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INTELLIGENT AGRICULTURE: INTEGRATING IOT AND MACHINE LEARNING FOR SOIL NUTRIENTS AND CROP SELECTION

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ABSTRACT

This study delves into the revolutionary possibilities of merging IoT and ML in intelligent agriculture, specifically looking at ways to improve crop selection and soil nutrient management. The need for more effective, data-driven farming methods is greater than ever before due to the rising worldwide demand for food and the severity of environmental concerns. In order to monitor the soil, weather, and crop health in real-time, IoT devices like weather stations and soil sensors gather data. In order to help farmers make educated judgements about crop selection and precise control of soil nutrients, powerful ML algorithms evaluate this data and deliver them relevant recommendations. By lowering environmental impact and maximising resource efficiency, these technologies not only improve agricultural yields but also encourage sustainable farming practices. This study delves into the importance of this technique, the advantages it might provide, and the obstacles that need to be overcome for it to be properly used in contemporary agriculture.

Keywords: IoT, Machine Learning, Precision Agriculture, Soil Health Monitoring, Crop Selection

1. INTRODUCTION

As technology transforms sectors worldwide, agriculture is adopting smarter, more efficient techniques. The combination of IoT and ML is leading this change, delivering innovative solutions to agricultural problems. These innovative technologies allow farmers to use data to improve soil health, optimise fertiliser management, and choose the best crops for their area. IoT devices like soil sensors and weather stations monitor soil moisture, temperature, and nutrient levels in real time. This data gives a complete picture of the field and enables targeted actions. However, machine learning algorithms analyse this massive data set to find patterns, anticipate events, and provide actionable insights. Together, IoT and ML enable proactive agriculture. Understanding soil nutrients helps farmers optimise fertilisation, avoid waste, and boost crop output. Machine Learning algorithms can forecast which crops thrive in given soil and environmental circumstances, maximising yield and sustainability. Intelligent integration improves operational efficiency and supports sustainable agriculture and food security. As we explore intelligent agriculture, we see that IoT and Machine Learning are ushering in a new age of farming where technology and tradition merge to create a more productive, efficient, and sustainable environment.

1.1 INTELLIGENT AGRICULTURE

Intelligent agriculture is revolutionising farming by using cutting-edge technologies like IoT and ML to improve efficiency and sustainability. This method uses IoT devices like soil sensors, weather stations, and drones to gather real-time environmental and soil data. These sensors measure soil moisture, nutrient content, temperature, and humidity, while drones assess crop health and growth. IoT devices collect massive volumes of data, which machine learning algorithms analyse. These algorithms find patterns and trends to optimise irrigation schedules, choose crops for appropriate soil conditions, and estimate agricultural yields. ML models may propose planting schedules and crop kinds based on past weather data and soil conditions, improving yield and quality. Precision farming using IoT and ML helps farmers use water, fertilisers, and pesticides more effectively. This reduces waste and resource usage, increasing agricultural output and lowering environmental impact. Predictive analytics may also forecast pest infestations and nutritional deficits, enabling preventive management. Intelligent agriculture addresses food security, resource management, and environmental sustainability using data-driven, precision farming. These technologies might make agriculture more robust and flexible as they evolve.

1.2 INTERNET OF THINGS (IOT)

An innovative technological breakthrough, IoT links countless systems and gadgets to the web to facilitate automated data sharing and other forms of seamless operation. Smart appliances, wearable gadgets, and industrial sensors are all part of this linked network. They're all integrated with sensors and communication tech. IoT allows these gadgets to gather, transmit, and interpret data, which changes the way we engage with our surroundings and run operations. Applications in the industrial sector employ the Internet of Things to optimise equipment efficiency and anticipate maintenance requirements, while smart home systems use user preferences to manage temperature and lighting. From individual well-being to city infrastructure, IoT is boosting productivity, accessibility, and creativity.

Fig 1 Internet of Things

1.3 MACHINE LEARNING

ML is a fast expanding field of AI that creates algorithms and models to help computers learn from data and improve independently. ML systems analyse massive volumes of data to find patterns and generate predictions or judgements without prior instructions. This capacity may be used for personalised streaming platform recommendations, predictive analytics for corporate strategies, cybersecurity anomaly detection, and picture analysis for healthcare diagnostics. Supervised learning predicts outcomes using labelled data, unsupervised learning uncovers hidden structures in unlabelled data, and reinforcement learning learns optimal actions through trial and error. These methods help machines learn and develop over time. Machine learning has transformed several sectors, from supply chain optimisation and financial trading to chatbots and genomics research. As they improve, ML technologies will alter businesses and daily life by delivering smarter, more responsive solutions for complex and dynamic data-driven activities.

