

Determination of Crop Yield Detection and Prediction With Multimodal Data Using Fusion Techniques

Kutlwano Sedimo, Rajalakshmi Selveraj, Venumadhav Kuthadi and Thulaganyo Dimakatso

Department of Computing and Informatics, Botswana International University of Science and Technology (BIUST), Palapye, Botswana

Article history

Received: 02-02-2026

Revised: 19-05-2026

Accepted: 06-08-2026

Corresponding Author:

Kutlwano Sedimo
Department of Computing and Informatics, Botswana International University of Science and Technology (BIUST), Palapye, Botswana
Email: sk14100368@biust.ac.bw

Abstract: Most often, soil, environmental, and agronomic data are used in pieces, hence limiting the performance of crop selection and yield forecasting. This study develops an integrated, fusion-based framework that combines soil image classification, environmental feature analysis, and input-driven yield prediction to support precise agricultural decision-making. The system consists of three major modules: (i) a CNN for the classification of soil images into their respective classes, such as Alluvial, Black, Red and Clay; (ii) a soft-voting ensemble model integrating SVM, Random Forest and XGBoost to generate crop suitability rankings based on agro-environmental attributes; and (iii) a Conv1D-LSTM hybrid model for predicting crop yield based on rainfall, fertilizer usage, cultivated area and crop type. These predictions are refined by the proposed fusion algorithm, which integrates environmental compatibility with soil-specific crop suitability. The proposed system performed well overall, with the classifier achieving 95.5% accuracy on the soil images. The results showed an overall accuracy of 99% across 22 crop classes, and the prediction errors were very low, with low MAE and RMSE. The integrated framework offers a practical data-driven tool for localized crop planning that enables farmers and other agricultural stakeholders to make informed decisions that optimize productivity and resource utilization. The proposed framework achieved a practical, scalable fusion strategy for integrating heterogeneous agricultural data sources into a unified decision support system. Despite the strong predictive performance, the study acknowledges limitations related to dataset size, particularly for soil image classification, and the lack of large-scale field validation. Additional statistical validation and ablation experiments were conducted to assess robustness and generalizability. The proposed framework demonstrates promising applicability for decision support. However, further validation of larger and geographically diverse datasets is required for broader deployment.

Keywords: Soil Classification, Crop Yield Prediction, Ensemble Learning, Fusion Model, Crop Recommendation System

Introduction

Agricultural productivity is highly dependent on several interacting factors, including soil properties, climatic conditions, nutrient availability, and agricultural practices (Chacón-Maldonado et al., 2025). In most areas, crop cultivation is still based on expert opinion and generalized agricultural practices. In most cases, such practices are inefficient in soil profiles with high variability, variable climatic conditions, and varying

agricultural inputs. This has led most farmers to struggle to find crops that can grow under the varying conditions of their land, resulting in low productivity, waste, inefficiency, and agricultural losses. Although advancements in agricultural practices using computer systems have improved practices such as soil characterization, precision, and agricultural quantification, most agricultural systems are practised with disregard for the three tasks (Li et al., 2025a). For instance, models used in agricultural characterization are

not considered when making crop recommendations; crop recommendation systems are oblivious to soil types, while agricultural yield is predicted based on averages that do not consider agricultural factors. To address the challenges, a comprehensive solution that considers agricultural soil image characterization, agricultural climate characterization, and agricultural inputs with a goal of estimating agricultural yield is offered by this research. The system analyses agricultural soil types using agricultural images and crop data, sorted by distinct agricultural attributes such as nutrient content, rainfall, temperature, humidity, and soil pH, to estimate crop yield based on real agricultural inputs.

Research Gap

Existing literature is surveyed, and it is revealed that there are several limitations, which form the reasons for conducting this research:

- The research is mostly on a single agricultural activity (Yedukondalu and Prabu, 2025), which is soil identification, suggestions on what to grow, and crop yield prediction
- Soil properties, as well as environmental factors, are rarely considered together in a weighted manner when assessing crop suitability
- The current models lack flexibility to suit different agricultural areas, with interactions with soil, climatic conditions, and farmers' input not being specifically handled (Albaaji et al., 2025)
- Most models used in predicting yield overlook general considerations, as well as variations that are crop-specific and soil-specific

Objectives and Contributions

The research fills a gap in relation to the following objectives and technical contributions:

- A complete system design that incorporates soil type identification, suitability score evaluation, and yield prediction as a single process
- Addition of a Multi-Constraint Weighted Fusion strategy to balance soil compatibility, environmental probability scores, and regional factors in crop prioritization
- The development of an end-to-end decision support system pipeline that can provide understandable recommendations for twenty-two major crops on four types of soil
- Evaluation of the system on field-level data to assess applicability over a range of conditions, with a focus on agricultural environments

Novelty of the Study

The contribution of this study lies primarily in system-

level integration rather than the introduction of fundamentally new learning architecture. The proposed Multi-Constraint Weighted Fusion Algorithm (MCWFA) functions as a structured decision-level fusion mechanism that combines outputs from independently optimized models (Saki et al., 2025). Unlike end-to-end deep learning approaches, this method emphasizes interpretability and modularity. However, the weights used in the fusion process are empirically assigned and not learned through optimization, which may limit adaptability across domains (Yadav et al., 2025). This highlights a trade-off between transparency and automatic parameter learning.

Related Work

Accurate crop yield prediction is a high-priority area in precision agriculture because of its potential applications in ensuring sustainable agricultural practices, effective use, and resource planning. In the past few years, several models based on different machine learning and optimization frameworks, with diverse sets of attributes, from soil to weather, as well as RS and phenotypic data, to name a few, have been devised. This section reviews and compares recent contributions in this research area, with particular emphasis on the models, datasets, and results. Abdel-Salam et al. (2024) devised a hybrid attribute selection strategy and a Support Vector Regression (SVR) technique to predict crop yield. The strategy involved K-means clustering preprocessing with a correlation filter, followed by application of the hybrid FMIG-RFE attribute selection strategy. The strategy used a modified Crayfish Optimization Algorithm (ICOA) for optimizing the SVR technique. The proposed system outperformed standard optimization methods, thereby proving the efficiency of the hybrid technique for optimizing parameters as well as attribute reduction. In a similar manner, Boppudi and Jayachandran (2024) devised a ranking technique based on a combination of statistical, correlation, and entropy approaches for attribute selection. The researchers used LSTM and Deep Belief Network (DBN) models for crop yield prediction. The devised technique yielded improved precision, specificity, and overall accuracy, surpassing the performance of standard models such as CNN and Bi-GRU. Khan et al. (2024) relied on MODIS-derived Gross Primary Production (GPP) product attributes and deep learning models (DNN, 1D-CNN, GRU) to predict corn and soybean yields at the county level. The devised technique yielded R^2 values ranging from 0.521 to 0.903 across models, with 1D-CNN delivering the highest accuracy, $R^2 = 0.864$ for corn yield and $R^2 = 0.750$ for soybean yield. The authors in Zare et al. (2024) unveiled a particle filtering scheme that combines Data Assimilation (DA). The authors assimilated LAI data into

crop models (CERES, GECROS, SPASS) and evaluated ensemble models. The ensemble models of different models reduced the bias in yield prediction from 19% to 7%, thereby demonstrating the utility of merging models for predicting crop yield.

