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Review Article

SmartAgroCare: An IoT & ML-Based Crop Health Monitoring System

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ABSTRACT

Agriculture is undergoing a digital transformation driven by emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT). This paper proposes a Crop Monitoring System that combines these technologies to enable real-time observation, analysis, and prediction of crop and soil conditions. The system utilises IoT-based sensors deployed across the field to collect key environmental and soil parameters, including temperature, humidity, soil moisture, pH level, and light intensity. These data are transmitted to a cloud platform for processing and analysis using ML algorithms. The AI component further enhances decision-making by detecting crop diseases, predicting yield, and identifying irrigation or nutrient requirements based on data patterns and image-based analysis. A web and mobile-based interface allows farmers to visualise the collected data, receive alerts, and take timely corrective actions. This intelligent integration helps in optimising water usage, reducing pesticide dependency, and improving overall crop productivity. Experimental evaluations and simulated results indicate that the system provides accurate, efficient, and scalable monitoring suitable for diverse agricultural environments.[1,4,5]

Keywords: Smart Agriculture, Crop Monitoring, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Precision Farming, Sustainable Agriculture.

Introduction

Agriculture is the foundation of human survival and economic growth, yet traditional farming methods often face challenges such as unpredictable weather conditions, pest infestations, and inefficient utilisation of natural resources. The rapid growth of the global population has further intensified the demand for enhanced productivity, precision, and sustainability in the agricultural sector. To overcome these limitations, the integration of advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) has emerged as a transformative approach in modern agriculture, enabling data-driven insights.

The proposed Crop Monitoring System utilises IoT-based sensors to collect real-time data on environmental and soil parameters such as temperature, humidity, pH level, moisture, and light intensity.

This integration of AI, ML, and IoT supports precision farming, improves productivity, minimises resource wastage, and promotes sustainable agricultural practices for a more resilient farming ecosystem.[1]

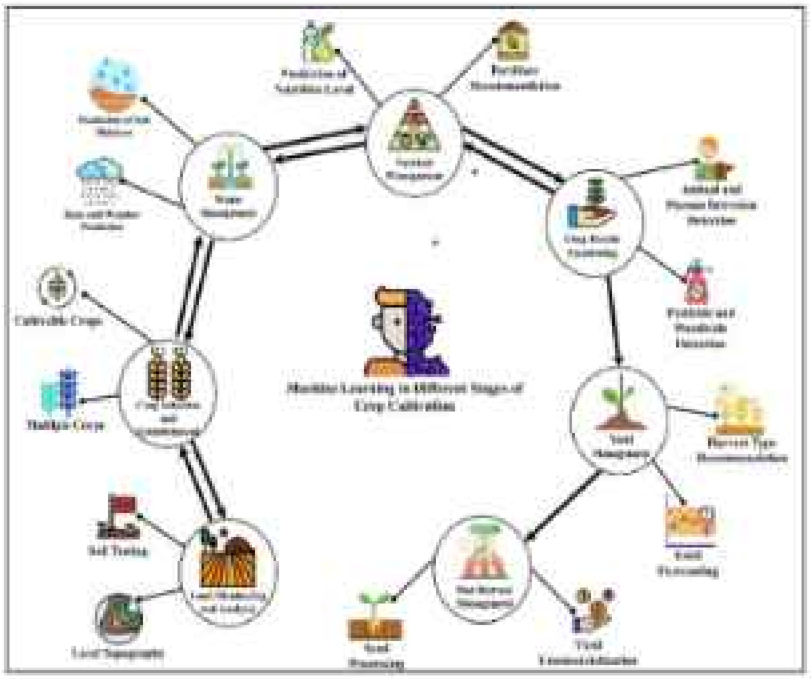

Figure 1.Machine Learning in Different Safes of Crop Cultivation

Literature Review and Gap Analysis

Aspect	What the Paper Achieved	Drawbacks Identified	How to Overcome / Improvements
Soil & Crop Analysis	Integrated soil analysis, irrigation, crop & fertilizer recommendations in one framework.	Limited generalization across different soils, crops, and climates.	Build modular, adaptive models for region-specific crops and soil types.
IoT Sensor Use	7-in-1 multifunctional sensor for NPK, pH, moisture, temp [5].	Costly & fragile in harsh rural conditions; requires maintenance.	Develop low-cost, rugged sensors, solar-powered, with offline storage.
Weather Data Integration	Weather API used for irrigation scheduling [4].	Dependent on stable internet connectivity, which is often missing in rural areas.	Use offline/edge AI models with periodic sync instead of continuous internet dependency.
User Interface	Prototype with chatbot support.	Current system is not fully farmer-friendly, lacks multilingual & offline support.	Build mobile app with local languages, voice assistant, and icons for illiterate farmers [2].
Economic Feasibility	Potential to improve yields & reduce costs.	Expensive sensors and computing needs may hinder adoption for smallholder farmers.	Government subsidies, affordable subscription models, or community-based shared IoT systems.
Privacy & Data Security	Mentions federated learning as future work.	Current system still depends on centralized data collection.	Implement federated learning + edge computing for privacy and reduced dependency on central servers.