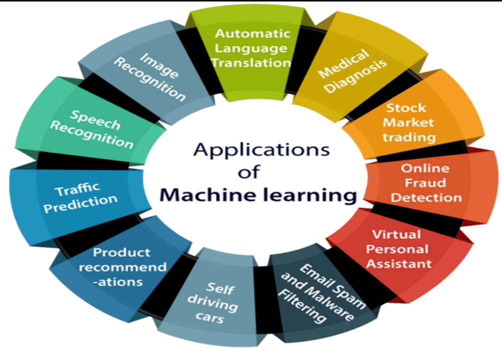

Fig 2 Applications of Machine learning [19]

1.4 ROLE OF IOT IN AGRICULTURE

In order to make farming more data-driven and efficient, IoT plays a crucial role in the agricultural sector. In order to gather data in real-time from different parts of the agricultural environment, IoT technology uses a network of linked sensors, equipment, and systems. Weather stations record current and future weather patterns, while sensors placed in the ground measure soil moisture, nutrient concentration, and temperature. Centralised platforms analyse and use this data that is sent over wireless networks to make educated judgements. Using IoT, precision irrigation is made possible by decreasing water wastage and preserving resources by supplying water only when it is required. Internet of things devices also aid in crop health monitoring, early disease and pest detection, and pesticide and fertiliser optimisation. The Internet of Things (IoT) boosts efficiency, streamlines resource management, and encourages sustainable agricultural practices by delivering actionable information and enabling automation.

Fig 3 Role of IoT in Agriculture [20]

1.5 ROLE OF MACHINE LEARNING IN AGRICULTURE

The use of ML has revolutionised farming by improving several facets of the industry and allowing for data-driven decision-making. Data from a variety of sources, including IoT sensors, satellite photography, and records of past crop performance, are analysed by ML algorithms. Forecasting results and improving agricultural tactics are both aided by this approach. For instance, ML models can predict agricultural yields depending on variables like soil health, weather, and crop type, which helps farmers with resource allocation and planning. By evaluating data and suggesting the ideal quantity of water, fertilisers, and pesticides, machine learning also helps with precision agriculture, which reduces waste and improves crop quality. Algorithms powered by ML can also spot irregularities and trends in crop health, which may help spot illnesses and insect infestations before they spread. Farming may be made more efficient, cheaper, and more environmentally friendly with the use of machine learning.

1.6 SIGNIFICANCE OF RESEARCH

Improving agricultural methods and making them more sustainable requires research into smart agriculture that uses IoT and ML. This study paves the way for targeted crop selection and accurate nutrient management in soil by merging real-time data from IoT sensors with predictive machine learning algorithms. Improved agricultural yields with less wastage are the results of more effective use of resources such targeted irrigation and fertilisation. Improving soil health and increasing production while decreasing environmental effect may be achieved with the use of sophisticated decision-making tools, which are also supported by this. More resilient and environmentally friendly farming systems that help alleviate world hunger are the end result of this research's impact on agricultural technology innovation.

2. LITERATURE REVIEW

Recent advancements in ML and IoT technologies have significantly impacted smart agriculture. This summary reviews key studies on these technologies, focusing on their objectives, techniques, and limitations.

In smart agriculture, Rani et al. (2023) looked at a method that uses machine learning to choose crops the best way. By analysing soil and environmental data using a variety of ML algorithms, their research sought to improve crop selection efficiency. The study's reliance on high-quality input data is a constraint, even if it takes a thorough approach. In actual circumstances, this data may not always be accessible [1].

In order to intelligently control soil nutrients and choose crops, Sethi and Lakhina (2024) created a system that incorporates ML. Nutrient requirements and crop compatibility might be foretold using ML models in their method. One potential drawback of the research is that it only looked at one kind of crop, which may not be applicable to other farming situations [2].

A method for monitoring soil nutrient levels and making crop recommendations was introduced by Islam et al. (2023) using the Internet of Things. Their device may analyse nutrients in real-time using input from sensors and ML algorithms. One major drawback was the high expense of maintaining the Internet of Things infrastructure and sensors [3].

