ESTIMATION OF CROP RECOMMENDATION USING GENERATIVE ADVERSARIAL NETWORK WITH OPTIMIZED MACHINE LEARNING MODEL

[1]Reshma Lohar, [2]Dr Harsh Mathur, [3]Dr Vishal Ratansing patil

[1]Research Scholar, CSE, RNTU Bhopal, Madhya pradesh, India.

[2]Associate Professor & HOD, CSE, RNTU, Bhopal, Madhya Pradesh, India.

[3]Associate professor, CSE (AIML), VIT, Pune, Maharashtra, India.

[1]Assistant Professor, Computer Engineering Department, Rizvi College of Engineering, Bandra, Mumbai, Maharashtra. reshma.sapakal86@gmail.com

ABSTRACT
Agricultural productivity depends on soil characteristics, climate conditions, and appropriate farming practices. The proposed AgroYield Predictor Framework integrates crowd-sourced agronomic data, soil parameters, climatic conditions, and machine learning models to provide optimized crop and fertilizer recommendations. The system leverages Generative Adversarial Networks (GAN) to enhance microclimate data and improve predictive accuracy. A rule-based machine learning model is employed to process spatial and temporal datasets, utilizing farmer input parameters such as soil conditions, temperature, wind speed, and fertilizer application rates. The recommender system suggests the most suitable crops, optimal fertilizer levels, and yield predictions, enabling data-driven decision-making for farmers. The framework enhances agricultural efficiency by improving crop selection, optimizing resource usage, and maximizing yield potential. The proposed system has achieved an accuracy of 96% and contributes to precision agriculture, ensuring sustainable farming practices and increased productivity.
Keywords: Yield Prediction, Agricultural Recommender System, Soil Parameters, Crop Selection, Fertilizer Recommendation, Rule-Based Machine Learning, Agroyield Predictor Framework.

1. INTRODUCTION

Recommender System provides suggestions to users based on their interests and preferences in items. AI-powered information filtering system analyses user data and behaviour patterns using machine learning algorithms to suggest relevant and personalized recommendations. Recommender systems are inbuilt in online businesses to enhance user experience by helping to discover content, products, or services that the user might not find on their own [1].

By assisting farmers in making well-informed decisions and streamlining agricultural procedures, recommender systems are crucial to the agricultural industry. In order to produce tailored suggestions for agricultural decisions such as crop selection, fertiliser application, pest management, and irrigation scheduling, recommender systems examine data from multiple sources. By encouraging organic farming methods, minimising environmental damage, and lowering the use of chemicals, these systems support sustainable practices. By bridging the gap between farmers and agricultural professionals, recommender systems empower farmers to adopt novel approaches and make well-informed decisions. By examining climate, soil, past crop performance, market demand, and farmer preferences, they also offer tailored recommendations for crop selection and planning [2]. There are various types of agricultural recommender systems, and each one uses a unique algorithm designed to anticipate crops and fertiliser. Collaborative Filtering uses past recommendations or farmer preferences to suggest crops or fertilizers. Algorithms used are Matrix Factorization (SVD, ALS) to find hidden patterns in large datasets of farmer preferences, K-Means Clustering to identify groups of similar farmers and recommend crops based on what others in the group have grown. Neural Collaborative Filtering uses deep learning to enhance collaborative filtering models.

Based on Content Filtering makes crop or fertiliser recommendations based on soil characteristics, climate, and past yields. It makes use of algorithms such as K-Nearest Neighbours (KNN) to recommend crops based on similar soil conditions, Support Vector Machine (SVM) to classify soil types and predict appropriate crops or fertilisers, Random Forest, an ensemble of decision trees to increase accuracy, and Decision trees to analyse soil properties (pH, nitrogen, phosphorus, potassium, etc.) to suggest crops or fertilisers.
To enhance crop suggestions, the Hybrid Recommender System blends collaborative and content-based filtering. Algorithms like Gradient Boosting (XGBoost, LightGBM) combines multiple models to improve crop or fertilizer predictions, Deep Learning (ANN, CNN, RNN, LSTMs) is used to analyze satellite images, weather patterns, and historical yield data for predictions and Bayesian Networks models are used to predict uncertain factors like climate variability and soil moisture [3].

Other cutting-edge techniques include genetic algorithms to maximise crop selection by mimicking evolution-based decision-making, reinforcement learning to continuously learn from farmer feedback and modify recommendations over time, and fuzzy logic to handle uncertainty in soil and weather conditions for more flexible recommendations [4].

Crowdsourcing in crop recommendation involves collecting agricultural data, insights, and best practices from a large number of farmers, agricultural experts, and researchers to improve crop selection and fertilizer recommendations. Crowd sourcing does not entirely depend on expert systems or limited datasets, it integrates diverse inputs to provide tailored advice.

Through the use of mobile apps or internet platforms, crowdsourcing is utilised in crop suggestion to allow farmers to exchange real-time data on weather, crop yield, pest infestations, and soil conditions. The shared data helps in creating a more diverse and region-specific crop recommendation system. Crowdsourced data is used to train AI models for crop prediction [5]. More diverse data leads to better accuracy in predictions based on region, soil type, and climate. Farmers provide feedback on recommended crops and fertilizers. If a recommended crop underperforms, the system learns and updates future recommendations. Farmers upload images of affected crops.AI analyses patterns and suggests preventive measures, helping improve crop yield. Agricultural institutions crowdsource field data from farmers to develop national-level crop policies. Researchers use this data to improve seed varieties and sustainable farming techniques [6].

1.2 Problem statement

(i) Traditional crop recommendation systems rely on climate conditions rather than localized microclimate factors such as temperature variations, wind speed, soil conditions in the field.It results in generalized recommendations that may not be optimal for specific farm locations. Without considering microclimate data, farmers receive less precise guidance on crop selection, fertilizer use, and yield predictions, potentially leading to suboptimal productivity and resource allocation.