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Methodology

The methodology adopted in this study integrates IoT-based real-time soil sensing, machine learning-based data modelling, and web deployment for delivering intelligent crop and fertiliser recommendations. The entire workflow is divided into three main stages: data acquisition, model development and training, and system design and implementation.

Data Acquisition and Preparation

Datasets were collected from ICAR (Indian Council of Agricultural Research), PAU (Punjab Agricultural University), and repositories like Kaggle, containing soil parameters (pH, N, P, K), humidity, rainfall, temperature, crop types, and fertiliser data. The data was cleaned, normalised, and prepared for model training, with crop type as the target variable. After deployment, real-time inputs from IoT sensors (for pH, moisture, NPK) and WeatherAPI (for climate data) will continuously feed the trained model for live crop and fertiliser recommendations.[3,4]

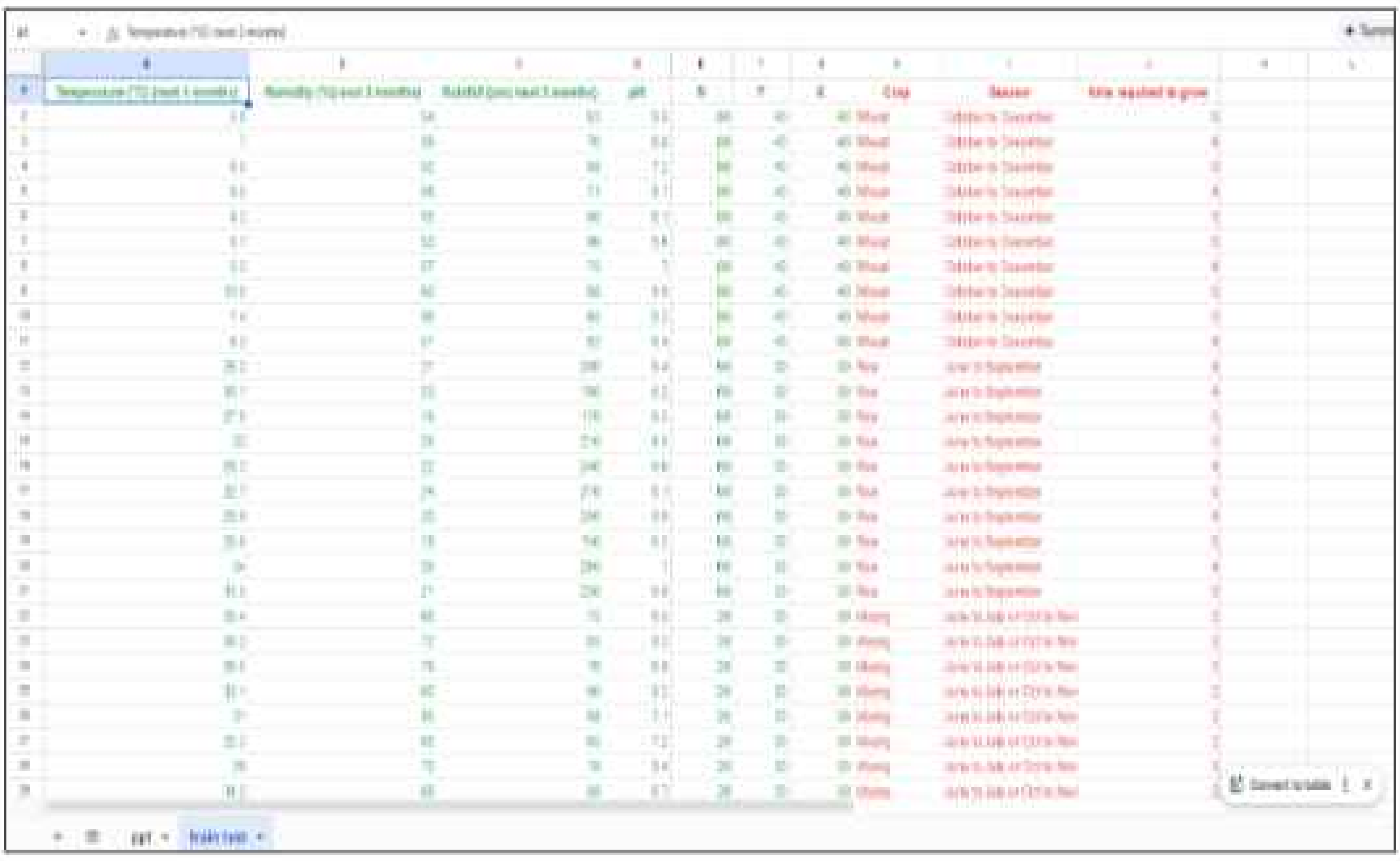

Figure 3.1.1.Dataset of Crop Recommendation

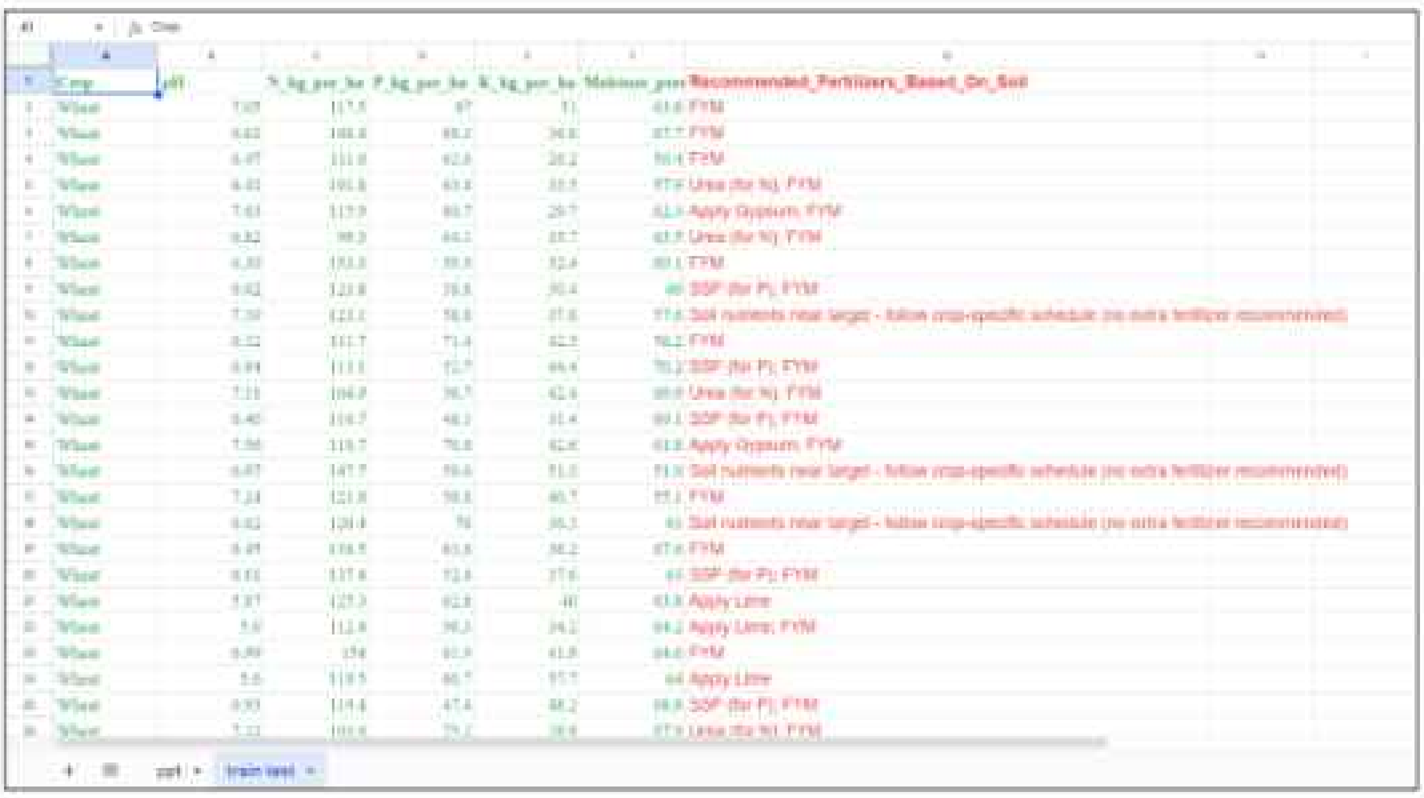

Figure 3.1.2.Dataset of Fertilization Recommendation

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Workflow

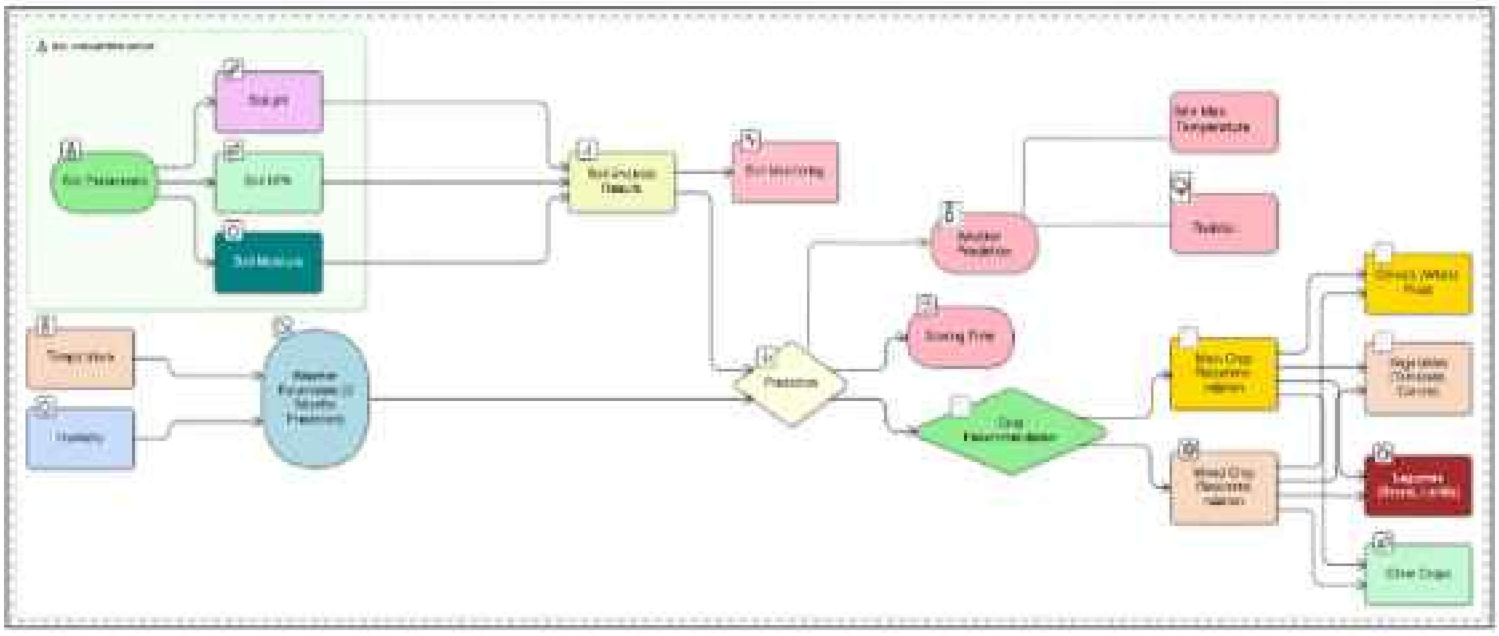

