



Review Article

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

Gursahiba Kaur<sup>1</sup>, Divyansh Mahajan<sup>2</sup>, Pooja Sharma<sup>3</sup>, Tarunpreet Kaur<sup>4</sup>, Shilpi Saxena<sup>5</sup>

<sup>1,2,3</sup>Research Scholar, <sup>4</sup>Assistant Professor (CSE), Department of Computer Science & Engineering, Khalsa College of Engineering & Technology

<sup>5</sup>Professor & Head of Department of Agriculture, Khalsa College of Engineering & Technology

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## I N F O

### Corresponding Author:

Shilpi Saxena, Department of Computer Science & Engineering, Khalsa College of Engineering & Technology

E-mail Id:

saxenashilpi076@gmail.com

Orcid Id:

<https://orcid.org/0009-0009-8082-7609>

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## A B S T R A C T

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.<sup>1,4,5</sup>

**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.<sup>1</sup>







Figure 1. Machine Learning in Different Stages 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.

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.<sup>3,4</sup>

Temperature (°C) (past 1 month)											Summary
	A	B	C	D	E	F	G	H	I	J	K
#	Temperature (°C) (past 1 month)	Humidity (%) (past 1 month)	Rainfall (mm) (past 1 month)	pH	N	P	K	Crop	Season	Rate required to grow	
1	15.5	65	50	6.5	30	40	40	Wheat	Cold/dry/Summer	10	
2	16.0	66	55	6.6	30	40	40	Wheat	Cold/dry/Summer	10	
3	16.5	67	60	6.7	30	40	40	Wheat	Cold/dry/Summer	10	
4	17.0	68	65	6.8	30	40	40	Wheat	Cold/dry/Summer	10	
5	17.5	69	70	6.9	30	40	40	Wheat	Cold/dry/Summer	10	
6	18.0	70	75	7.0	30	40	40	Wheat	Cold/dry/Summer	10	
7	18.5	71	80	7.1	30	40	40	Wheat	Cold/dry/Summer	10	
8	19.0	72	85	7.2	30	40	40	Wheat	Cold/dry/Summer	10	
9	19.5	73	90	7.3	30	40	40	Wheat	Cold/dry/Summer	10	
10	20.0	74	95	7.4	30	40	40	Wheat	Cold/dry/Summer	10	
11	20.5	75	100	7.5	30	40	40	Wheat	Cold/dry/Summer	10	
12	21.0	76	105	7.6	30	40	40	Wheat	Cold/dry/Summer	10	
13	21.5	77	110	7.7	30	40	40	Wheat	Cold/dry/Summer	10	
14	22.0	78	115	7.8	30	40	40	Wheat	Cold/dry/Summer	10	
15	22.5	79	120	7.9	30	40	40	Wheat	Cold/dry/Summer	10	
16	23.0	80	125	8.0	30	40	40	Wheat	Cold/dry/Summer	10	
17	23.5	81	130	8.1	30	40	40	Wheat	Cold/dry/Summer	10	
18	24.0	82	135	8.2	30	40	40	Wheat	Cold/dry/Summer	10	
19	24.5	83	140	8.3	30	40	40	Wheat	Cold/dry/Summer	10	
20	25.0	84	145	8.4	30	40	40	Wheat	Cold/dry/Summer	10	
21	25.5	85	150	8.5	30	40	40	Wheat	Cold/dry/Summer	10	
22	26.0	86	155	8.6	30	40	40	Wheat	Cold/dry/Summer	10	
23	26.5	87	160	8.7	30	40	40	Wheat	Cold/dry/Summer	10	
24	27.0	88	165	8.8	30	40	40	Wheat	Cold/dry/Summer	10	