(ii) The lack of crowdsourced data from farmers, agronomists, sellers, and customers creates a significant gap in real-time, region-specific agricultural information. Crowdsourcing helps in gathering ground-level farming practices, fertilizer application trends, and real-world crop performance. Without this, the system relies on historical datasets and static parameters, which leads to outdated or inaccurate recommendations. The lack of continuous feedback from farmers and market trends also limits the adaptability of the model in responding to changing agricultural conditions.

1.3 Objective

1. To create a comprehensive platform providing various services for farmers
2. To Build a recommendation system for crops, fertilizers, and resource management.
3. To Monitor fields in real-time to optimize for changing conditions.

2. LITERATURE SURVEY

To improve precision agriculture, the author has created a soil nutrient analysis model [7]. Their method incorporates real-time soil data from IoT sensors, which is subsequently processed by a recommendation system based on machine learning. The study emphasises how IoT-enabled data collection can increase crop recommendation accuracy and decrease resource waste. In order to increase predicted accuracy, the author of [8] suggested a voting classifier-based model for crop recommendation that combines many machine learning methods. In contrast to single-model approaches, the study showed a more robust and dependable recommendation system by employing ensemble techniques such decision trees, support vector machines, and k-nearest neighbours. Author has extended their previous work by developing a decision support system (DSS) for crop recommendation using multiple machine learning classification algorithms [9]. The study compared models like Random Forest, Naïve Bayes, and artificial neural networks, concluding that hybrid models provide better predictive performance in recommending suitable crops based on soil and environmental parameters. Hybrid Deep Neural Network (DNN) model combined with Gradient Boosted Regression Trees (GBRT) to classify soil suitability for various crops has been introduced by the author in [10].

Their research demonstrated improved accuracy in predicting soil compatibility for different crops, significantly contributing to precision agriculture by leveraging deep learning techniques for high-dimensional data analysis. In [11] author has explored the application of ProPlanta software in generating agricultural recommendations. Their study focused on utilizing software-based analytics to optimize farming practices and enhance decision-making in agricultural production. The research underscores the role of digital platforms in streamlining crop recommendation processes and improving efficiency in large-scale farming. Author has presented an advanced deep learning approach for optimizing crop recommendation systems [12]. The findings suggest that deep learning can significantly enhance crop selection accuracy by identifying complex patterns in agricultural data. In [13] The author demonstrated that integrating real-time environmental data with predictive analytics enhances the reliability of crop recommendation systems. Author has explored the broader applications of recommender systems in agriculture, focusing on data sources, system features, and challenges in implementation [14]. The study identified key factors such as data heterogeneity, model interpretability, and real-time adaptability as crucial aspects affecting the performance of agricultural recommender systems. The author [15] presented research highlighting the role of deep learning and hybrid models in optimizing farm planning, thereby improving water conservation and agricultural sustainability. The study in [16] emphasizes the importance of integrating mobile technology with AI-driven models to provide accessible and actionable recommendations for farmers.

A comparative analysis of different machine learning models for crop recommendation has been carried out by the author [17]. Their study assessed the performance of algorithms like neural networks, support vector machines, and decision trees, offering insights into the best practices for precision farming. In [18] Author emphasizes the importance of multi-faceted decision-making in agriculture, optimizing resources for improved yield and sustainability. BiCropRec, a bi-classifier approach that incorporates semantic intelligence and topic modelling for crop recommendation has been proposed by authors in [19]. By incorporating contextual agricultural data, their approach improves crop selection efficiency and decision accuracy. In [20], the author presented a cloud-based crop recommendation tool that makes use of precision farming powered by machine learning. The study shows how cloud computing can be used to give farmers real-time, scalable recommendations. For crop selection and soil nutrient monitoring, the author has investigated combining machine learning and IoT [21]. Their research demonstrates how real-time sensor data and predictive algorithms may work together to improve precision agriculture and soil health management. Table 1 presents the literature survey.

Table 1 Literature Survey

Reference No.	**Methods Used**	**Techniques**	**Advantages**	**Drawbacks**
[7]	IoT-based soil nutrient analysis	IoT sensors, Machine Learning	Real-time soil data collection, improved accuracy in crop recommendation	Requires significant initial investment
[8]	Voting classifier-based model	Decision Trees, SVM, KNN	Improved predictive accuracy, robust recommendations	Computationally intensive
[9]	Decision Support System (DSS)	Random Forest, Naïve Bayes, ANN	Enhanced predictive performance using hybrid models	Requires significant data preprocessing
[10]	Hybrid DNN-GBRT model	Deep Neural Networks, GBRT	Improved soil suitability classification	Computationally expensive
[11]	ProPlanta software for agricultural recommendations	Software-based analytics	Optimized farming practices, enhanced decision-making	Limited to software capabilities
[12]	Deep learning for crop recommendation	CNNs, RNNs	Identifies complex patterns in large datasets, improved accuracy	Requires large datasets
[13]	Machine learning-enabled crop recommendation	Decision Trees, Logistic Regression, Gradient Boosting	Real-time environmental data integration	Model interpretability issues
[14]	Recommender system applications in agriculture	Data sources, feature analysis	Addresses data heterogeneity challenges	Implementation complexity