Figure 3.2.1.Workflow of Crop Recommendation

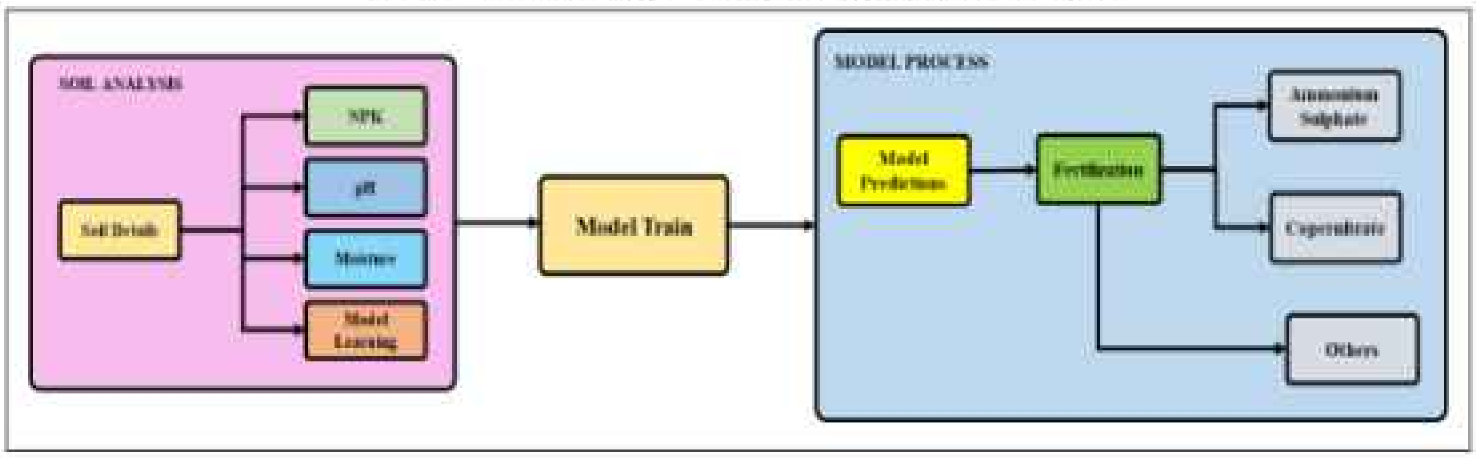

Figure 3.2.2.Workflow of Fertilization Recommendation

Model Development and Training

A Random Forest Classifier was implemented in Python (scikit-learn) for crop recommendation due to its robustness and accuracy in handling nonlinear soil–weather relationships. The dataset was split into 80% training and 20% testing sets, and evaluated using accuracy, precision, recall, and a confusion matrix. The model achieved about 99% accuracy and precision, showing excellent reliability and minimal misclassification for real-world agricultural prediction tasks.[3]