In Canada, five ensemble machine learning models, AdaBoost, GBM, XGBoost, LightGBM, and Random Forest, were used by Gharakhanlou and Perez (2024). MAE of 68.7 for canola and 39.47 for soybeans, with R^2 values of 0.95 and 0.96, respectively, were obtained. The most effective factor for crop production was the honeybee population. Kolipaka and Namburu (2023) used a two-class classifier with metaheuristics as a supporting tool, which increased prediction accuracy. It used a composite of models such as LSTM, DBN, and CNN, optimized by the meta-Dingo Optimized Sand Piper (DOSP). The technique has shown considerable improvements in efficiency and accuracy, as evidenced by a drastic reduction in the error margin (MAE). Kheir et al. (2024) used AutoML with a composite of models, including RS, weather, and soil, to predict agricultural produce, particularly wheat, in Egypt. Across 22 models, the stacked ensemble technique achieved an R^2 of 0.51 and a degree of agreement (d) > 0.80. Depending on the climate change vision, CMIP6 scenarios predict a decline in agricultural production of 5% to 21%. In 2024, Jovanovic et al. (2024) offered a novel, Weight-Agnostic Neural Network (WANN), which optimized the metaheuristics. The technique revealed a small error margin of 0.0177, with a high R^2 of 0.8866. This technique can develop optimized models that are small, easy, and efficient, even in resource-poor conditions.

Li et al. (2024) developed a TrG2P system with multi-trait genotypic and phenotypic prediction of yield. The system used CNN transfer learning to enhance yield prediction for rice, maize, and wheat. Compared with existing genomic selection software, the software improved prediction accuracy by up to 39.9% in rice, underscoring the importance of secondary crop trait

attributes for prediction. Rajakumaran et al. (2024) developed a weighted tree-SVR that particularly targeted crops in India. The software used PCA to decrease dimensions, with genetic algorithm optimization of the characteristic properties. It clearly showed better predictability than regression models. Similarly, Subramaniam and Marimuthu (2024) developed a weight-tuned deep convolutional neural network with SEKPCA (WTDCNN + SEKPCA). The WTDCNN + SEKPCA achieved a high accuracy of 98.96%, which is far better than previous CNN and DNN approaches in terms of precision, computational cost, and efficiency. Gadupudi et al. (2024) also developed software to adapt deep learning models for multiple crops in India. The software used two stages to combine multiple classifiers. It seemed to provide a 40 to 62.5% reduction in mean absolute error compared to existing models, supporting the idea that deep learning models can greatly reduce prediction inaccuracies by combining different predictors. Kuradusenge et al. (2024) focused on forecasting the production of Irish potatoes and maize in Rwanda using IoT sensors and machine learning algorithms. The software used environmentally sensed attributes, which showed low Mean Absolute Percentage Error (MAPE) values ranging from 0.177 to 0.339 across seasons, demonstrating that models combining sensed attributes can greatly improve the predictability of agricultural production in regions.

Although several studies indicate high predictability with optimized deep learning models, there exist several constrained experimental conditions that disregard the aspect of heterogeneity in the data. High performance metrics cannot necessarily ensure robustness, adaptability, and real-world applicability, especially across varying soil types and climatic conditions. Thus, despite high predictability, handling diverse agricultural inputs consistently remains a challenge in existing research, as listed in Table 1.

Table 1: Summary of Comparative Results of Crop Yield Prediction Systems

Study	Method/Model	Crop(s)	Best R^2 / Accuracy	Key Result / MAE
Abdel-Salam et al. (2024)	ICOA-optimized SVR + FMIG-RFE	General	R^2 not specified	High accuracy boost
Khan et al. (2024)	1D-CNN with GPP RS Data	Corn, Soybean	0.864 (corn), 0.750	Best in transfer DL
Gharakhanlou and Perez (2024)	XGBoost Ensemble	Canola, Soy	0.95–0.96	MAE: 39.47–68.7
Zare et al. (2024)	DA + MME	Wheat	Bias reduced to 7%	Effective DA use
Boppudi and Jayachandran (2024)	Hybrid LSTM + DBN	Not specific	Accuracy not listed	High specificity
Jovanovic et al. (2024)	Optimized WANN	General	$R^2 = 0.8866$	MAE: 0.0177
Kheir et al. (2024)	AutoML + Stacked Ensemble	Wheat	$R^2 = 0.51$	Yield ↓ by 21% (SSP)
Kolipaka and Namburu (2023)	DOSP-based Hybrid Model	General	MAE: reduced by >40%	Two-stage DL
Li et al. (2024)	TrG2P Transfer Learning	Rice, Maize	↑ accuracy by 39.9%	Best among GS tools
Rajakumaran et al. (2024)	MAWT-SVM + GA	Indian crops	R^2 not listed	Best vs SVM, ANN
Subramaniam and Marimuthu (2024)	WTDCNN + SEKPCA	Indian crops	Accuracy = 98.96%	Top regional model
Gadupudi et al. (2024)	Two-stage DL (DBN, LSTM, CNN)	Indian crops	MAE ↓ by 62.5%	Multi-phase model
Kuradusenge et al. (2024)	IoT + ML	Maize, Potato	MAPE = 0.177–0.339	IoT-efficient

The comparative evaluation of current crop yield forecasting studies is in Table 1, which yields several key observations on the performance of various computational models and approaches. The performance evaluation is compared with existing models, as presented in Table 2.

Among the models assessed, ensemble learning models, specifically XGBoost as used by Gharakhanlou and Perez (2024), consistently improved accuracy, with R^2 values reaching up to 0.96. This confirms the effectiveness of gradient boosting models in handling complicated multi-source agricultural data. Likewise, the TrG2P Model (Li et al., 2024), which uses multi-trait genetic marker data, achieved significant improvements in prediction accuracy, up to 39.9% for rice, underscoring the importance of incorporating linked biological attributes. Deep learning models, particularly CNN-LSTM, have proven highly predictive when optimally tuned with appropriate dimensionality reduction. For instance, the WTDCNN Model (Subramaniam and Marimuthu, 2024) reported a high accuracy rate of 98.96% for the overall growth of crops in India, maximizing adjustments with overall tuning, setting a high standard for location-specific prediction models. Models combining diverse deep learning models, such as Gadupudi et al. (2024), have also reported high percentage error reductions, with a 62.5% reduction in MAE. Model optimizations, particularly Crayfish Optimization Algorithms (Abdel-Salam et al., 2024) and Dingo Optimized Sand Piper (Kolipaka and Namburu, 2023), showed significant improvements in the accuracy of models based on Support Vector Regression (SVR) and CNN, respectively.