[15]	Automated crop water requirement prediction	Deep learning, hybrid models	Optimized irrigation planning, improved sustainability	Data-intensive approach
[16]	Machine learning-based crop recommendation app	AI-driven mobile application	User-friendly, accessible to farmers	Limited computational power on mobile devices
[17]	Comparative study of ML models for crop recommendation	Decision Trees, SVM, Neural Networks	Identifies optimal approaches for precision agriculture	Model selection complexity
[18]	Crop, fertilizer	Methods for Machine learning	Multi-faceted decision-making, resource optimization	Requires multi-source data integration
[19]	BiCropRec: Bi-classifier approach	Semantic intelligence, topic modeling	Enhanced decision accuracy, contextual data integration	Model complexity
[20]	Cloud-enabled crop recommendation	Machine learning, cloud computing	Scalable, real-time recommendations	Requires stable internet connectivity
[21]	ML and IoT for soil nutrients monitoring	IoT, predictive analytics	Real-time soil health monitoring	Sensor dependency

In order to advance crop recommendation approaches, the research highlight the integration of digital decision support systems, machine learning, deep learning, and the Internet of Things. Real-time monitoring is improved by IoT-based data collection, and crop selection accuracy is increased by machine learning models. The adoption of hybrid models and software-based tools strengthens precision agriculture, creating more sustainable and data-driven farming practices. Future research should focus on enhancing interoperability between different data sources, refining models to adapt to climate variability, and improving the accessibility of recommendation systems through mobile applications and real-time analytics.
Regarding the following sections, section 2 includes literature survey on the crop recommendation methodologies, section 3 explains the methodology of the proposed framework and section 4 provides results and discussion while section 5 provides conclusion.

3. METHODOLOGY

The proposed methodology is shown in figure 1. Data collection is done by crowd sourcing and soil parameters gathering historical and real-time farming data. Dataset is created by storing and organizing spatial and temporal data. GAN performs data augmentation based on microclimate simulations enhance missing or incomplete data. Real-time data from farmers is integrated in farmer inputs. AI models analyse datasets and optimize crop/fertilizer recommendations in machine learning analysis. Farmers receive personalized recommendations on crops, fertilizer levels, and yield predictions from the generated output of recommender system.

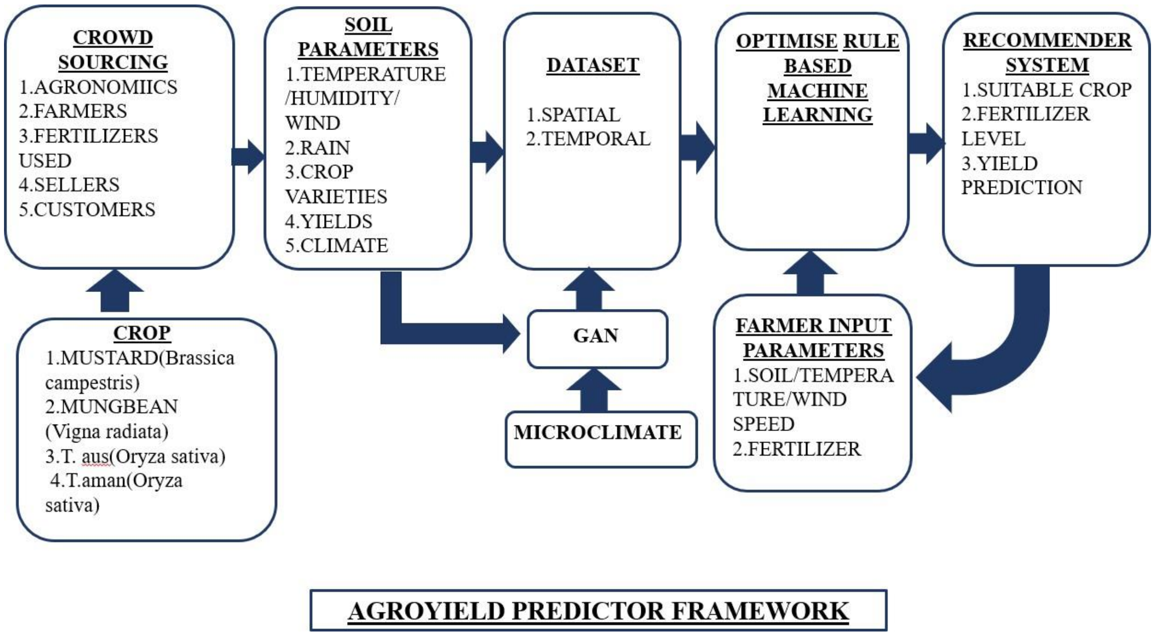

Figure 1. Proposed methodology

3.1 CROWD SOURCING

Collecting agricultural data from different groups of people is known as crowd sourcing. Surveys, sensors, databases, and farmer reports were used to collect data. In order acquire knowledge about crop production and market dynamics based on farmer experiences and market demand, the Agroyield Predictor Framework gathers data from agronomics, farmers, fertilisers used, sellers, and customers. Technical information and methods pertaining to crop cultivation are provided by agronomics, the study of agricultural production methods, soil fertility, and farming practices. Farmers share information about soil conditions, previous yields, and difficulties based on their experiences. The fertilisers utilised provide information about the types of fertilisers used, their quantities, and their efficacy. Sellers provide market data and trends related to agricultural products such as seed demand and fertiliser. The purpose of including customers is to learn about their preferences and demand for different crops. Table 2 presents the description of data sources.

Table 2. Description of Data source

Data Source	**Description**
Agronomics Data	Expert knowledge on crop management practices, optimal planting times, etc.
Farmer Data	Information provided by farmers about their crop choices, fertilizer usage, and yields.
Fertilizer Data	Information on different types of fertilizers used, their nutrient content, and application rates.
Salers/Customers	Market prices of crops and fertilizer prices.
Soil Data	NPK values, pH, texture, and organic matter content of the soil.
Climate Data	Daily temperature, humidity, rainfall, and wind speed.