Tools and Technologies Used

The implementation employs Python as the primary programming language, utilizing the following key libraries and frameworks:

- **Scikit-learn:** for model training and evaluation.
- **Pandas, NumPy:** for data manipulatio4n and preprocessing.
- **Matplotlib, Seaborn:** for visual analytics and confusion matrix visualisation.
- **Flask:** Flask RESTful API used to connect model and front-end.
- **HTML, CSS, JavaScript:** for user interface development.
- **WeatherAPI:** for weather parameter integration in live mode.

This integrated pipeline ensures that the proposed system can evolve from offline model training to real-time prediction and recommendation delivery, facilitating intelligent agricultural decision-making for diverse climatic and soil conditions.[4]

Results and Discussion

Crop Recommendation Results

Comparison of Different Model Results:

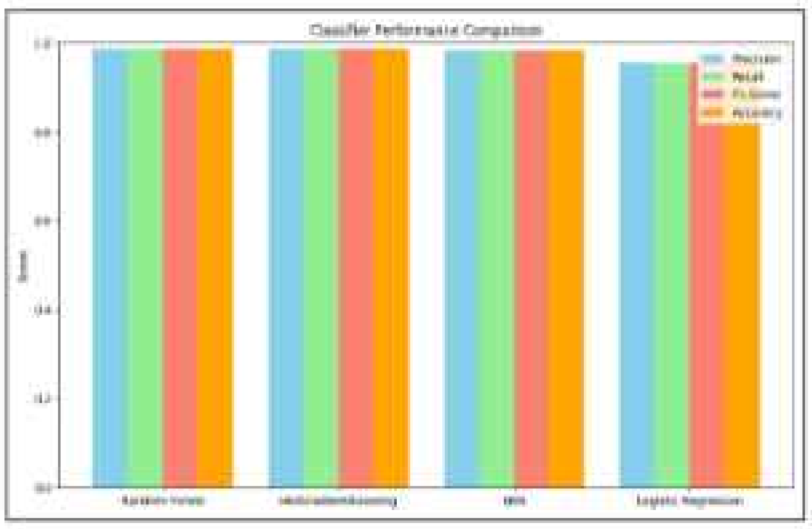

Figure 4.1.1.Bar graph showing comparison of various accuracy parameters

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Model	Crop Prec	Crop Rec	Crop F1	Crop AUC	Season Prec	Season Rec	Season F1	Season AUC
Random Forest	0.9929	0.9929	0.9929	0.9961	0.9929	0.9929	0.9929	0.9961
HistGradientBoosting	0.9928	0.9928	0.9928	0.9959	0.9928	0.9925	0.9928	0.9959
KNN	0.9904	0.9904	0.9903	0.9948	0.9904	0.9904	0.9903	0.9948
Logistic Regression	0.9488	0.9488	0.9488	0.9730	0.9329	0.9498	0.9488	0.9730

Figure 4.1.2.Recall, F1-Score, AUC OF Fertilization recommendation

Best Model Result (Random Forest):