25	27.5	89	170	8.9	30	40	40	Wheat	Cold/dry/Summer	10	
26	28.0	90	175	9.0	30	40	40	Wheat	Cold/dry/Summer	10	
27	28.5	91	180	9.1	30	40	40	Wheat	Cold/dry/Summer	10	
28	29.0	92	185	9.2	30	40	40	Wheat	Cold/dry/Summer	10	
29	29.5	93	190	9.3	30	40	40	Wheat	Cold/dry/Summer	10	
30	30.0	94	195	9.4	30	40	40	Wheat	Cold/dry/Summer	10	
31	30.5	95	200	9.5	30	40	40	Wheat	Cold/dry/Summer	10	
32	31.0	96	205	9.6	30	40	40	Wheat	Cold/dry/Summer	10	
33	31.5	97	210	9.7	30	40	40	Wheat	Cold/dry/Summer	10	
34	32.0	98	215	9.8	30	40	40	Wheat	Cold/dry/Summer	10	
35	32.5	99	220	9.9	30	40	40	Wheat	Cold/dry/Summer	10	
36	33.0	100	225	10.0	30	40	40	Wheat	Cold/dry/Summer	10	
37	33.5	101	230	10.1	30	40	40	Wheat	Cold/dry/Summer	10	
38	34.0	102	235	10.2	30	40	40	Wheat	Cold/dry/Summer	10	
39	34.5	103	240	10.3	30	40	40	Wheat	Cold/dry/Summer	10	
40	35.0	104	245	10.4	30	40	40	Wheat	Cold/dry/Summer	10	
41	35.5	105	250	10.5	30	40	40	Wheat	Cold/dry/Summer	10	
42	36.0	106	255	10.6	30	40	40	Wheat	Cold/dry/Summer	10	
43	36.5	107	260	10.7	30	40	40	Wheat	Cold/dry/Summer	10	
44	37.0	108	265	10.8	30	40	40	Wheat	Cold/dry/Summer	10	
45	37.5	109	270	10.9	30	40	40	Wheat	Cold/dry/Summer	10	
46	38.0	110	275	11.0	30	40	40	Wheat	Cold/dry/Summer	10	
47	38.5	111	280	11.1	30	40	40	Wheat	Cold/dry/Summer	10	
48	39.0	112	285	11.2	30	40	40	Wheat	Cold/dry/Summer	10	
49	39.5	113	290	11.3	30	40	40	Wheat	Cold/dry/Summer	10	
50	40.0	114	295	11.4	30	40	40	Wheat	Cold/dry/Summer	10	
51	40.5	115	300	11.5	30	40	40	Wheat	Cold/dry/Summer	10	
52	41.0	116	305	11.6	30	40	40	Wheat	Cold/dry/Summer	10	
53	41.5	117	310	11.7	30	40	40	Wheat	Cold/dry/Summer	10	
54	42.0	118	315	11.8	30	40	40	Wheat	Cold/dry/Summer	10	
55	42.5	119	320	11.9	30	40	40	Wheat	Cold/dry/Summer	10	
56	43.0	120	325	12.0	30	40	40	Wheat	Cold/dry/Summer	10	
57	43.5	121	330	12.1	30	40	40	Wheat	Cold/dry/Summer	10	
58	44.0	122	335	12.2	30	40	40	Wheat	Cold/dry/Summer	10	
59	44.5	123	340	12.3	30	40	40	Wheat	Cold/dry/Summer	10	
60	45.0	124	345	12.4	30	40	40	Wheat	Cold/dry/Summer	10	
61	45.5	125	350	12.5	30	40	40	Wheat	Cold/dry/Summer	10	
62	46.0	126	355	12.6	30	40	40	Wheat	Cold/dry/Summer	10	
63	46.5	127	360	12.7	30	40	40	Wheat	Cold/dry/Summer	10	
64	47.0	128	365	12.8	30	40	40	Wheat	Cold/dry/Summer	10	
65	47.5	129	370	12.9	30	40	40	Wheat	Cold/dry/Summer	10	
66	48.0	130	375	13.0	30	40	40	Wheat	Cold/dry/Summer	10	
67	48.5	131	380	13.1	30	40	40	Wheat	Cold/dry/Summer	10	
68	49.0	132	385	13.2	30	40	40	Wheat	Cold/dry/Summer	10	
69	49.5	133	390	13.3	30	40	40	Wheat	Cold/dry/Summer	10	
70	50.0	134	395	13.4	30	40	40	Wheat	Cold/dry/Summer	10	
71	50.5	135	400	13.5	30	40	40	Wheat	Cold/dry/Summer	10	
72	51.0	136	405	13.6	30	40	40	Wheat	Cold/dry/Summer	10	