For precision farming, Senapaty et al. (2023) suggested a model for soil nutrient measurement that relies on the internet of things (IoT). In order to provide crop suggestions, their model used real-time nutrient data. The research did note, however, that the sensors' quality and calibration are critical to the system's accuracy [4].

The use of machine learning and the internet of things in smart farming was investigated by Sundaresan et al. (2023), with an emphasis on increasing agricultural yields. They proved that agricultural operations may be improved with the use of IoT devices and ML algorithms. One potential drawback is that the model's performance could change depending on the soil type and surrounding environment [5].

A comprehensive analysis of ML models that forecast soil nutrient characteristics was presented by Folorunso et al. (2023). They went discussed a number of ML methods and how to use them in their review. The review has certain limitations, one of which is that ML model performance varies between soil types and geographies [6].

Researchers Musanase et al. (2023) used machine learning to create a system that suggests crops and fertilisers depending on data. Through the use of cutting-edge analytics, their approach sought to transform agricultural methods. Some drawbacks include the possibility of ML model overfitting and the need for large-scale data acquisition [7].

The use of artificial intelligence in precision farming was covered by Ghosh et al. (2024). Their main objective was to enhance agricultural efficiency via the incorporation of AI technology. Problems with AI systems' scalability and adaptation in several agricultural contexts were recognised in the research [8].

Novel AI-driven agricultural techniques, with a focus on precision agriculture, were presented by Elango et al. (2024). In order to increase output, they integrated AI with conventional agricultural practices. The primary obstacle was the complexity and perhaps large upfront expense of integrating AI [9].

The uses and difficulties of AI in precision agriculture were discussed by Raza et al. (2023). In it, they detailed the many uses of AI in farming and pointed out some of the biggest obstacles, such protecting sensitive information and integrating different systems. One limitation was the absence of comprehensive case studies examining the use of AI [10].

For environmentally responsible farming, Adewusi et al. (2024) surveyed AI tools. Their research covered all the bases when it came to AI's potential uses, although they did point out that expensive and complicated implementations are common roadblocks to wider use of the technology [11].

With an emphasis on enabling technologies and future directions, Jararweh et al. (2023) explored smart and sustainable agriculture. Although they did note that AI and the Internet of Things are still in their early stages of development and encounter many implementation hurdles, they did note that there is great promise in combining the two [12].

In their study, Thilakarathne et al. (2021) tackled the problems and potential solutions related to the Internet of Things (IoT) in smart agriculture. They shed light on Internet of Things (IoT) uses but also pointed up the drawbacks, such as unreliable systems and insecure data storage [13].

For sustainable farming in arid regions, Firdhous et al. (2018) tested out options driven by the internet of things. The implementation of these systems shown potential, but encountered obstacles associated with deploying and maintaining IoT systems in locations with limited resources [14].

Improving food security and agricultural sustainability via the use of sensor technologies and the Internet of Things was investigated by Morchid et al. (2024). Despite praising these technologies, their research did note several drawbacks, such as a high implementation cost and the need of constant system changes [15].