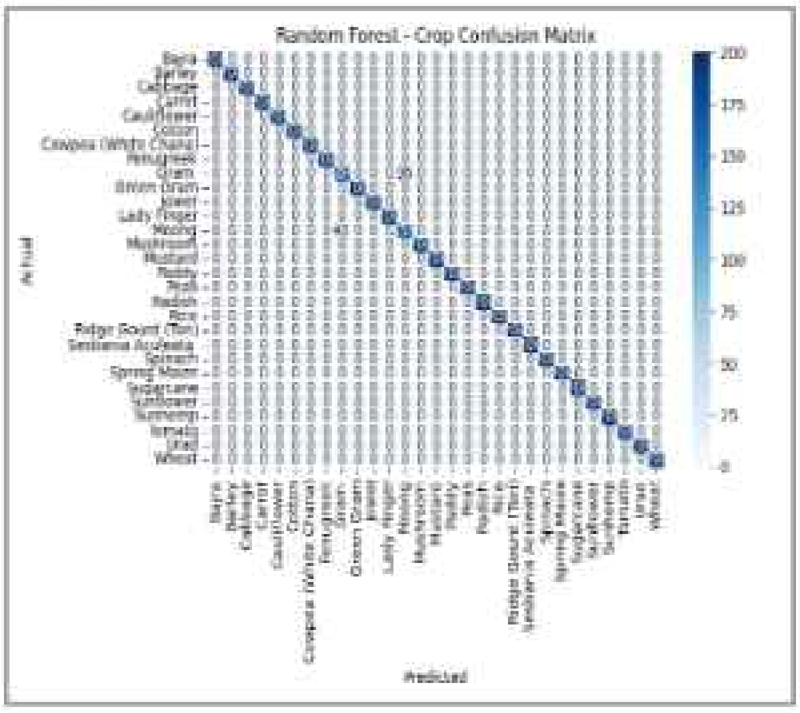

Figure 4.1.3.Random Forest Accuracy matrix

Class	Precision	Recall	F1-Score	Accuracy
Bajra	1	1	1	0.9867
Barley	1	1	1	0.9867
Cabbage	1	1	1	0.9867
Carrot	1	1	1	0.9867
Cauliflower	1	1	1	0.9867
Cotton	1	1	1	0.9867
Cowpea (White Chana)	1	1	1	0.9867
Fenugreek	1	1	1	0.9867
Gram	0.8	0.82	0.8099	0.9867
Green Gram	1	1	1	0.9867
Jowar	1	1	1	0.9867
Lady Finger	1	1	1	0.9867
Moong	0.8154	0.795	0.8051	0.9867
Mushroom	1	1	1	0.9867
Mustard	1	1	1	0.9867
Paddy	1	1	1	0.9867
Peas	1	1	1	0.9867
Radish	1	1	1	0.9867
Rice	1	1	1	0.9867
Ridge Gourd (Tori)	1	1	1	0.9867
Sesbania Aculeata	1	1	1	0.9867
Spinach	1	1	1	0.9867
Spring Maize	1	1	1	0.9867
Sugarcane	1	1	1	0.9867
Sunflower	1	1	1	0.9867
Sunhemp	1	1	1	0.9867
Tomato	1	1	1	0.9867
Urad	1	1	1	0.9867
Wheat	1	1	1	0.9867
Accuracy			**0.9867**	**0.9867**
Macro Avg	**0.9867**	**0.9867**	**0.9867**	**0.9867**
Weighted Avg	**0.9867**	**0.9867**	**0.9867**	**0.9867**

Figure 4.1.4.Accuracy parameters of data labels in Random Forest

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Fertilization Recommendation Results

Comparison of Different Models:

Model	Accuracy	Precision	Recall	F1-Score	AUC
Random Forest	0.938108	0.936694	0.938216	0.935226	0.966529
Decision Tree	0.901947	0.901865	0.902066	0.900720	0.946947
Gradient Boosting	0.906815	0.904205	0.906936	0.904322	0.949585
Logistic Regression	0.399166	0.380531	0.399068	0.371314	0.674500
SVM (RBF)	0.422114	0.428083	0.422573	0.392530	0.687210
K-Nearest Neighbors (KNN)	0.854659	0.856490	0.854923	0.846572	0.921406

Figure 4.2.1.Accuracy, Precision, Recall, F1-Score, AUC of Fertilization Recommendation