73	51.5	137	410	13.7	30	40	40	Wheat	Cold/dry/Summer	10	
74	52.0	138	415	13.8	30	40	40	Wheat	Cold/dry/Summer	10	
75	52.5	139	420	13.9	30	40	40	Wheat	Cold/dry/Summer	10	
76	53.0	140	425	14.0	30	40	40	Wheat	Cold/dry/Summer	10	
77	53.5	141	430	14.1	30	40	40	Wheat	Cold/dry/Summer	10	
78	54.0	142	435	14.2	30	40	40	Wheat	Cold/dry/Summer	10	
79	54.5	143	440	14.3	30	40	40	Wheat	Cold/dry/Summer	10	
80	55.0	144	445	14.4	30	40	40	Wheat	Cold/dry/Summer	10	
81	55.5	145	450	14.5	30	40	40	Wheat	Cold/dry/Summer	10	
82	56.0	146	455	14.6	30	40	40	Wheat	Cold/dry/Summer	10	
83	56.5	147	460	14.7	30	40	40	Wheat	Cold/dry/Summer	10	
84	57.0	148	465	14.8	30	40	40	Wheat	Cold/dry/Summer	10	
85	57.5	149	470	14.9	30	40	40	Wheat	Cold/dry/Summer	10	
86	58.0	150	475	15.0	30	40	40	Wheat	Cold/dry/Summer	10	
87	58.5	151	480	15.1	30	40	40	Wheat	Cold/dry/Summer	10	
88	59.0	152	485	15.2	30	40	40	Wheat	Cold/dry/Summer	10	
89	59.5	153	490	15.3	30	40	40	Wheat	Cold/dry/Summer	10	
90	60.0	154	495	15.4	30	40	40	Wheat	Cold/dry/Summer	10	
91	60.5	155	500	15.5	30	40	40	Wheat	Cold/dry/Summer	10	
92	61.0	156	505	15.6	30	40	40	Wheat	Cold/dry/Summer	10	
93	61.5	157	510	15.7	30	40	40	Wheat	Cold/dry/Summer	10	
94	62.0	158	515	15.8	30	40	40	Wheat	Cold/dry/Summer	10	
95	62.5	159	520	15.9	30	40	40	Wheat	Cold/dry/Summer	10	
96	63.0	160	525	16.0	30	40	40	Wheat	Cold/dry/Summer	10	
97	63.5	161	530	16.1	30	40	40	Wheat	Cold/dry/Summer	10	
98	64.0	162	535	16.2	30	40	40	Wheat	Cold/dry/Summer	10	
99	64.5	163	540	16.3	30	40	40	Wheat	Cold/dry/Summer	10	
100	65.0	164	545	16.4	30	40	40	Wheat	Cold/dry/Summer	10	
101	65.5	165	550	16.5	30	40	40	Wheat	Cold/dry/Summer	10	
102	66.0	166	555	16.6	30	40	40	Wheat	Cold/dry/Summer	10	
103	66.5	167	560	16.7	30	40	40	Wheat	Cold/dry/Summer	10	
104	67.0	168	565	16.8	30	40	40	Wheat	Cold/dry/Summer	10	
105	67.5	169	570	16.9	30	40	40	Wheat	Cold/dry/Summer	10	
106	68.0	170	575	17.0	30	40	40	Wheat	Cold/dry/Summer	10	
107	68.5	171	580	17.1	30	40	40	Wheat	Cold/dry/Summer	10	
108	69.0	172	585	17.2	30	40	40	Wheat	Cold/dry/Summer	10	
109	69.5	173	590	17.3	30	40	40	Wheat	Cold/dry/Summer	10	
110	70.0	174	595	17.4	30	40	40	Wheat	Cold/dry/Summer	10	
111	70.5	175	600	17.5	30	40	40	Wheat	Cold/dry/Summer	10	
112	71.0	176	605	17.6	30	40	40	Wheat	Cold/dry/Summer	10	
113	71.5	177	610	17.7	30	40	40	Wheat	Cold/dry/Summer	10	
114	72.0	178	615	17.8	30	40	40	Wheat	Cold/dry/Summer	10	
115	72.5	179	620	17.9	30	40	40	Wheat	Cold/dry/Summer	10	
116	73.0	180	625	18.0	30	40	40	Wheat	Cold/dry/Summer	10	
117	73.5	181	630	18.1	30	40	40	Wheat	Cold/dry/Summer	10	
118	74.0	182	635	18.2	30	40	40	Wheat	Cold/dry/Summer	10	
119	74.5	183	640	18.3	30	40	40	Wheat	Cold/dry/Summer	10	
120</											