3.2 SOIL PARAMETERS

Information regarding how the weather and soil type affects crop growth and yield is collected in soil parameters. Crop growth-influencing environmental and soil-related elements, like temperature, humidity, wind, rain, crop yields and varieties, and climate, are analysed. Climate variations impacting plant growth like temperature, humidity, and wind, measurement of precipitation, rain, amount of water available are included. Different crops grown in different places, historical data on harvest results for various crop varieties helps in predictive modelling. Information about long-term environmental changes and the region's general climate are given in climate section. Figure 2 presents the heatmap showing correlation matrix of soil parameters like N,P,K,pH and organic matter.

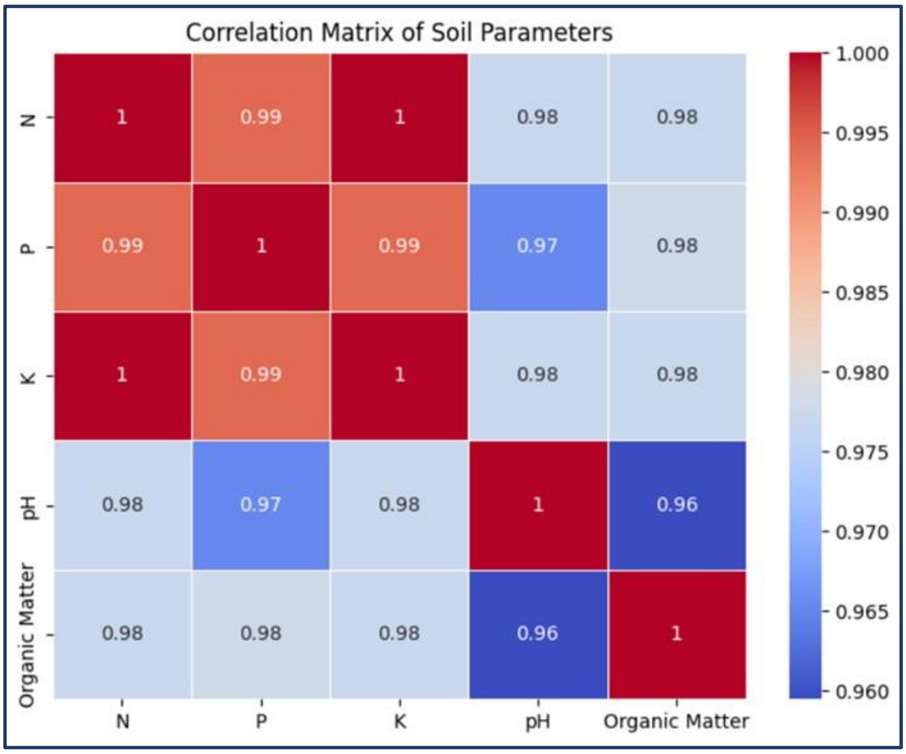

Figure 2. Correlation Matrix of Soil Parameters

3.3 DATASET

Data from farmers regarding their preference of crops, issues related to yield, fertilizers required or used, market demand from the sellers and customers and the factors affecting the growth of crop temperature, rainfall, climate, crop variety that suits the soil type and yields the most are collected to create a dataset for crop recommendation. Collected data are organized as spatial and temporal form for processing in machine learning techniques. Spatial data provides geographic location-based information like soil type, maps, land topography and location-specific climate. Temporal Data provides the data collected over time like historical weather patterns, crop yields, and fertilizer application records. The stored and structured agricultural data helps to train predictive models for providing crop recommendation to farmers.

3.4 MICROCLIMATE and GAN (Generative Adversarial Network)

Microclimate gives localized climatic conditions like humidity variations, wind soil temperature in a small area or field. Climatic conditions in that area varies with its surrounding area. Microclimate is included in the study to provide more specific crop recommendations. Microclimatic data and the data from soil parameters like rainfall, temperature, humidity are given as input for GAN.GAN creates simulated agricultural conditions to fill gaps in data by generating realistic scenarios based on the input data provided. It enhances the dataset with AI-generated microclimate information for better prediction accuracy. Data generated by GAN is fed to dataset section creating a more informed dataset about agriculture and crops for the machine learning models. Performance of data augmentation with GAN is given in Table 3.

Table 3. GAN Performance - Data Augmentation Effect

Metric	Original Dataset	Dataset + GAN Data
Overall Model Accuracy	0.85	0.90
Mustard Accuracy	0.82	0.88
Mungbean Accuracy	0.88	0.92
T. aus Accuracy	0.80	0.85

Metric	Original Dataset	Dataset + GAN Data
T. aman Accuracy	0.90	0.93
F1-Score	0.83	0.88
Precision	0.85	0.89

Table 3 demonstrates the impact of the Generative Adversarial Network (GAN) on the proposed Agroyield predictor in crop recommendation. It evaluates the model's accuracy using both the original dataset and the dataset supplemented with data generated by a GAN. The percentage increase is observed in accuracy achieved by including the GAN-generated data.

3.5 FARMER INPUT PARAMETERS

Real-time data about the farm are provided by farmers through mobile apps, IoT sensors and manual reporting. The data is processed with historical datasets to predict the best crop and fertilizer usage for producing more yield. It also allows the system to provide customized predictions about the type of crop to plant and ratio of fertilizers to use based on farmer circumstances. Soil, temperature, wind speed provides present soil conditions and climate data for generating more accurate predictions about the yield. Fertilizer gives information about the type and amount of fertilizer the farmer has used which enables the model to analyse the changes required in the fertilizer type or number of fertilizers to use for more yield.