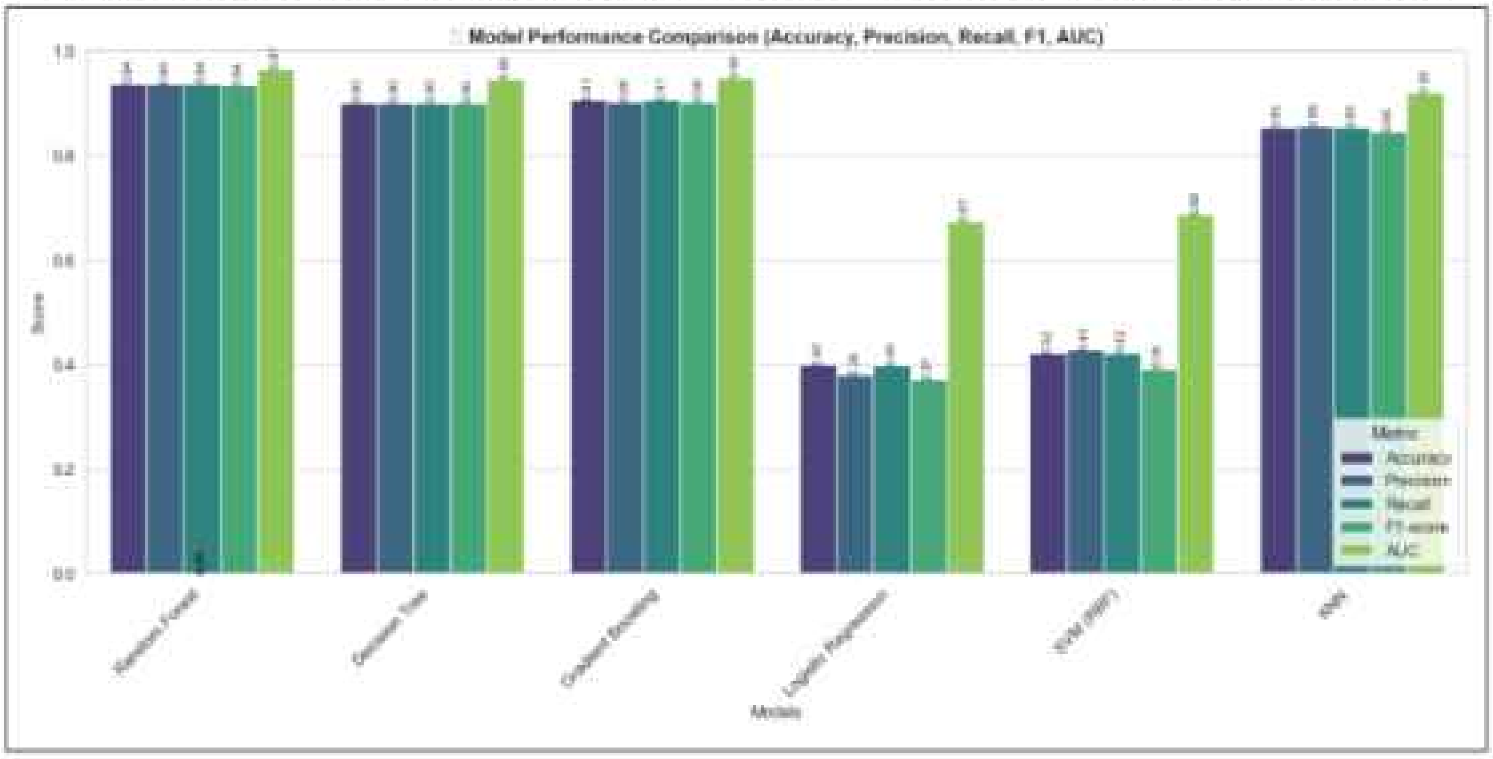

Figure 4.2.2.Bar Graph showing comparison of various accuracy parameters

Random Forest Model Training's Results (Best one):

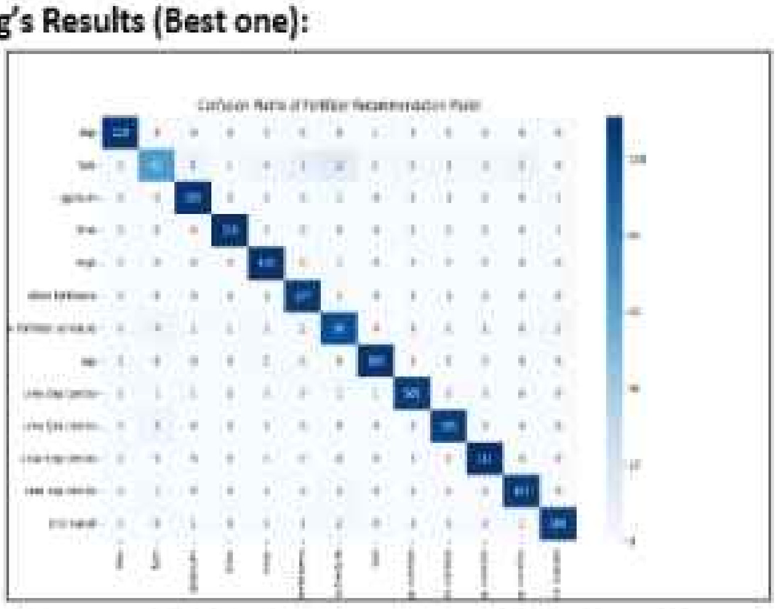

Figure 4.2.3.Confusion matrix of Random Forest

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Classification Report:

	precision	recall	f1-score	support
dap	0.97	0.99	0.98	110
fym	0.86	0.59	0.70	111
gypsum	0.93	0.97	0.95	111
lime	0.98	0.99	0.99	111
mop	0.93	0.99	0.96	111
other fertilizers	0.91	0.97	0.94	110
routine fertilizer schedule	0.83	0.88	0.86	111
ssp	0.96	0.97	0.97	111
urea dap combo	0.97	0.95	0.96	110
urea fym combo	0.95	0.95	0.95	110
urea mop combo	0.97	1.00	0.98	111
urea ssp combo	0.95	0.97	0.96	110
zinc based	0.95	0.95	0.95	111
accuracy			0.94	1438
macro avg	0.94	0.94	0.94	1438
weighted avg	0.94	0.94	0.94	1438