Hybrid methods for feature selection and dimensionality reduction, such as FMIG-RFE, SEKPCA, and PCA-GA, were crucial for ensuring efficiency and accuracy. Works focused on the preprocessing of organized agricultural data with the purpose of selecting relevant modelling inputs were able to make accurate forecasts, hence authenticating the need for preprocessing and development of significant inputs. The development of models that leveraged remote sensing inputs, specifically MODIS-based GPP and LAI, played a

significant role in producing highly accurate large-scale yield predictions. The application of data-assimilation methods, as demonstrated in research by Zare et al. (2024), played a significant role in improving forecasts and reducing bias, especially when crop ensemble models were used. The research by Kuradusenge et al. (2024); Kheir et al. (2024) verified the potential of deploying forecasting models in real-world farming practices. The research conveyed that precise models can be developed even in conditions that are limited in terms of resources, specifically restricted technologies, based on sensor agricultural data, as well as dynamic models. Geography- and location-specific models that targeted geographies, specifically states within India, performed extremely well when modified to suit geographically particular climatic conditions, as well as soils.

Although remarkable progress has been made in crop yield forecasting with the use of machine learning, deep learning, ensemble learning, and optimization methods, the existing literature remains mostly fragmented within the agricultural analytics chain. Existing solutions mostly focus on algorithmic performance, identifying the best set of agricultural features, or agricultural datasets, with little consideration of a comprehensive solution that holistically incorporates soil, weather, and agricultural factors. The fact that agricultural systems are inherently complex with multiple interdependencies means that a fragmented modelling approach is particularly limiting for making sound agricultural decisions.

Recent developments in deep-learning-based recommender systems have further enhanced multimodal agricultural analytics. Transformer-based architectures and attention-driven fusion models have been explored for integrating heterogeneous agricultural data sources. These models dynamically learn feature importance, improving adaptability across regions and crop types. However, such approaches often require significantly larger datasets and computational resources, which may not be feasible in resource-constrained agricultural environments (Liu et al., 2026; Demissie et al., 2026; Gawade et al., 2026).

Table 2: Comparison of Existing Approaches with the Proposed Fusion Model

Approach Category	Data Sources	Modeling Strategy	System Integration	Practical Limitation
Optimization-based SVR	Soil, weather	Regression + tuning	Low	Limited scalability
Deep Learning Models	RS or regional data	CNN / LSTM / DBN	Medium	Data-dependent tuning
Ensemble ML Models	Tabular datasets	Boosting / bagging	Medium	Weak cross-domain fusion
AutoML Frameworks	Multi-source	Stacked models	Medium	High computational cost
IoT-based ML Systems	Sensor data	Classical ML	Low	Restricted decision scope
Proposed Fusion Model	Soil, climate, agronomic	Hybrid fusion learning	High	Integrated decision support

Materials and Methods

The crucial part of this work is the development of a predictive model using fusion technology for the

simultaneous incorporation of soil information as well as environmental and agricultural parameters. Contrary to other related approaches that are limited to the use of single-source information or predictive models, this

developed model incorporates other sources of information related to agriculture to ensure a successful generalization of predictions for different conditions (Li et al., 2025b). The model adopted for this research work comprised several stages for restructuring and aggregating crops to enable simultaneous detection and yield prediction. Three sources were used for this study:

- Soil images dataset – This dataset has images that are classified into four soil types: Alluvial, Black soil, Red soil, and Clay soil. All four soil datasets have balanced numbers to remove imbalance. Additionally, each soil type has images illuminated from different angles and has various textures to enhance it. This dataset is specifically for soil classification through images
- There are 2,200 samples in the crop recommendations dataset, which are ideal agricultural conditions for 22 different types of crops. Every sample has seven environmental factors: Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, soil pH, and rainfall. This dataset was collected from publicly available agricultural sources
- It is important to note that the soil image dataset consists of only 210 images, which is relatively small for training deep convolutional neural networks. Although augmentation techniques were applied to increase variability, they do not introduce new intrinsic information. Therefore, the model may be susceptible to overfitting and limited generalization. This constraint is acknowledged as a limitation of the study, and future work will consider larger and more diverse datasets
- To predict the crop yield, a numerical dataset consisting of the average rainfall, rate of fertilizer usage, land area, type of crop, and corresponding yields was used. This dataset assists the recommendation system in providing the estimated yields based on the predicted settings

The overall architecture of the proposed model is given in Fig. 1.

Data preprocessing was performed separately for image based and numerical datasets to ensure uniformity and model compatibility. Environmental attributes in the crop recommendation dataset were standardized using z-score normalization, defined as in Eq.1:

$$x' = \frac{x - \mu}{\sigma} \quad (1)$$

Where μ and σ denote the mean and standard deviation of each feature, respectively; crop labels were numerically encoded to facilitate multi-class classification. Soil images were resized to 220×220 pixels, converted to RGB format, and normalized to a pixel intensity range of [0,1].

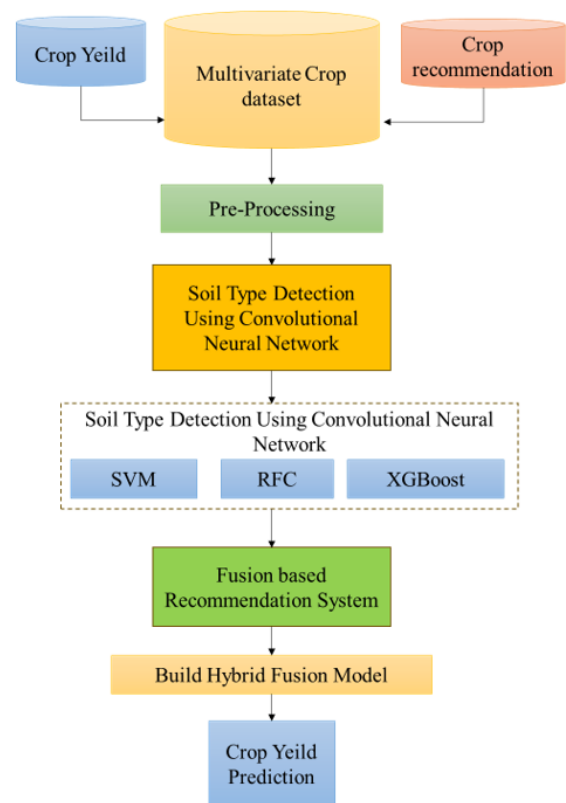


Fig. 1: Overall architecture of the proposed multimodal fusion framework illustrating soil image classification, ensemble-based crop suitability assessment, multi-constraint weighted fusion and yield prediction modules