### Workflow

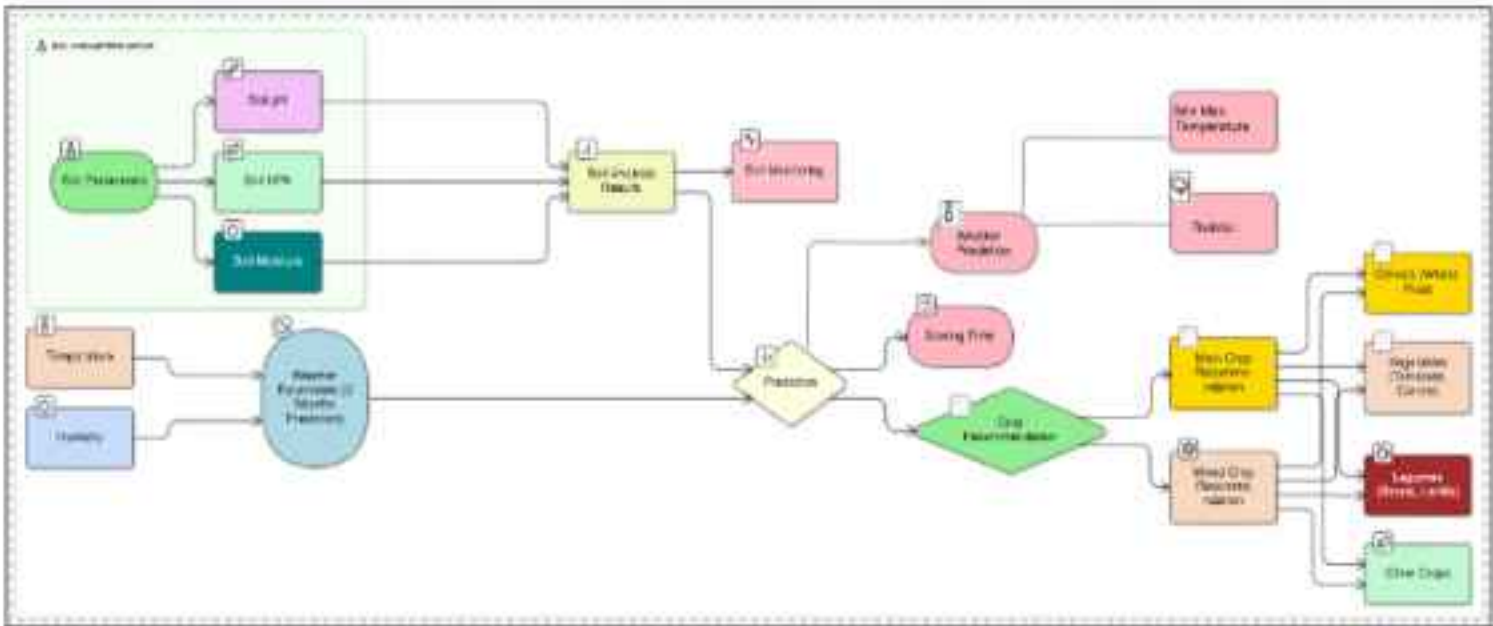


Figure 3.2.1. Workflow of Crop Recommendation

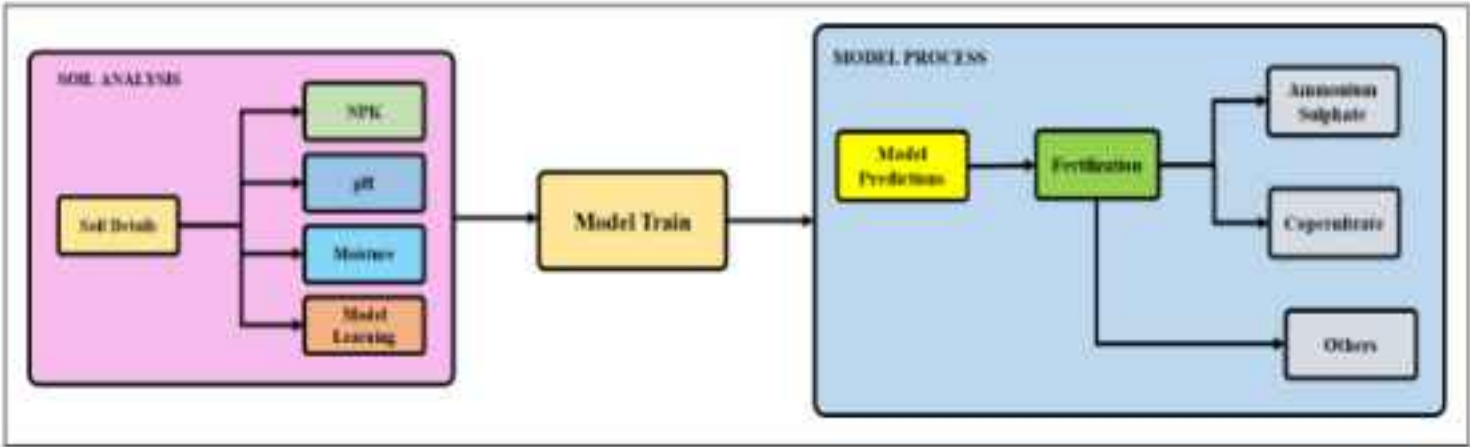


Figure 3.2.2. Workflow of Fertilization Recommendation

### 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.<sup>5</sup>

### 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 manipulation 