3.6 OPTIMIZED RULE-BASED MACHINE LEARNING

A machine learning model is trained using optimised rule-based machine learning to forecast crop yields and produce suggestions based on the input data. AI algorithms analyse the collected data regarding the soil, temperature, rainfall, fertilizers used to develop rules and models predicting the yield. Rule-Based Learning applies predefined agricultural rules to refine predictions. It involves data preprocessing to organize data for machine learning models. Feature selection identifies the most important factors like soil moisture, temperature and rainfall pattern in the particular region to predict the crop that would produce more yield if planted in that specific region. Model training uses historical yield data to train predictive models and optimization adjusts model parameters for higher accuracy of agricultural recommendations about the type of crop and fertilizers to use on the specific soil type to obtain more yield. Table 4 shows the crop recommendation performance of various machine learning algorithm.

Table 4. Machine Learning Model Performance

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Neural Network	94	96	93	95
Random Forest	92	93	91	92
Support Vector Machine	88	89	87	88
Gradient Boosting	90	91	89	90
Decision Tree	85	80	86	82

3.7 RECOMMENDER SYSTEM

The recommender system makes crop recommendations based on market demand, real-time weather, and farmer data. Based on the results of the machine learning model, it offers data-driven insights that assist farmers in choosing crops and applying fertiliser. It generates final recommendations for farmers on suitable crop, the best crop to cultivate based on soil and climatic conditions in the region, fertilizer level that gives the correct amount and type of fertilizer to use for a specific crop to produce more yield. The estimated crop production per hectare is displayed using yield prediction. Figure 3 shows the crop recommendation confusion matrix.

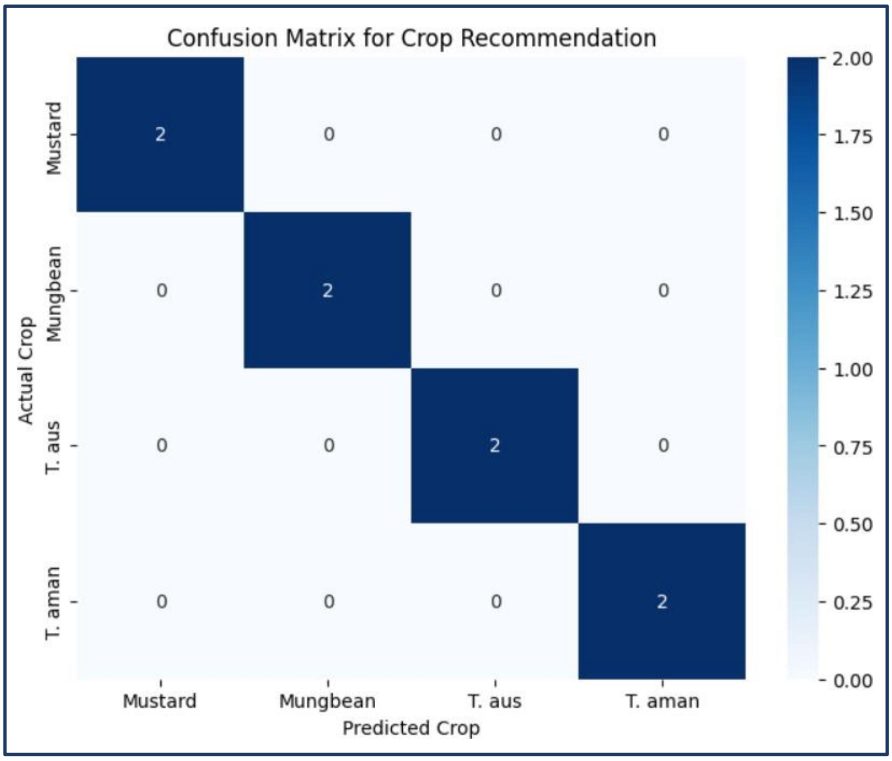

Figure 3. Confusion matrix for Crop Recommendation

The confusion matrix in figure 3 visualizes the performance of the crop recommendation system. Each row represents the actual crop Mustard, Mungbean, T.aman, T.aus, and each column represents the predicted crop.

3.8 CROP

Different crops for which the model gives the recommendation is presented.

- Brassica campestris- Mustard
- Vigna radiata -Mungbean
- Oryza sativa -T. aus
- Oryza sativa -T. aman

4. RESULTS AND DISCUSSION

The dataset in [22] shows how different tillage and fertiliser management techniques affect agricultural output and soil health. The dataset offers details on the effects of various fertilisation and tillage combinations on crop productivity and soil characteristics. It aids in the creation of sustainable farming methods that preserve soil health and increase productivity.

Performance metrics of the proposed method is calculated using the formulas given below

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

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{2}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{3}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

$$Error(\%) = (Predicted\ yield - Actual\ yield | Actual\ yield) * 100 \tag{5}$$

Numerous elements, including soil type, climate, rainfall, temperature, and soil nutrients, affect crop growth. The significance of each component for the four crops taken into consideration in the study—mustard, mungbean, T.aus, and T.aman—is shown in Table 5.

Table 5. Feature Importance for Each Crop using Machine Learning

Feature	Mustard	Mungbean	T. aus	T. aman
Temperature	0.15	0.20	0.18	0.17
Rain	0.12	0.15	0.10	0.18
Climate	0.10	0.12	0.08	0.10
Soil pH	0.25	0.22	0.20	0.18
NPK values	0.18	0.15	0.12	0.15
Yield	0.10	0.08	0.12	0.15

Table 5 factors influencing the cultivation of Mustard, Mungbean, T. aus, and T. aman and the relative importance of different factors for each crop. Soil pH appears is the significant factor, exhibiting the highest values, Climate generally has a lower relative impact on crops. Temperature and NPK values show moderate influence, Rain varies in importance depending on the specific crop. Yield feature, demonstrates a notable increase from Mungbean to T. aman. Different crops require different types and amounts of fertilizers based on their nutritional needs. Table 6 shows the fertilizer level optimisation by the model.