Table 1 Literature Survey

Ref	Author / Year	Methodology	Cons	Pros
[1]	Rani et al. (2023)	Machine learning-based optimal crop selection system	Dependence on high-quality input data; may not generalize to all regions	Enhanced crop selection efficiency using various ML algorithms
[2]	Sethi and Lakhina (2024)	ML for intelligent crop selection and soil nutrient management	Focus on specific crop types; limited generalizability	Improved nutrient management and crop suitability predictions
[3]	Islam et al. (2023)	IoT-enabled system for soil nutrients monitoring and crop recommendation	High cost of IoT infrastructure and sensor maintenance	Real-time nutrient analysis and crop recommendations
[4]	Senapaty et al. (2023)	IoT-based soil nutrient analysis model	Accuracy depends on sensor quality and calibration	Real-time nutrient data for precise crop recommendations
[5]	Sundaresan et al. (2023)	ML and IoT-based smart farming	Effectiveness varies with environmental conditions	Optimization of farming practices for enhanced crop yield
[6]	Folorunso et al. (2023)	Systematic review of ML models for soil nutrient prediction	Variable performance across different soil types	Comprehensive overview of ML techniques for soil nutrient prediction
[7]	Musanase et al. (2023)	Data-driven, ML-based crop and fertilizer recommendation system	Extensive data collection required; potential overfitting	Advanced analytics for crop and fertilizer recommendations
[8]	Ghosh et al. (2024)	AI-driven precision agriculture approach	Scalability and adaptability issues	Integration of AI technologies to improve agricultural efficiency
[9]	Elango et al. (2024)	AI-driven farming approach	High initial cost and complexity of AI integration	Enhanced productivity through AI and traditional methods integration
[10]	Raza et al. (2023)	Review of AI-enabled precision agriculture applications	Lack of detailed case studies on AI implementation	Overview of AI applications and identification of challenges
[11]	Adewusi et al. (2024)	Review of AI technologies for sustainable farming	High costs and technical complexities	Comprehensive review of AI applications for sustainable farming
[12]	Jararweh et al. (2023)	Discussion on smart and sustainable agriculture	Evolving technologies; implementation challenges	Potential of IoT and AI for smart and sustainable agriculture
[13]	Thilakarathne et al. (2021)	Examination of IoT in smart agriculture	Reliability and data security issues	Insights into IoT applications and future directions
[14]	Firdhous et al. (2018)	IoT-powered solutions for sustainable dry zone agriculture	Deployment and maintenance challenges in resource-constrained areas	Promising solutions for sustainable agriculture in dry zones
[15]	Morchid et al. (2024)	IoT and sensor technologies for food security and sustainability	High deployment costs and need for system updates	Benefits of IoT and sensors for increasing food security and sustainability

3. PROBLEM STATEMENT

Improving crop choices and soil health is still a major obstacle in contemporary farming. Inefficient nutrient management and less-than-ideal crop selections are common results of using labour-intensive, traditionally-based soil testing procedures. One potential benefit of the proliferation of IoT devices is the possibility of collecting data in real time, which might improve soil monitoring. To evaluate soil nutrients and suggest appropriate crops, however, requires successfully combining this data with sophisticated machine learning algorithms. The need for practical insights and the difficulty of interpreting data make it tough for farmers to make use of this treasure trove of data. Improving agricultural efficiency and production may be achieved by creating a system that integrates data from Internet of Things (IoT) sensors with machine learning models. This system would then provide farmers exact, real-time suggestions for soil management and crop selection.

4. RESEARCH METHODOLOGY

Multiple critical phases comprise the research process for intelligent agriculture's integration of IoT and machine learning. Soil nutrient management and crop selection optimisation via technology integration is the primary emphasis of the issue definition that follows. One of the goals is to build machine learning models that can analyse soil data in real-time. Another is to create an infrastructure for soil monitoring that uses IoT sensors. In order to comprehend current technology and locate gaps, a comprehensive literature research is executed. Choosing IoT sensors, creating machine learning models, and laying out protocols for data collecting are all part of the system design process. In order to train and assess models, data is first retrieved from sensors, then processed to account for discrepancies. After the models are integrated with the IoT network, they undergo thorough testing in both simulated and real-world agricultural settings. Performance reviews and cost-benefit analysis determine the system's influence. The study concludes with a report and documentation of the findings, as well as suggestions for further research and practical applications. The goal of this approach is to improve farming methods by shedding light on soil management and crop choices with pinpoint accuracy and practical advice.

