be used to train a model and evaluate a baseline, whereas IoT sensor data presents real-time variability, noise and time dynamics that may be experienced in practice in a farm setting. As a compatibility measure, the two datasets were normalized in terms of feature, time and unit to make the data compatible. The real-life environmental dynamics were used to create synthetic IoT streams in order to model the scenario of constant field observation. This mixed-data fusion method is stronger in models, has a better generalization ability, and allows the DSS to be applied in both the controlled and real-time agricultural context.

6.2 Benefits for Farmers and Agricultural Stakeholders

The decision support system proposed had significant advantages to the farmers and other stakeholders in the agricultural sector since it made it possible to give correct, timely and actionable advice on how to manage their farms. The farmers also enjoyed the benefits of optimized irrigation schedule which minimized the amount of water used and also, made the available water be well utilized. Recommendation of precision fertilization enhanced the health of the soil and reduced overuse of chemicals, which lowered the cost of inputs and the environmental effects.

Early disease detection indicators gave farmers early warning to take preventive measures that minimized losses of crops and increased the quality of yield. The agricultural players like the agronomists, policymakers and supply chain managers were able to get useful information about the trends in crop health and the patterns of resource use. The system allowed making evidence-based decisions and improved planning and resource distribution on regional and farm levels. Also, the interface made complex analysis outputs easy to understand as recommendations and made it easier to use and be adopted by farmers. In general, the DSS led to productivity, cost efficiency, and sustainability in the agricultural value chain.

The proposed AI-based DSS has a well-organized workflow of an experiment to be carried out by the team to specify its clarity, reproducibility, and sturdiness. At the beginning, the multi-source data of Kaggle datasets, streams of IoT sensors and historical farm records were combined and preprocessed by using normalization and missing values methods. The data was then divided into training (70%), validation (15%), and testing (15) to make sure that it is not judged one-sidedly. The machine learning models such as Random Forest, SVM, XGBoost, and LSTM were trained on the same input features so that they are treated equally in comparison. The grid search and cross-validation (k=5) were used to tune the hyperparameters to maximize the performance of the model. Accuracy, precision, recall, F1-score, and RMSE were used as the evaluation metrics to evaluate the accuracy and regression performance. Also, the efficiency of the systems in terms of using resources (water usage, fertilizer optimization, and the time of decision response) was assessed. This systematic process model allows to be confident that the proposed DSS is not only technically valid but also applicable in practice to the context of precision agriculture in the real world.

6.3 Scalability and Real-World Deployment Challenges

Although the performance of the proposed AI-based DSS looks promising, there are several challenges that will have to be tackled to make it applicable in large scale. IoT sensor systems and communication infrastructure are expensive to install, and this may not be affordable to small-scale farmers. System performance and consistency may be impacted by irregular sensor quality, rural connectivity problems and data reliability. Employing machine learning models to real-life agricultural setting would also demand constant data re-feedback and model re-training to ensure precision due to varied weather and soil conditions. The advanced models like deep learning networks might have specific computational needs that can be a bottleneck when using edges in resource-heavy resources. Moreover, the issue of interoperability between various hardware platforms and agricultural management systems is also a burning problem. The solutions to these problems will involve affordable sensor technology, well-developed communication system, and scalable cloud or edge computing architecture. There will be a strong need to conduct collaborative work between researchers, industry, and policymakers to support the use of AI-driven agricultural decision support systems and their long-term implementation.

6.4 Trust, Transparency and Explicability Reflections

The development of AI-based decision support systems in the field of agriculture is highly dependent on trust and transparency. The system would most likely lead to farmers relying on recommendations because they offer them understandable insights on the results of the decision. Machine learning models that are black-box do not usually provide transparency, and users find it difficult to understand the process in which decisions are formed. The use of explainable AI methods can also contribute to the improved credibility of the system by attracting attention to the important aspects that affect the recommendation, including the level of soil moisture or weather. Another factor to be considered is data privacy and security since agricultural data tend to have sensitive information about farm operations and productivity. Building trust is crucial to ensure that the users feel safe in their data handling and that they are working within the data protection standards. High-adoption rates and sustainable precision agriculture applications of AI-based decision support systems can be achieved through a greater focus on transparency, interpretability, and data security.

7. Conclusion And Future Scope

The study introduced a precision agriculture management system based on AI that combined multi-source agricultural data, machine learning analytics, and intelligent recommendation systems to improve the level of decision-making at the farm level. The outcomes of the experiment showed that the system proposed had great prediction accuracy and dependable performance on irrigation scheduling, fertilization planning, and disease risk assessment. The models that have been evaluated, gradient boosting-based method demonstrated the highest accuracy and minimal error rate in prediction and outperformed the other models: Random Forest, Support Vector Machine, and LSTM models in terms of the overall reliability of decisions taken. This prediction analysis proved how ensemble learning was successful in the prediction of non-linear correlations among soil parameters, climatic conditions, and crop responses. The system also ensured that the response time to decisions was considerably lower as it provided real-time advice via an automated electronic interface, which made farm management decision-making actions faster and more accurate than traditional methods. A resource optimization analysis revealed significant increases in the efficiency of water-use, fertilizer-use and stability of crop yield. The presented framework proved to have high scalability and adaptability to a range of different environmental factors, proving it as appropriate to the contemporary precision agriculture practices. Nevertheless, the work also noted shortcomings with respect to dataset size, sensor affinity and the real-time deployment due to the resource constraints associated with computational needs. Future studies will be based on the incorporation of explainable AI methods, edge-processing and adaptive learning strategies to enhance the transparency and scalability of the system. In general, the suggested decision support structure developed a solid, evidence-based methodology of sustainable and intelligent agricultural management.

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