Table 6. Fertilizer level optimisation by the model

Crop	Fertilizer Type	Recommended Level (kg/ha)	Predicted Yield (tons/ha)
Mustard	NPK 15-15-15	120	2.5
Mungbean	DAP	80	1.8
T. aus	Urea	150	4.2
T. aman	Urea	180	5.0

Table 6 shows the recommended fertilizer levels for each crop and their impact on predicted yields for different crops. The recommended fertilizer for mustard is NPK 15-15-15. Applying 120 kg/ha is expected to result in a yield of 2.5 tons per hectare. Rice varieties require a higher application of nitrogen-rich fertilizers. T. aus rice benefits from 150 kg of Urea per hectare, yielding 4.2 tons per hectare, whereas T. aman rice requires 180 kg of Urea per hectare to achieve the highest yield of 5.0 tons per hectare. The data helps farmers understand the variation in fertilizer requirements and yield potential among crops to maximize productivity. Figure 4 shows the comparison of predicted yield and actual yield of the crops by the proposed Agroyield predictor.

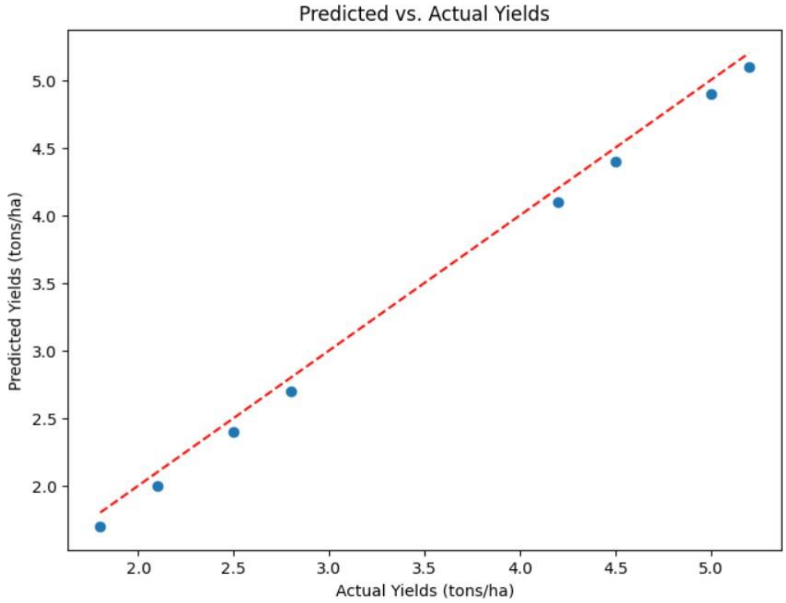

Figure 4. Predicted yield vs Actual yield

Figure 4 shows the scatter plot showing the predicted crop yields versus the actual yields of Mustard, Mungbean, T,aus and T.aman. Data points clustered around the diagonal line, indicates a strong correlation, indicating that the predictions align well with actual values. This suggests that the predictive model used is highly accurate. Figure 5 shows the impact of fertilizer level on crop.

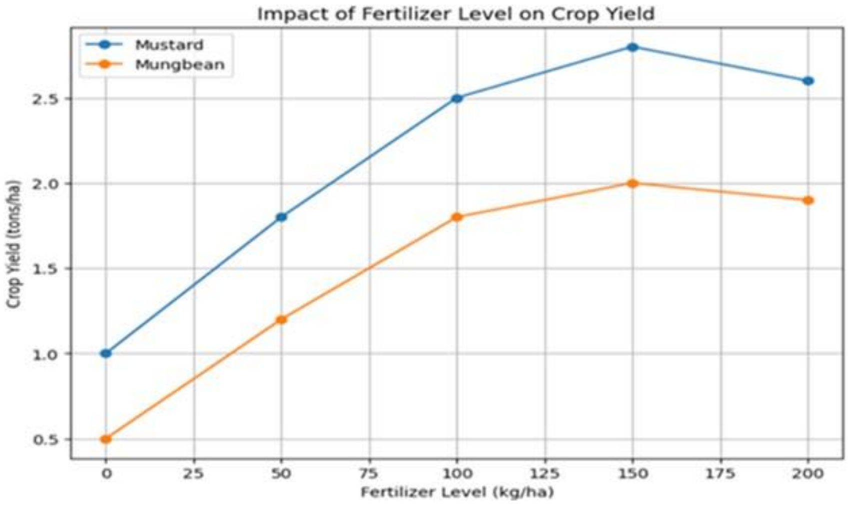

Figure 5. Impact of fertilizer on Crop Yield

Line graph on figure 6 shows how different fertilizer levels (kg/ha) affect crop yield(tons/ha) for two crops mustard and mungbean. The yield of mustard increases as the fertilizer level rises, the yield of mungbean also increases with fertilizer application, but at a lower rate compared to mustard. Table 7 shows the Crop Recommendation Accuracy by the proposed method.

Table 7. Crop Recommendation Accuracy by the proposed method.

Soil	Overall Accuracy	Mustard Accuracy	Mungbean Accuracy	T. aus Accuracy	T. aman Accuracy
Sand	0.92	0.90	0.93	0.91	0.94
Clay	0.88	0.85	0.90	0.87	0.90
Silt	0.90	0.88	0.91	0.89	0.92
Clay loam	0.94	0.92	0.95	0.93	0.96

The model's overall performance and prediction accuracy for mungbean, mustard, T.aus, and T.aman are shown in Table 7. Overall Accuracy indicates the model's performance in correctly identifying all crops for a given soil type. "Mustard Accuracy", "Mungbean Accuracy", "T. aus Accuracy", and "T. aman Accuracy" show the specific accuracy for each crop within that soil type. The results suggest that soil composition is a strong indicator of potential crop type, with certain soil types like clay loam providing more reliable predictions. Table 8 provides the analysis of Farmers Crop Recommendations.