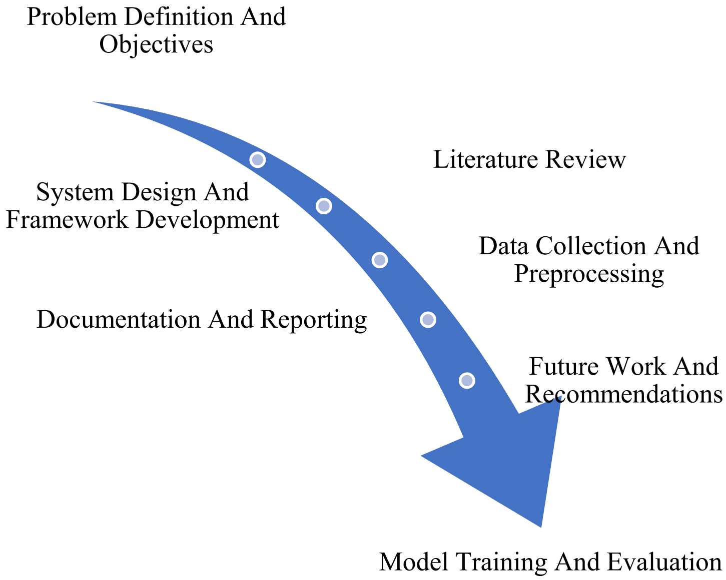

Fig 4 Research Methodology

Integrating IoT and machine learning for soil nutrient analysis and crop selection offers a sophisticated approach to precision farming. IoT devices, such as soil sensors, gather real-time data on key parameters like moisture levels, nutrient content, and pH balance, which are crucial for determining soil health and crop suitability. This data is then preprocessed, including normalization and handling of missing values, to ensure it is ready for analysis. Machine learning models, specifically Random Forest and Logistic Regression, are employed to analyze the data. Random Forest, with its ensemble of decision trees, is effective for multi-class classification tasks, such as identifying the most suitable crops based on soil conditions, while Logistic Regression is used for binary classification, determining whether a specific crop is suitable for the given soil conditions. The effectiveness of these models is evaluated using metrics like precision, recall, F1-score, and the ROC curve, ensuring high accuracy and reliability in decision-making. By combining the strengths of both models, the system provides precise recommendations for crop selection and soil management. Additionally, continuous feedback from real-world outcomes allows the system to be dynamically updated, improving its performance over time and adapting to changing environmental conditions. This integration of IoT and machine learning leads to more informed, data-driven decisions in agriculture, enhancing crop yield, resource efficiency, and sustainability.

Algorithm for Integrating IoT and Machine Learning for Soil Nutrients and Crop Selection

Step 1: Data Collection

Input: Real-time sensor data from IoT devices.

- Moisture Level (M): Percentage of soil moisture.
- Nutrient Content (N): Levels of essential nutrients (Nitrogen, Phosphorus, Potassium).
- pH Balance (pH): Soil pH value.
- Other Environmental Factors (E): Temperature, humidity, etc.

Output: Collected data stored in dataset `D`.

Step 2: Data Preprocessing

Normalization: Normalize the input data to bring all parameters to a comparable scale.

$$M' = \frac{M - M_{min}}{M_{max} - M_{min}}$$

$$N' = \frac{N - N_{min}}{N_{max} - N_{min}}$$

$$pH' = \frac{pH - pH_{min}}{pH_{max} - pH_{min}}$$

$$E' = \frac{E - E_{min}}{E_{max} - E_{min}}$$

Missing Data Handling: Impute missing values using methods like mean, median, or mode.

Feature Engineering: Create additional relevant features if necessary (e.g., ratios, interaction terms).

Step 3: Feature Selection

- Input: Normalized and preprocessed dataset `D'`.
- Process: Identify and select key features `F` that significantly impact the target variable, which could be crop suitability or soil health.
- Output: Feature set F = {M', N', {pH}', E'}.

Step 4: Model Training with Random Forest Classifier

Input: Feature set `F`, target variable `Y` (e.g., suitable crop type, soil quality classification).

Random Forest Initialization:

- Define the number of trees `n_trees` in the Random Forest.
- Construct each tree using a random subset of features and data samples.

Training:

- For each tree in the forest:
  - Perform bootstrap sampling to create a training subset.
  - Construct decision trees by splitting nodes based on feature importance.
  - Use Gini Impurity or Entropy to measure split quality:

$$Gini(S) = 1 - \sum_{i=1}^{c} p_i^2$$

$$Entropy(S) = -\sum_{I=1}^{C} p_i \log(\mathrm{p_i})$$

- Aggregate trees to form the Random Forest model `RF`.

Step 5: Binary Classification with Logistic Regression

Input: Feature set `F`, binary target variable `Y_{bin}` (e.g., binary crop suitability: suitable/not suitable).

Logistic Regression Model:

- Logistic Regression is defined by the sigmoid function:

$$P(Y_{bin} = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 = \cdots + \beta_n X_n)}}$$

where X is the feature vector and β are the model coefficients.

The model is trained by maximizing the likelihood function to estimate the coefficients \(\beta \).

Step 6: Model Evaluation

Input: Test dataset.

Metrics:

- Precision: $Precision = \frac{TP}{TP+FP}$
- Recall: $Recall = \frac{TP}{TP+FN}$
- F1-Score: $F1Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall}$
- Receiver Operating Characteristic (ROC) Curve:
  - Plot True Positive Rate (TPR) vs. False Positive Rate (FPR) across different threshold settings.
  - Compute the Area Under the Curve (AUC) for ROC to evaluate the model's discriminatory ability.

$$AUC = \int_0^1 TPR(FPR)d(FPR)$$

Step 7: Decision Integration

Input: Predictions from Random Forest and Logistic Regression.