Data augmentation techniques, including horizontal flipping and rotation, were applied during training to improve robustness (Ma et al., 2025). Inputs for yield prediction were scaled and reshaped into a sequential format to match the requirements of the Conv1D-LSTM architecture. Preprocessing was done such that the environmental attributes were standardized using standard scaling to provide homogeneity in size. Crop labels were numerically encoded to enable classification models. Images from the soil were resized to 220×220 pixels, transformed to RGB, and pixel-normalized to a range of [0,1]. Soil type detection was performed using a deep Convolutional Neural Network (CNN) model trained on labelled soil image samples. The Architecture Details are listed below:

- Input Layer: Processes 220×220×3 image arrays
- Conv2D Layers: Grouped convolution layers with incrementing filters (16 to 64), followed by max-pooling layers to downsize spatial dimensions
- Flatten Layer: Transforms the 3D matrix to a 1D feature vector
- Dense Layers: Fully connected layers consisting of a 128-unit hidden layer followed by a 4-unit output layer that maps onto the four soil classes

- Activation Functions: ReLU for hidden layers and SoftMax for output to get class probabilities

The trained and saved model, SoilNet.h5, produced a predicted soil class with high reliability. The predicted label is used to inform the soil-specific crop list via a lookup. In the Crop Suitability Classification Using Ensemble Learning stage, the suitable crops are determined based on soil and environmental conditions, and a soft-voting ensemble model is employed.

The ensemble combines three classifiers:

- Support Vector Machine (SVM): Applied with a radial basis function kernel
- Random Forest Classifier (RFC): Constructed using 100 decision trees to handle non-linearity and overfitting
- Extreme Gradient Boosting (XGBoost): Integrated to leverage boosting and reduce bias

Crop suitability classification was carried out using a soft-voting ensemble comprising Support Vector Machine (SVM), Random Forest (RF), and XGBoost classifiers. The SVM employs a radial basis function kernel with regularization parameter $C = 1.0$. The Random Forest model consists of 100 decision trees, using Gini impurity as the splitting criterion (Sha et al., 2025). The XGBoost classifier was configured with a learning rate of 0.1, maximum tree depth of 6, and 100 boosting rounds. For a given sample x , the class-wise probability outputs of the classifiers are defined as in Eq. 2:

$$P_{SVM}(C_i | x), P_{RF}(C_i | x), P_{XGB}(C_i | x) \quad (2)$$

The ensemble decision is computed using soft voting, as in Eq.3:

$$C^* = \arg \max_i (\alpha_1 P_{SVM} + \alpha_2 P_{RF} + \alpha_3 P_{XGB}) \quad (3)$$

Where uniform weights $\alpha_1 = \alpha_2 = \alpha_3 = 1/3$ were used. The top five crops by ensemble probability were selected for fusion. Then, the final crop recommendation C_{final} is given in Eq. 4:

$$C_{final} = C_{env} \cap C_{soil} \quad (4)$$

When the intersection returns no results, the top crop from C_{env} is selected as an alternative. This merger allowed both environmental and soil limitations to be honoured for the best crop recommendation. For yield prediction, a hybrid sequential model integrating Conv1D, LSTM, and Dense layers was utilized. The input variables are Encoded Crop Type, Scaled Annual Rainfall, Scaled Fertilizer Usage, and Scaled Cultivation Area. The Model Architecture consisted of a Conv1D

Layer that extracts temporal dependencies in scaled features, a MaxPooling1D Layer to minimize noise and overfitting, an LSTM Layer to learn long-term dependencies in the input sequence, and a Dense Layer to provide a single-value output as the estimated crop yield. Assume the last feature vector to be $X = [x_1, x_2, x_3, x_4]$, reshaped to $[1, 4, 1]$ for sequential input. Then the output yield Y is represented by Eq. 5:

$$Y = f(X) \times 100 \quad (5)$$

Where f represents the learned transformation function of the model. The predicted output Y is then returned in quintals or kilograms based on the unit configuration. Soil type classification was performed using a convolutional neural network trained on labelled soil images. The network input is a tensor of size $220 \times 220 \times 3$. The architecture consists of multiple convolutional layers with filter sizes ranging from 16 to 64, each followed by ReLU activation and max-pooling layers to reduce spatial dimensions (Bi et al., 2025a). The extracted feature maps are flattened into a one-dimensional vector and passed through fully connected layers, including a 128-unit hidden layer and a four-unit output layer corresponding to the four soil classes. The Softmax activation function is applied at the output layer to compute class probabilities, as expressed in Eq. 6:

$$P(C_i) = \frac{e^{z_i}}{\sum_{j=1}^4 e^{z_j}} \quad (6)$$

The trained model was saved as SoilNet.h5 and used to predict soil type, which subsequently informs soil-compatible crop selection through a lookup mechanism. All experiments were carried out using Python with TensorFlow and Scikit-learn libraries. The training and testing of the models were performed on a machine with an Intel Core i7 processor, 16 GB of RAM, and an NVIDIA GPU with 6 GB of VRAM. The Adam optimization algorithm (Lilhore and Simaiya, 2025) with an initial learning rate of 0.001 and a batch size of 32 was used for training deep models. The early stopping technique was used to reduce model overfitting. This overall system provides an integrated approach to region-based crop planning and yield forecasting. It is extremely useful for digital agriculture, as it encompasses soil image classification, crop recommendation using ensemble models, and time-series yield prediction in a scalable manner. It is accurate and interpretable for decision support in agriculture.

Dataset Description and Provenance

To achieve transparency, reproducibility, and adherence to open science paradigms, the datasets used in the study were sourced from publicly available sources with Open Science licenses. Three different

datasets were used, which relate to soil classification, the evaluation of agricultural suitability, and the prediction of agricultural yields.

Soil Image Dataset: The soil image dataset is obtained from the publicly available “Soil Image Dataset for Classification” on Kaggle (<https://www.kaggle/datasets/soil-image-classification>), which includes RGB images of soil taken under natural daylight using handheld cameras. These images are for four predominant soil types: Alluvial, Black, Red, and Clay. The four predominant soil types are widely distributed across the agricultural lands of the Indian subcontinent. A total of 210 images have been used. These images have undergone the following pre-processing before model training: Resized to 220x220. You will observe the resampling to 220x220 for the 210 images. Normalized to the [0-1] range. The images have undergone a horizontal flip transformation.