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.<sup>4</sup>

### Results and Discussion

#### Crop Recommendation Results

Comparison of Different Model Results:

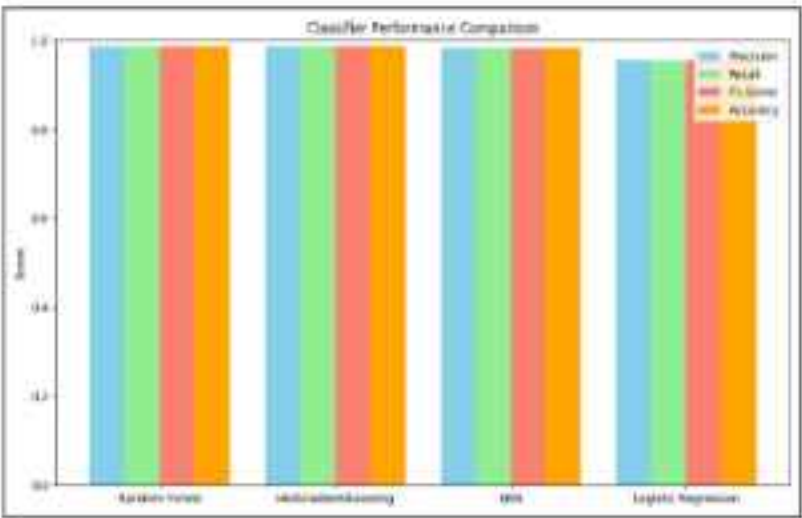


Figure 4.1.1. Bar graph showing comparison of various accuracy parameters

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):