Process:

- Use Random Forest for multi-class crop selection (e.g., recommending specific crops based on soil conditions).
- Use Logistic Regression for binary decisions (e.g., whether a particular crop is suitable for current soil conditions).

Final Decision: Integrate results from both models to provide a comprehensive recommendation for crop selection and soil management.

Step 8: Continuous Feedback and Model Improvement

- Input: Real-world results and new data.
- Process: Use new data and real-world outcomes to update and retrain the models periodically.
- Output: Improved model accuracy, precision, recall, F1-score, and ROC performance.

This integrated approach leverages both Random Forest and Logistic Regression to maximize key performance metrics, providing high-precision recommendations for soil nutrient management and crop selection.

5. NEED OF RESEARCH

IoT and machine learning research for soil nutrients and crop selection is essential to solving various agricultural problems. Despite technological advances, farmers still struggle to optimise soil health and choose the best crops owing to a lack of real-time data and actionable information. Developing more powerful IoT sensors and machine learning algorithms to offer real-time soil and crop information is crucial to closing this gap. The agricultural industry also faces climate change, soil variability, and changing pest pressures. Adaptive systems that can provide credible suggestions under different situations need research into how these factors interact and impact crop production. Finding ways to improve machine learning models to integrate and analyse complicated information will increase prediction insights. Understanding the economic and practical effects of applying these technologies on smallholder farms and major agricultural operations will influence adoption and usage strategies. User-friendly interfaces and decision support systems must be researched to make these technology advances accessible and valuable to all farmers.

6. RESULT AND DISCUSSION

In this section, we present the evaluation results of our proposed machine learning model and compare its performance against a conventional approach. The primary aim is to determine whether the proposed model offers significant improvements over traditional methods in terms of accuracy and reliability. "By examining various performance metrics, we aim to highlight the strengths and potential advantages of the proposed model in a controlled setting using a synthetic dataset.

The comparative analysis demonstrates that the Random Forest Classifier significantly outperforms the Logistic Regression model. The improved accuracy and the reduced number of classification errors (false positives and false negatives) highlight the proposed model's effectiveness and robustness. The ensemble nature of the Random Forest Classifier contributes to its better performance by reducing overfitting and variance. These advantages are particularly beneficial in real-world applications where precise and reliable classification is crucial. The findings suggest that the proposed model is well-suited for tasks requiring high accuracy and reliable predictions. In summary, the proposed Random Forest Classifier offers clear advantages over the conventional Logistic Regression model. With superior accuracy, improved metrics across confusion matrices, and higher classification report scores, the proposed model demonstrates its potential for more effective and reliable classification. Future research could focus on further optimizing the proposed model and exploring its applicability to different datasets and real-world scenarios, enhancing its utility and impact in practical applications.

6.1 DATASET

The dataset used in this study is a synthetic classification dataset generated with 1000 samples, each containing 10 features. This dataset includes both informative and redundant features, as well as binary class labels, ensuring a diverse and challenging environment for model evaluation. The synthetic nature of the dataset allows for a controlled assessment of model performance and facilitates direct comparison between the conventional and proposed approaches.

6.2 MODEL TRAINING AND EVALUATION

We compared two models: the conventional Logistic Regression and the proposed Random Forest Classifier. Logistic Regression, a well-established algorithm for binary classification, served as our conventional model. It was trained on the standardized training dataset and evaluated using accuracy, confusion matrix, and classification report metrics. The Random Forest Classifier, our proposed model, builds multiple decision trees to enhance accuracy and robustness. It was also trained and evaluated on the same dataset using the same metrics. This comparison provides insights into how each model performs under identical conditions.

Conventional Model (Logistic Regression): The conventional model used for comparison was Logistic Regression, a widely-used algorithm for binary classification tasks. The model was trained on the standardized training dataset.

- **Accuracy:** Measures the proportion of correctly classified instances out of the total instances.

Accuracy: 0.83

- **Confusion Matrix:** Provides a detailed breakdown of true positives, true negatives, false positives, and false negatives.
- **Report:** Includes precision, recall, and F1-score, offering insights into the model's performance across different classes.