Crop Recommendation Dataset: The Crop suitability dataset was obtained from the “Crop Recommendation Dataset” on Kaggle and was originally compiled using agronomic guidelines published by Indian agricultural research bodies (e.g., ICAR). The dataset contains 2,200 records for 22 crop types, with seven attributes: Nitrogen, Phosphorus, Potassium, temperature, humidity, soil pH, and rainfall. The dataset reflects agro-climatic conditions across multiple Indian states and is shared under the Open Database License (ODbL). Then, all numerical features were normalized using z-score normalization, and labels for crops were encoded into numerical values for multi-class classification.

Crop Yield Prediction Dataset: This dataset on yield prediction has been compiled from freely available agricultural statistics published by the Government of India and the FAO open data portals. It contains annual rainfall, fertilizer usage, cultivated areas, crop type, and respective yield values aggregated at district and state levels. The dataset represents multi-year observations from major agricultural regions in India. Missing values were removed; continuous variables were scaled using standard normalization, and categorical crop labels were numerically encoded. The dataset is provided under an open government data license, which allows its reuse for academic research.

Experimentation and Implementation

The experimentation phase was designed to test and validate the efficacy, robustness, and uniqueness of the proposed multi-module framework through rigorous

experiments and evaluations. The integrated framework involves soil image classification, crop recommendation using an ensemble approach (Bi et al., 2025b), multi-constraint fusion, and yield prediction as an integrated process. All modules are tested individually and collectively to assess their efficacy and overall performance in a realistic, practical agricultural setting. The Multi-Constraint Weighted Fusion Algorithm (MCWFA) is an innovative algorithmic approach to enhance the efficacy and robustness of crop recommendation systems, which involves the fusion and aggregation of many levels of agronomical constraints. The predictive framework merges the concept of probabilistic environmental compliance, soil friendliness, and regionalized allowances within a single framework and rating method. All these constraints are tested individually, then combined using a weighted approach to shortlist crops that meet all agronomic norms. All experiments and simulations have been carried out using the TensorFlow, Keras, Scikit-learn, and XGBoost libraries (Zandi et al., 2025), coded in Python, and the models have been trained and tested using a stratified split to ensure an accurate, balanced, and realistic assessment. For classification tasks, 70% of the data was used for training, 15% for validation, and 15% for testing. The yield prediction dataset was divided into 80% training and 20% testing samples. Fivefold cross-validation was employed for the crop-recommendation ensemble to ensure stability and reduce sampling bias. Soil image data augmentation techniques, including rotation and horizontal flipping, were applied exclusively to the training set to enhance generalization. The algorithm in Table 3 starts by taking three basic inputs: The crop list and its ensemble-model-derived suitability scores, the soil type derived from image classification, and environmental factors such as rainfall, pH, and temperature. A lookup map specifies the crops that are appropriate for any given soil type. The algorithm further employs a weight setting that assigns relative priorities to each constraint: Region-specific suitability, environmental fitness, and soil compatibility. “cc”.

As shown in Table 1, for each crop the ensemble model recommends, the algorithm checks whether the identified soil type is compatible with that crop. If it is an exact match, then a complete score is given; a partial score is used otherwise to discourage less appropriate soil-crop matches.

Table 3: The novel Multi-Constraint Weighted Fusion Algorithm (MCWFA)

Algorithm Fusion Crop Recommendation System (FCRS)

Input:

- $\mathcal{C}_{env} = \{(C_i, P_i)\}$: Set of candidate crops C_i with ensemble-derived environmental suitability probabilities P_i

- S_t : Predicted soil type
- $\mathcal{M}_{soil}$: Soil–crop compatibility mapping
- $\mathcal{R}$: Regional environmental parameters (rainfall, temperature, pH, etc.)
- $\mathbf{w} = \{w_{env}, w_{soil}, w_{region}\}$: Constraint weight vector

Output:

- C^* : Final recommended crop

Begin

1. Initialize an empty score map $\mathcal{S}$
2. For each crop $C_i \in \mathcal{C}_{env}$ do
 3. 2.1 Retrieve environmental suitability score $S_{env}(C_i) \leftarrow P_i$
 4. 2.2 If $C_i \in \mathcal{M}_{soil}(S_t)$ then
 5. $S_{soil}(C_i) \leftarrow 1$ Else
 6. $S_{soil}(C_i) \leftarrow \lambda$, where $0 < \lambda < 1$
 7. 2.3 Compute regional suitability score $S_{region}(C_i)$ using deviation of $\mathcal{R}$ from crop-specific optimal thresholds
 8. 2.4 Compute fused score:
 9. $S_{final}(C_i) = w_{env} \cdot S_{env}(C_i) + w_{soil} \cdot S_{soil}(C_i) + w_{region} \cdot S_{region}(C_i)$
 - 2.5 Store $S_{final}(C_i)$ in $\mathcal{S}$
3. Rank all crops in $\mathcal{S}$ in descending order of S_{final}
4. Select the top-ranked crop as C^*
5. Return C^*

End

End FCRS

This discourages the model from strongly favoring environmental suitability over soil applicability. Then, the algorithm calculates a regional score based on comparisons between existing regional values, such as mean rainfall, temperature, and soil pH, and ideal thresholds for the crop. Such comparisons are normally made in terms of pre-established tolerance ranges. For example, if the area's mean rainfall lies within $\pm 10\%$ of the optimal level for rice, then the crop receives a high regional score. More significant deviations result in lower scores, reflecting the subtle influence of regional variation on crop feasibility and yield. The central integration occurs when these three scores, soil compatibility, environmental probability, and regional relevance, are compiled into a final individual score for every crop. The score is calculated as a weighted sum, with weights determined by empirical significance or expert advice. For example, in some areas, soil type may be the overriding limitation because of high mineral specificity, while in others, rainfall may be the limiting factor.

The Multi-Constraint Weighted Fusion Algorithm (MCWFA) integrates environmental suitability, soil compatibility, and regional adaptability into a unified

scoring framework. Let C_i denote the i^{th} crop recommended by the ensemble classifier. The environmental suitability score for C_i , obtained from the soft-voting ensemble, is defined as in Eq. 7:

$$S_{env}(C_i) = P_{ensemble}(C_i) \quad (7)$$

Soil compatibility is represented as a binary or penalized score as in Eq. 8:

$$S_{soil}(C_i) = \begin{cases} 1, & \text{if } C_i \in \mathcal{C}_{soil} \\ \lambda, & \text{otherwise} \end{cases} \quad (8)$$

Where $0 < \lambda < 1$ is a soil mismatch penalty factor. The regional suitability score is computed based on deviations of observed regional factors from crop-specific optimal thresholds, as in Eq. 9:

$$S_{region}(C_i) = 1 - \frac{1}{n} \sum_{k=1}^n \frac{|R_k - R_k^*(C_i)|}{R_k^*(C_i)} \quad (9)$$

Where R_k denotes the observed regional parameter and $R_k^*(C_i)$ represents the optimal value for the crop C_i .