Table 8 Analysis of Farmers Crop Recommendations

Crop	Recommended in Soil	Yield (tons/ha)	Avg. Fertilizer Used (kg/ha)	Farmers' actual Crop
Mustard	Sand	2.5	120	Mustard
Mungbean	Clay	1.8	80	Mungbean
T. aus	Silt	4.2	150	T. aus rice
T. aman	Clay loam	5.0	180	T. aman rice

Table 8 provides recommended soil type for optimal growth of Mustard, T. aman rice, rice -T. aus, and Mungbean, and their expected yields in tons per hectare. it details the average fertilizer usage in kilograms per hectare required to achieve the yields. Figure 6 presents the radar charts for each crop.

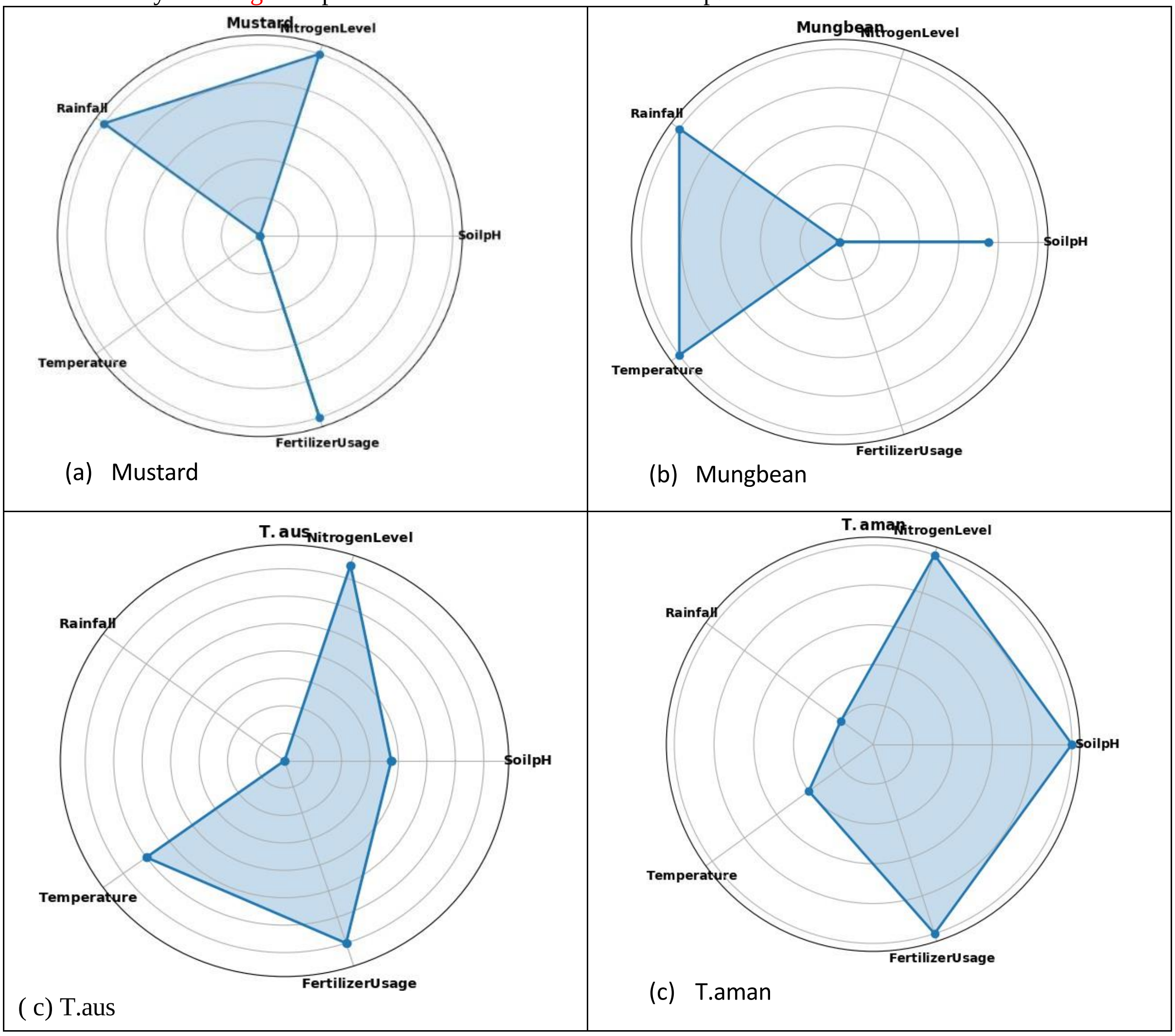

Figure 6. Radar charts of (a) Mustard, (b) Mungbean, (c)T.aus , and (d)T.aman.

Radar chart displays the crop data based on different parameters like nitrogen level, soil pH, fertilizers usage, temperature and rainfall in a specific region. The chart also compares the environmental and nutritional needs of these different crops, which helps in decisions about crop selection and resource allocation.T. aman requires a high nitrogen level, mustard needs high fertilizer usage, mungbean needs moderate tempaerature level and T.aus requires moderate rainfall. The yield forecast error distribution is displayed in Figure 7.