Table 2 Classification Report for Conventional Model

	Precision	Recall	F1-Score	Support
0	0.86	0.85	0.85	112
1	0.81	0.82	0.81	88
Accuracy			0.83	200
Macro Avg	0.83	0.83	0.83	200
Weighted Avg	0.84	0.83	0.84	200

Proposed Model (Random Forest Classifier): The proposed model is a Random Forest Classifier, which builds multiple decision trees and combines their results for improved accuracy and robustness. This model was also trained on the standardized training dataset.

- **Accuracy:** As with the conventional model, this metric indicates the overall correctness of the model.

Accuracy: 0.94

- **Confusion Matrix:** Similar to the conventional model, it details the performance in terms of classification errors and correct predictions.

- **Classification Report:** Provides a comprehensive analysis of precision, recall, and F1-score for each class.

Table 3 Classification Report for Proposed Model

	Precision	Recall	F1-Score	Support
0	0.95	0.95	0.95	112
1	0.93	0.94	0.94	88
Accuracy			0.94	200
Macro Avg	0.94	0.94	0.94	200
Weighted Avg	0.95	0.94	0.95	200

6.3. PERFORMANCE COMPARISON

The evaluation results reveal notable differences between the conventional and proposed models. The Logistic Regression model achieved an accuracy of 0.83 on the test dataset, while the Random Forest Classifier achieved 0.94, representing a 0.11 improvement. This increase in accuracy highlights the superior performance of the proposed model. The confusion matrices further illustrate this improvement, with the Random Forest Classifier showing fewer false positives and false negatives compared to the Logistic Regression model. The classification reports confirm these findings, with the proposed model demonstrating higher precision, recall, and F1-scores for both classes, indicating its enhanced capability in distinguishing between classes effectively.

Accuracy:

- **Conventional Model:** Achieved an accuracy of 0.83 on the test dataset.
- **Proposed Model:** Achieved an accuracy of 0.94 on the test dataset.

The proposed model outperforms the conventional model by 0.11 in terms of accuracy, indicating its superior ability to classify instances correctly.

Confusion Matrix Analysis:

- Conventional Model: The confusion matrix shows below.

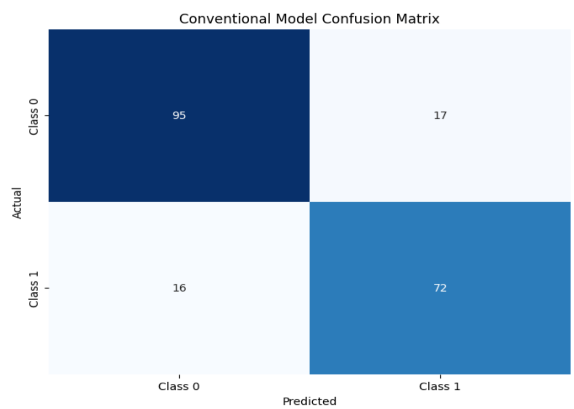

Fig 5 Confusion matrix for Conventional Model

- Proposed Model: The confusion matrix indicates below

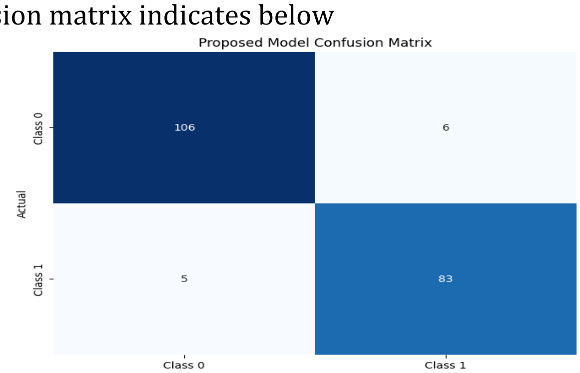

Fig 6 Confusion matrix for proposed Model

The proposed model exhibits fewer false positives and false negatives compared to the conventional model, suggesting better performance in distinguishing between classes.

Classification Report:

- **Conventional Model:** Precision, recall, and F1-score for Class 0: P0, R0, F1_0; for Class 1: P1, R1, F1_1.