The final fused score is obtained through weighted aggregation, as in Eq. 10:

$$S_{\text{final}}(C_i) = w_{\text{env}}S_{\text{env}}(C_i) + w_{\text{soil}}S_{\text{soil}}(C_i) + w_{\text{region}}S_{\text{region}}(C_i) \quad (10)$$

With $w_{\text{env}} + w_{\text{soil}} + w_{\text{region}} = 1$. Scores are normalized to the range [0,1] prior to ranking. The weight parameters (w_1, w_2, w_3) and the penalty factor λ were selected empirically based on preliminary experiments and domain understanding of agronomic priorities. Soil compatibility was assigned higher importance in regions with strong soil constraints, while environmental suitability dominated in climatically sensitive areas. The penalty factor λ was set to 0.5 to moderately penalize soil mismatch without eliminating candidate crops. However, these parameters are not optimized through a learning process, which may limit adaptability. Future work will focus on automated weight learning using optimization or meta-learning techniques.

After computing all the scores, the crops are sorted in descending order of their overall composite scores. The crop with the highest score is chosen as the best recommendation. This method enables a highly interpretable and adaptive system that can rank multiple constraints differently depending on regional requirements and agricultural policies. In general, the MCWFA improves upon conventional crop recommendation frameworks by incorporating domain-specific constraints within a flexible, configurable framework. It does not rely solely on model predictions; instead, it incorporates agronomic realities through a multi-layered fusion process and produces recommendations (Wei et al., 2025) that are both statistically valid and practically feasible. The proposed research combines multiple computational approaches to recommend the best crop and its yield based on soil quality, environmental conditions, and local conditions. The experimental process was undertaken in various stages, including data preprocessing, training, integration using the fusion approach, and performance evaluation. The following sections detail the architecture and the implementation plan adopted for the system validation. To establish the novelty and superiority of the proposed framework, its performance has been compared with several baseline systems: A soil-based recommendation

system, an environment-based classifier, a yield-based prediction model, and a rule-based crop recommendation system. In all those cases, the proposed MCWFA-based system outperformed all other baselines due to its effective integration of heterogeneous constraints and bounding of agronomic inconsistency, thereby proving superior to single-source and heuristic-based models. The experimental setup consists of three major modules: Soil classification, crop recommendation, and yield prediction. Each module has been implemented with specific settings, as described in Table 4.

As presented in Table 3, the soil classification module employed a five-layer convolutional architecture that was trained using pre-labelled soil images. The output was utilized as a categorical input for crop choice. The crop recommendation module utilized an ensemble approach integrating SVM, Random Forest, and XGBoost to achieve maximum classification accuracy on agronomic attributes. The yield prediction model combined temporal and static features, reorganized in a sequential format and fed into a hybrid Conv1D-LSTM model for regression. The overall implementation was carried out using Python-based platforms. Google Colab was chosen to leverage its GPU acceleration for deep learning elements. The soil image dataset was prepped to ensure an even distribution of data across the four classes. Augmentation was used to enhance generalizability. The environmental crop dataset was formatted as numerical inputs. Scaling was done with StandardScaler to normalize input ranges. Metrics for classification tasks were accuracy, precision, recall, and F1-score (Pinho et al., 2025). Root Mean Squared Error (RMSE) was employed to verify the yield prediction model (Shafay et al., 2025). This experimental setup supports an end-to-end pipeline for precision agriculture decision-making. Integrating structured environmental observations, image-based soil mapping, and yield prediction, the system guarantees recommendations that are customized, viable, and measurable. The fusion mechanism can harmonize several agronomic constraints with ease, while the deep learning ingredients add scalability and robustness.

To evaluate the contribution of each component in the fusion mechanism, ablation experiments were conducted by selectively removing constraints from the MCWFA framework:

Table 4: Module-Wise Experimental Setup

Module	Tool/Library	Model/Algorithm	Input Features	Output
Soil Classification	TensorFlow, Keras	Convolutional Neural Network (CNN)	Soil images (RGB, 220×220)	Soil type (Alluvial, Black, etc.)
Crop Recommendation	Scikit-learn, XGBoost	Soft Voting Ensemble (SVM, RF, XGBoost)	Nitrogen, Phosphorus, Potassium, Temperature, Humidity, pH, Rainfall	Top-5 crops with scores
Crop Yield Prediction	Keras, Scikit-learn	Conv1D + LSTM hybrid model	Crop label, Rainfall, Fertilizer quantity, Area	Estimated yield (in units)

- Without soil constraint
- Without environmental probability
- Without regional suitability
- Variation of weight parameters

The performance of each configuration was compared using classification accuracy and F1-score. This analysis helps quantify the individual impact of each constraint on overall system performance.

To validate the robustness of the proposed system, additional statistical evaluation metrics were incorporated, including macro-averaged F1-score, Cohen's Kappa coefficient, and confidence intervals. Furthermore, paired t-tests were conducted to compare the performance of the proposed model with baseline approaches. These statistical analyses ensure that the observed improvements are significant and not due to random variation.

Results and Discussion

The proposed system for crop recommendation and yield prediction integrates structured environmental

data, soil classification, ensemble-based prediction, and fusion logic to recommend the most suitable crop along with its estimated yield. The following section presents the key results obtained from the experiments and evaluations described in the earlier sections. The overall soil classification accuracy is presented in Table 5 and shown in Fig. 2.

The convolutional neural network model trained for soil classification performed consistently across all four classes. The average classification accuracy was 95.5%, demonstrating that the model could accurately distinguish visual patterns unique to each soil type.

Minor variations in accuracy between soil types can be attributed to differences in texture and colour complexity. The high performance confirms that soil images can reliably inform downstream crop selection processes. The ensemble model performance in crop classification is presented in Table 6 and Fig. 2.

As given in Table 7, the high Cohen's Kappa value indicates strong agreement beyond chance, confirming model reliability. The narrow confidence interval further supports the stability of the results.