Accuracy: 0.9381
Macro-average AUC: 0.9865

Figure 4.2.4.Accuracy parameters of data labels in Random Forest

User Interface

Figure 4.3.1.User interface of Fertilization Recommendation

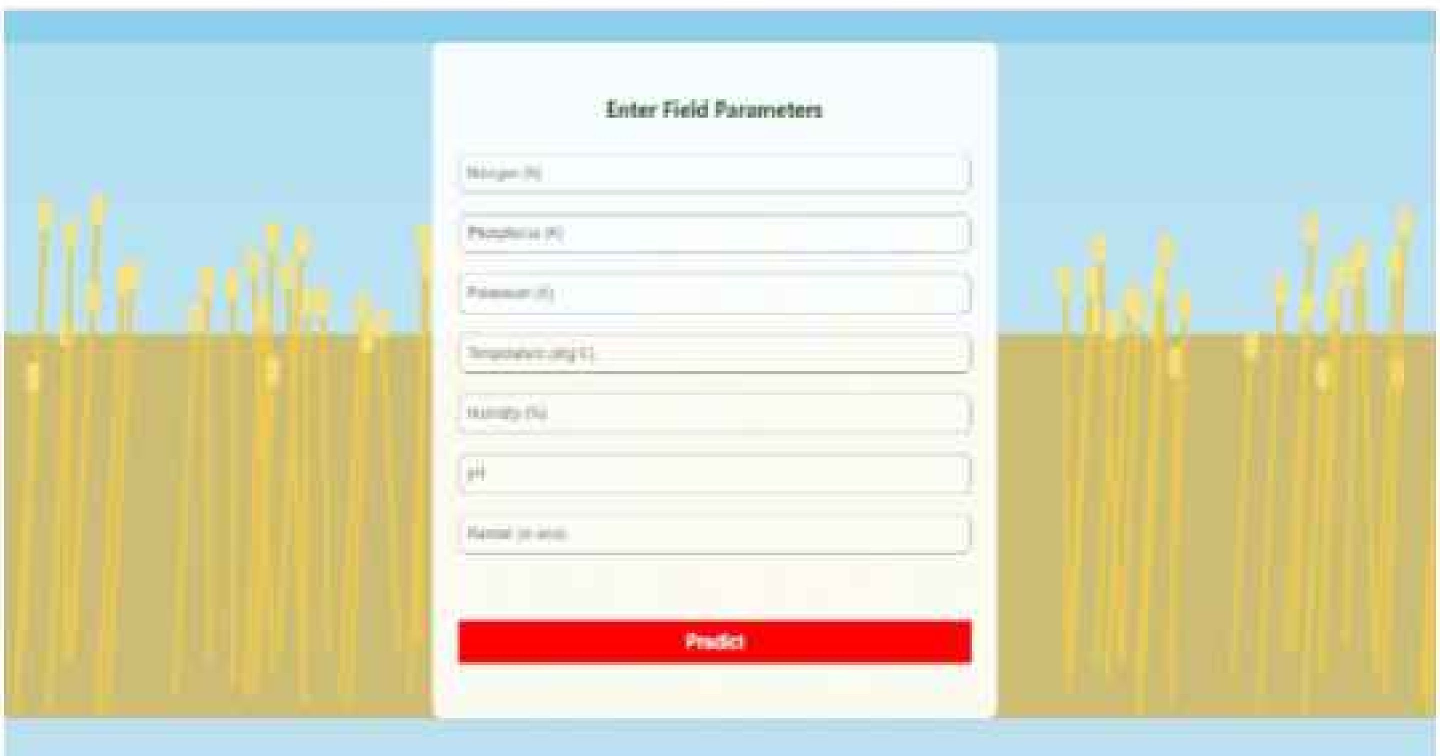

Figure 4.3.2.User Interface of Crop Recommendation

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Figure 4.3.3.User Interface of Crop Recommendation: Output Page

Conclusion

SmartAgroCare provides a cost-effective and transparent approach to precision farming by merging IoT sensing, weather intelligence, and machine learning to support data-driven agricultural decisions. The system not only enhances fertiliser and irrigation efficiency but also promotes sustainable resource utilisation and improved crop yield. By providing real-time insights through an accessible web interface, it empowers farmers to make timely and informed choices that directly impact productivity and profitability. Moreover, its adaptable design allows seamless integration with additional sensors or APIs, ensuring scalability for varied regional and crop-specific needs. Future work will focus on large-scale deployment, cross-regional testing under diverse climatic conditions, and continuous enhancement through advanced analytics and user feedback. In the long run, SmartAgroCare aims to bridge the technological gap between modern research and field-level implementation, contributing to global food security and the advancement of sustainable agricultural practices.[1]

Although the proposed IoT & ML Crop Health Monitoring framework shows strong performance, several operational and methodological limitations are there as there is a lack of real-field testing, highlighting the need for future on-ground trials to validate the proposed solutions.

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