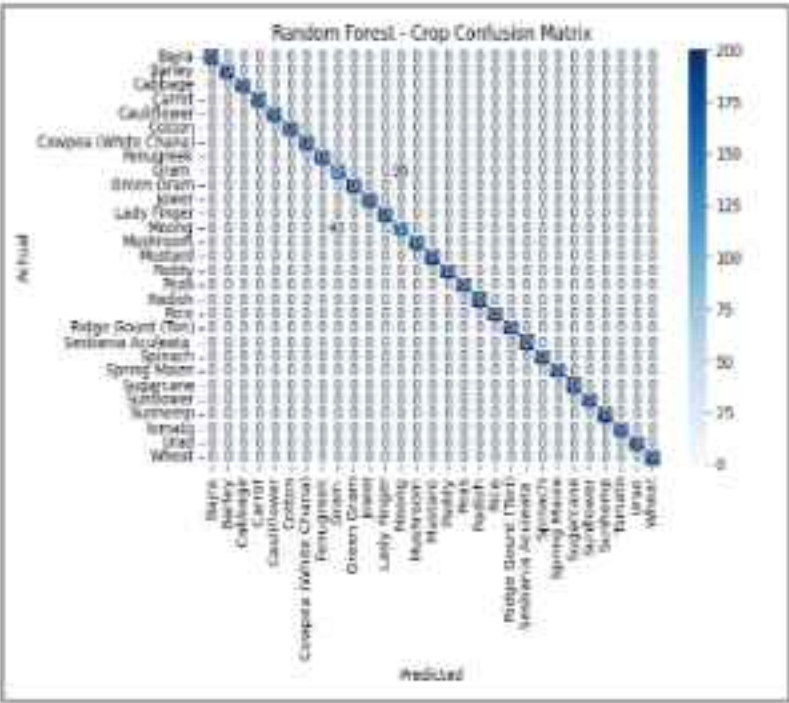


Figure 4.1.3.Random Forest Accuracy matrix

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



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

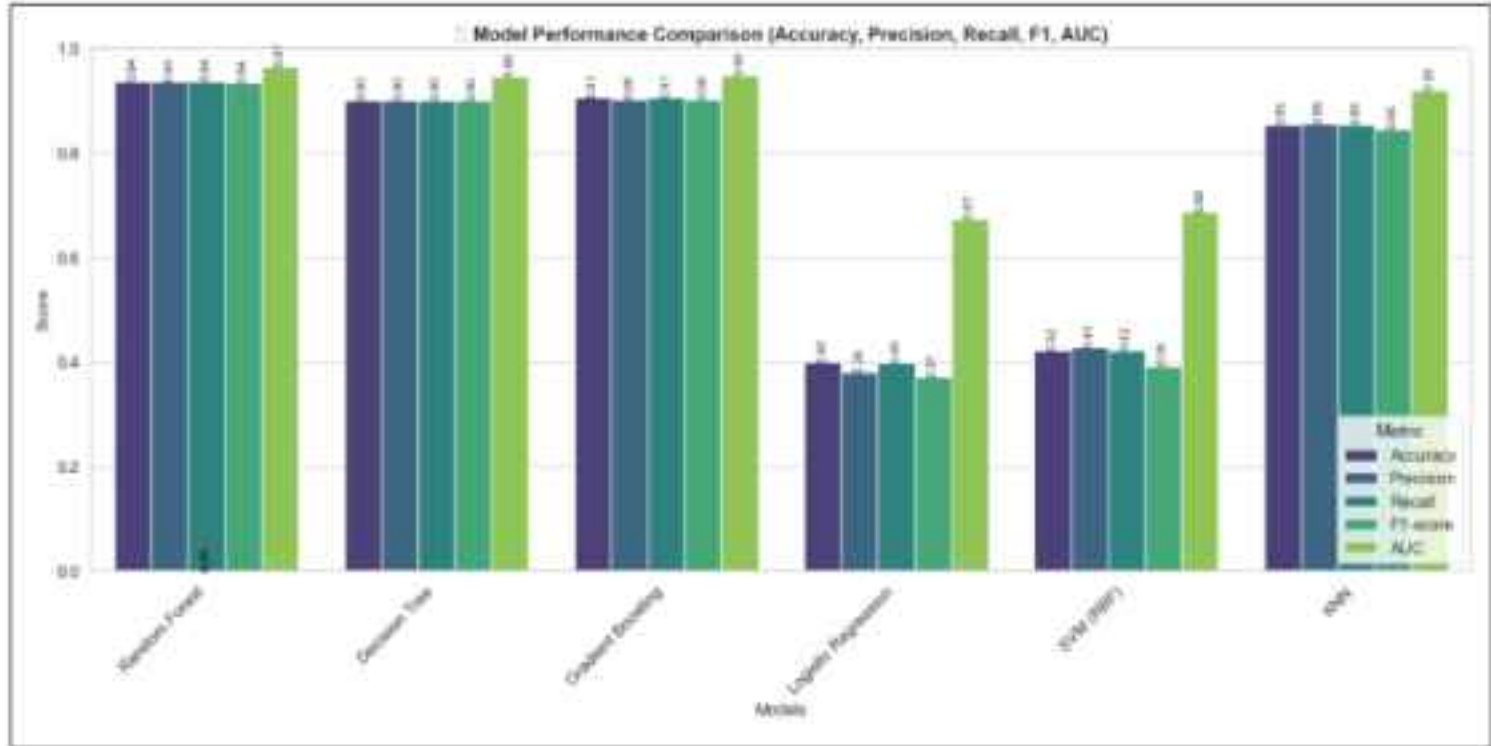


Figure 4.2.2.Bar Graph showing comparison of various accuracy parameters