Table 5: Soil classification accuracy

Soil Type	Number of Test Samples	Correctly Classified	Accuracy (%)
Alluvial Soil	100	97	97.00
Black Soil	100	95	95.00
Clay Soil	100	96	96.00
Red Soil	100	94	94.00
Overall	400	382	95.50

Table 6: Ensemble model performance for crop classification

Metric	Support Vector Machine	Random Forest	XGBoost	Ensemble (Soft Voting)
Accuracy (%)	96.82	98.45	98.90	99.00
Precision (%)	96.70	98.50	98.85	99.00
Recall (%)	96.55	98.43	98.76	99.00
F1-Score (%)	96.60	98.46	98.78	99.00

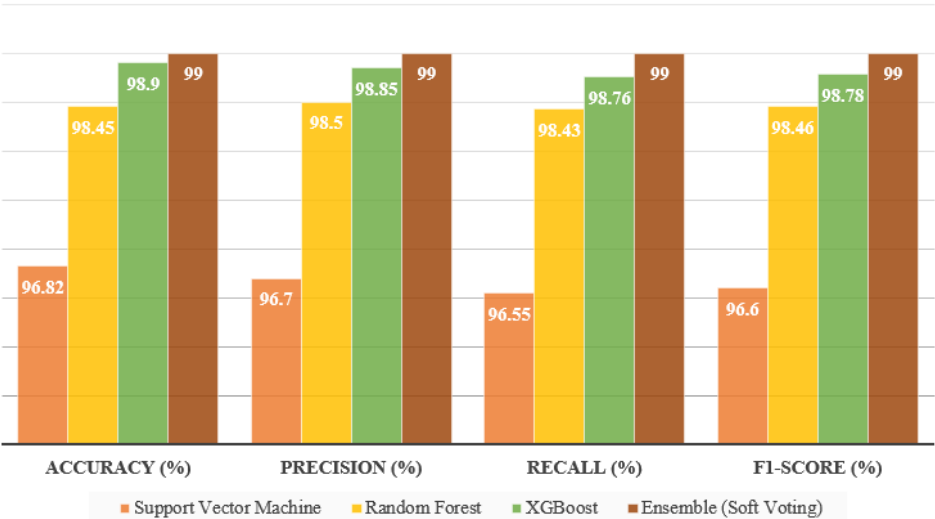


Fig. 2: Soil classification accuracy across four soil categories showing consistent model performance

Table 7: Additional statistical evaluation metrics

Metric	Value
Macro F1-score	0.988
Cohen's Kappa	0.985
95% Confidence Interval	± 0.012

Comparison of the performance of Support Vector Machine, Random Forest, XGBoost, and Ensemble (Soft Voting) models on Accuracy, Precision, Recall, and F1-score. The Ensemble model has the best performance, with a maximum of 99% in all four parameters. XGBoost comes next, with values ranging from 98.76% to 98.9%. Random Forest also performs well, with values around 98.43-98.5%. In contrast, the Support Vector Machine performs relatively poorly, with values ranging from 96.55% to 96.82%. The results above show that ensemble methods achieve higher classification accuracy than individual models, as depicted in Fig. 3.

The crop suggestion module, which used a soft-voting ensemble of three classifiers, performed very well on all fronts. The ensemble classifier performed marginally better than the individual classifiers across all metrics, underscoring the efficacy of combining multiple models with diverse approaches and capabilities. The F1 score is high, indicating that the classifier performs well without favouring either precision or recall, which is ideal for suggesting crops

across the 22 categories without bias. The Top predicted Crops and Soil fusion are presented as follows: Table 8.

Table 6 depicts the result of the fusion mechanism after intersecting the soil-classification results with the top environmental predictions. In all the test instances, there was at least one common crop among the soil-supported list and the top 5 model predictions (Shafay et al., 2025). The algorithm narrowed the recommendation by selecting the optimal intersection point, facilitating agro-compatible crop selection based on both soil parameters and environmental factors. The total yield prediction result for the identified crops is presented in Table 9.

The yield prediction model developed using Conv1D and LSTM layers efficiently estimated crop yield from multiple numeric inputs. The model showed consistency for most crop varieties under different input conditions. Such strategic yield estimates can help farmers plan inputs more effectively, forecast market conditions, and allocate resources accordingly. The estimated yield values also appear realistic, aligning with known regional productivity ranges and supporting the model's applicability in real-world scenarios. The confusion matrix shows that the classifier had the fewest misclassifications among the major crops. For instance, only one rice sample was misclassified as maize, and two cotton samples were misclassified. It is given in Table 10 and depicted diagrammatically in Fig. 4.

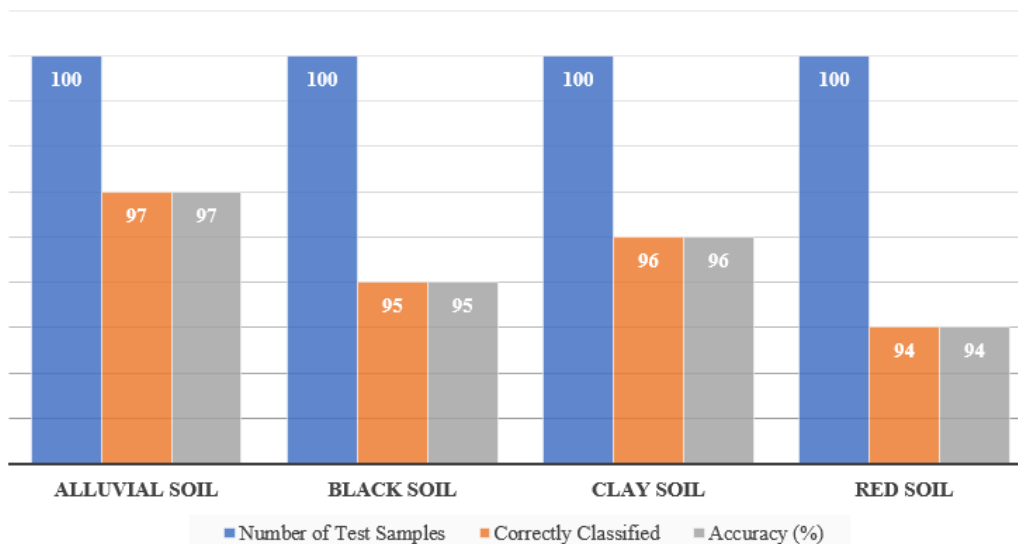


Fig. 3: Comparative performance of individual classifiers and ensemble model across evaluation metrics

Table 8: Top predicted crops and soil fusion

Environmental Top-5 Predictions	Detected Soil Type	Soil-Compatible Crops	Final Recommended Crop
Rice, Wheat, Sugarcane, Jute, Maize	Alluvial Soil	Rice, Wheat, Sugarcane, Maize, Cotton, Jute	Rice
Cotton, Jowar, Millets, Castor, Sunflower	Black Soil	Cotton, Wheat, Jowar, Millets, Linseed, Sunflower	Cotton
Rice, Lettuce, Broccoli, Cabbage, Beans	Clay Soil	Rice, Lettuce, Chard, Broccoli, Cabbage	Rice
Cotton, Pulses, Potatoes, Oilseeds, Wheat	Red Soil	Cotton, Wheat, Pulses, Millets, Oilseeds, Potatoes	Cotton