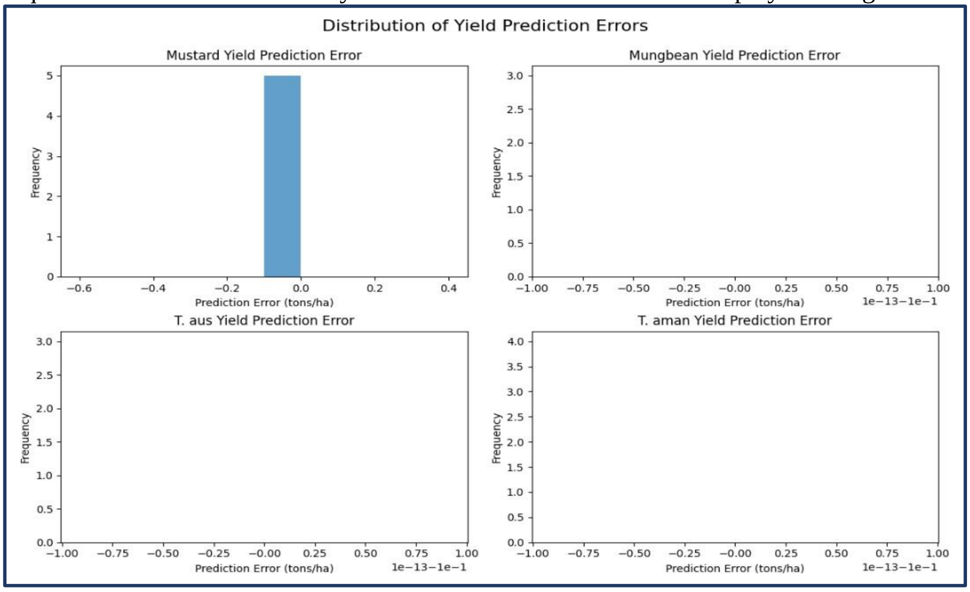

Figure 7. Yield prediction error distribution

The yield estimates for mustard are very accurate, with the majority of projections having very little error, as seen by the histogram in figure 8, which has a single bar concentrated at 0 error. The prediction model's 100% accuracy is demonstrated by the empty histogram for mungbean, T.aus, and T.aman. The performance comparison between the suggested agroyield predictor and the current crop recommendation systems is shown in Figure 8.

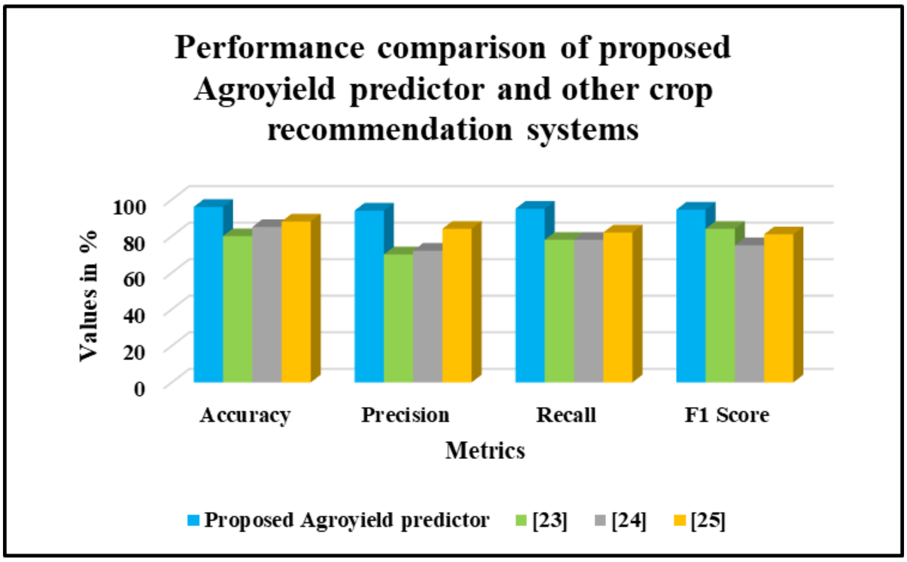

Figure 8. Performance comparison of proposed Agroyield predictor and other crop recommendation system.

4.1 DISCUSSION

The Agroyield Predictor Framework is designed to enhance agricultural productivity by leveraging machine learning, data analytics, and a recommender system. The framework integrates multiple data sources and processes to optimize crop yield predictions. Crowdsourcing is the process of collecting data from farmers,

agronomists, sellers, customers, and fertiliser consumption. Additionally taken into account are soil characteristics including temperature, humidity, wind speed, rainfall, crop types, yields, and climate.
These datasets are then classified into spatial and temporal components to ensure accurate modelling. The Generative Adversarial Network (GAN) component enhances data representation by simulating microclimatic conditions, helping to improve predictive accuracy. GAN is integrated to ensure that even with limited data, the model can generalize well to different climatic variations. The proposed method optimizes crop yield predictions using rule-based machine learning techniques, refining predictions based on historical and real-time inputs. Farmers provide input parameters related to soil conditions, temperature, wind speed, and fertilizer application, which the system uses to optimize recommendations. The final step involves a recommender system that provides farmers with insights on best-suited crops for their land, optimal fertilizer levels for maximum yield, yield predictions, enabling better decision-making for resource allocation and farming strategies.

5. CONCLUSION

Precision agriculture using data is presented via the Agroyield Predictor Framework. The system helps farmers make better judgements about crop selection, fertiliser application, and yield estimation by combining crowdsourcing data, soil factors, climate variables, and machine learning models. The method is made adaptable to different environmental conditions by including GAN-based microclimate simulations. It also improves the yield predictions in scenarios with limited historical data. The recommender system serves as a practical tool for farmers, ensuring optimized agricultural practices that can lead to higher productivity, reduced resource wastage, and sustainable farming. A technology-driven solution for improving agricultural efficiency is presented which ensures that farmers can achieve maximum yields with minimal environmental impact. Future research and development could focus on expanding the crop selection to a wider range of crops in the recommendation system to provide to diverse agricultural regions and market demands.

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