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

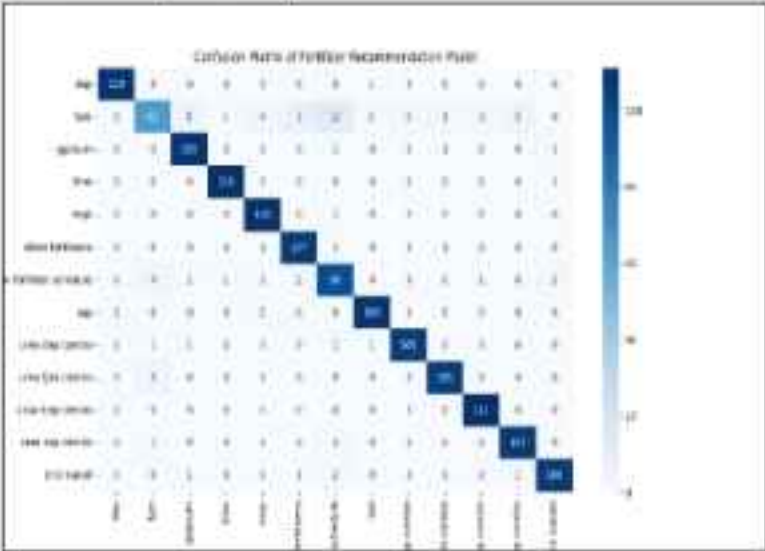


Figure 4.2.3.Confusion matrix of Random Forest

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: 0.9665

Figure 4.2.4.Accuracy parameters of data labels in Random Forest

User Interface