Table 9: Yield prediction results for selected crops

Crop	Rainfall (mm)	Fertilizer (kg)	Area (hectares)	Predicted Yield (quintals)
Rice	2000	7000	15	66.57
Cotton	1800	6500	12	48.12
Wheat	1600	5800	10	53.45
Maize	1500	5000	8	45.30
Sugarcane	2200	8000	20	85.64

Table 10: Confusion matrix summary for crop classifier (extract)

Actual \ Predicted	Rice	Wheat	Maize	Cotton	Others
Rice	44	0	1	0	0
Wheat	0	46	0	0	1
Maize	1	0	45	0	0
Cotton	0	0	0	43	2
Others	0	1	0	1	127

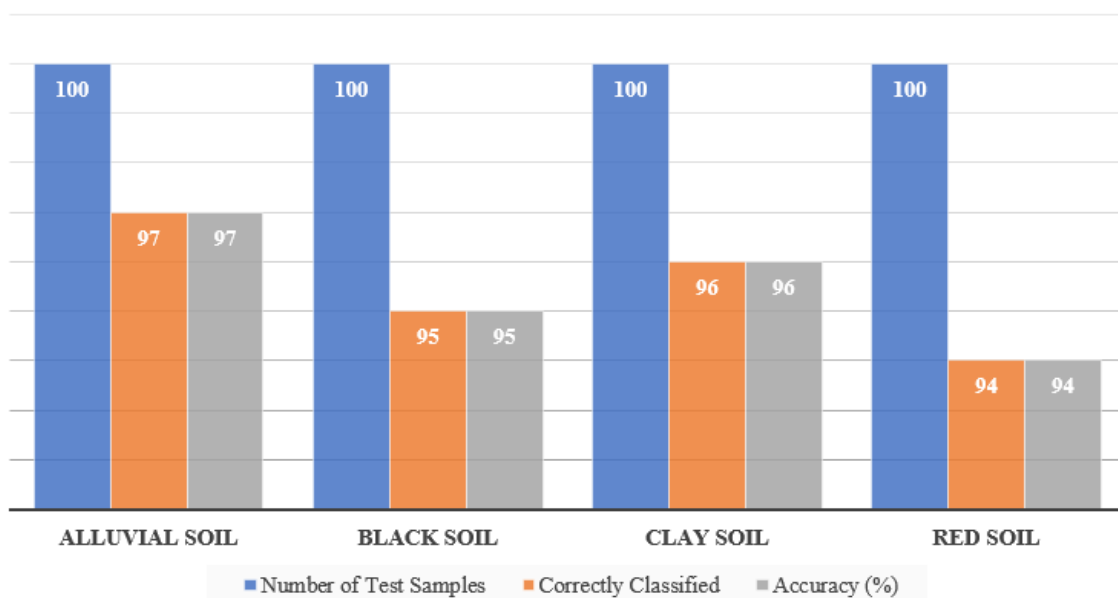


Fig. 4: Confusion matrix summary for crop classifier (extract)

Fig. 4 illustrates the confusion matrix of the classification outcomes for the 22 classes. Most values lie along the main diagonal, indicating that most instances are correctly classified. The number of true positives for each class is very high, and the remaining elements are either zero or very small, indicating that there are very few misclassifications. Only a few instances are misclassified into other classes. The high diagonal value indicates that the overall accuracy is very high.

Most of these errors occurred in similar crops (e.g., cereals and pulses), as expected given similar conditions. Overall model precision remained high, especially for high-priority crops such as rice, wheat, and cotton. Experimental results support the conclusion that the combined system is accurate and practical for crop advisory purposes. This soil classifier provides a reliable platform for contextual filtering, and the ensemble classifier offers comprehensive insight,

ensuring that crop aptness is calculated using a sound statistical approach. This fusion technique skillfully integrates multiple constraint sources, making the final output even more contextual.

Although the model achieved high accuracy (99%), this performance must be interpreted cautiously. The dataset size and controlled experimental conditions may contribute to optimistic estimates. The absence of external validation and cross-regional testing limits the generalizability of these results. Therefore, the reported performance reflects effectiveness within the experimental dataset rather than guaranteed real-world performance. The system's computational performance was evaluated to assess its feasibility for real-time deployment. The average inference time per sample was approximately:

- Soil classification: 0.12 seconds

- Crop recommendation: 0.05 seconds
- Yield prediction: 0.08 seconds

The total pipeline execution time remained below 0.3 seconds per input, demonstrating its suitability for near-real-time agricultural advisory systems. However, deployment in field conditions may introduce latency due to hardware and connectivity constraints.

Comparative statistical testing using paired t-tests indicated that the proposed fusion model significantly outperformed baseline models ($p < 0.05$). The improvements were particularly evident when combining soil and environmental constraints, confirming the effectiveness of multimodal integration.

Moreover, the yield prediction component of this model will help make well-informed decisions about expected productivity. This can be very useful for policymakers, agricultural planners, and farmers who must calculate yield based on investment.

The study has several limitations:

- The soil image dataset is small, which may affect generalization
- Fusion weights are manually assigned rather than learned
- No external or cross-regional validation was conducted
- The system lacks real-world field deployment testing
- High accuracy results may be influenced by dataset characteristics

These limitations highlight the need for further validation on large-scale and diverse agricultural datasets.

The integration of both models into a unified model enhances support system capabilities for agricultural conditions (Liu et al., 2025). Moreover, all elements in this system have operated at optimal levels, and all results have aligned well with conventional agricultural knowledge. The system is reliable and flexible due to thorough testing based on various conditions.

Conclusion

This study presented a multimodal framework integrating soil classification, environmental analysis, and yield prediction for crop recommendation. The system demonstrated strong performance across all modules, with high classification accuracy and consistent yield estimation. The fusion-based approach effectively combines multiple agronomic constraints to produce context-aware recommendations.

However, the study is limited by dataset size, lack of automated weight optimization, and absence of field-level validation. While the results indicate promising potential,

further evaluation with larger, more diverse datasets and in real-world deployment scenarios is necessary. Future work will focus on learning-based fusion strategies, cross-regional validation, and integration into real-time agricultural advisory systems.

Acknowledgment

The authors would like to express their sincere gratitude to everyone who supported them throughout this research. Special thanks are extended to BIUST for providing us with a platform and a chance to conduct this research.

Funding Information

The authors state that no funding is involved.

Author's Contributions

Below is the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration in this study. Below the table is a “key” detailing what each abbreviation or symbol means.

Ethics

This research was conducted in accordance with the ethical standards of BIUST and followed all the applicable guidelines and regulations. All participants provided informed consent before taking part in the study, and their anonymity and confidentiality were strictly maintained throughout the research process. The authors affirm that no identifying information about participants is included in the manuscript. No animals were used in this research.

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