Figure 4.3.1.User interface of Fertilization Recommendation

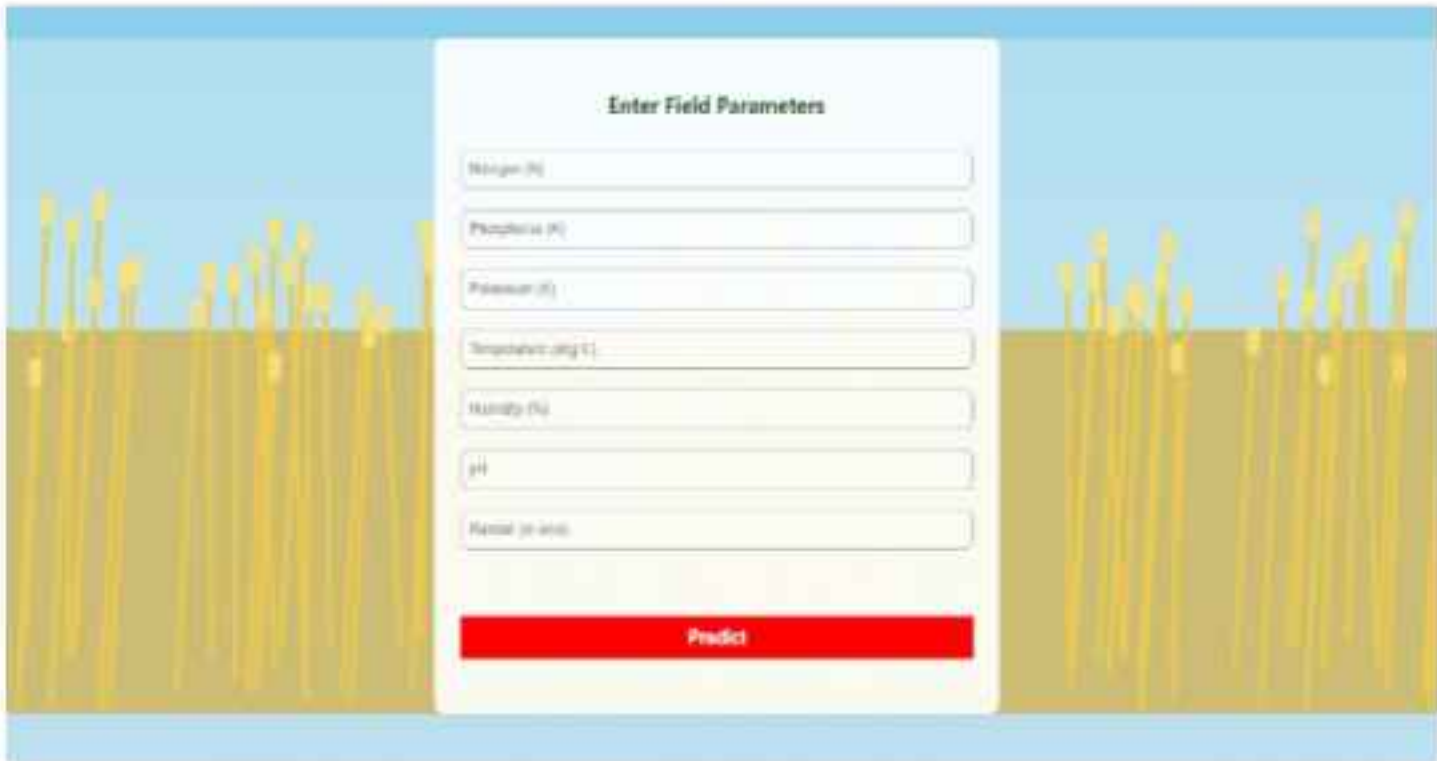


Figure 4.3.2.User Interface of Crop Recommendation



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.<sup>2</sup>

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.

## References

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