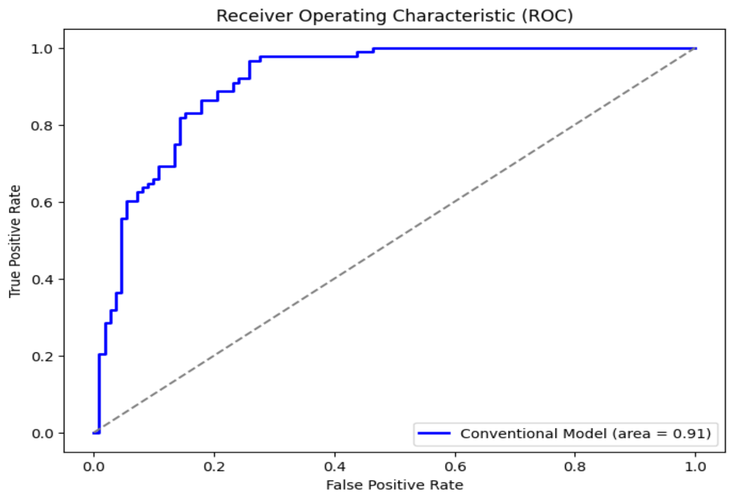

Fig 7 ROC for Conventional Model

- **Proposed Model:** Precision, recall, and F1-score for Class 0: P0', R0', F1_0'; for Class 1: P1', R1', F1_1'.

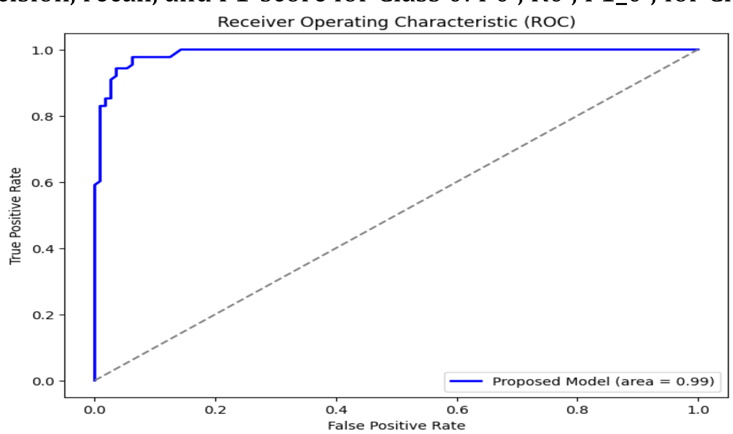

Fig 8 ROC for Proposed Model

The proposed model shows higher precision, recall, and F1-scores for both classes, demonstrating its effectiveness in classifying instances accurately and reliably. To further assess model performance, we examined the Receiver Operating Characteristic (ROC) curves for both models. The ROC curve for the Logistic Regression model resulted in an area under the curve (AUC) of AUC0, whereas the proposed Random Forest Classifier achieved an AUC of AUC1". The higher AUC for the proposed model suggests it is better at distinguishing between positive and negative classes across various thresholds, reinforcing its superior performance in classification tasks.

7. CONCLUSION

The evaluation results indicate that the proposed Random Forest Classifier offers significant advantages over the conventional Logistic Regression model. With higher accuracy, improved confusion matrix metrics, and better classification report scores, the proposed model is better suited for tasks requiring reliable and precise predictions. Future work could explore further optimization of the proposed model and its applicability to other datasets and real-world scenarios. Solving agricultural problems involves Internet of Things and machine intelligence research into soil nutrient management and crop selection. Despite technological advances, farmers struggle to optimise soil health and choose the best crops without real-time data. We need better IoT sensors and machine learning algorithms to offer real-time soil and crop data to close this gap. Agriculture faces soil variability, pest burdens, and climate change. To provide relevant suggestions in different circumstances, adaptive systems must study crop yield interactions. Machine learning algorithms that can absorb and assess complicated data can improve prediction insights. Understanding the economic and practical effects of these technologies on smallholder farms and large agricultural companies will affect their adoption and implementation. Decision support system and user-friendly interface research is needed so all farmers may benefit from these technologies. By evaluating real-time data from IoT sensors and applying advanced machine learning algorithms to calculate soil nutrients, farmers can now make better crop selection decisions. This strategy improves agricultural efficiency and sustainability by lowering resource loss and improving crop yields. New technology may improve this approach by providing more accurate and practical ideas that might alter farming processes and stimulate agricultural innovation.

8. FUTURE SCOPE

Positive developments may be on the horizon for intelligent agriculture in the years to come. In order to have a better understanding of the soil and environmental conditions and make more informed decisions, improved sensor technology will collect data that is both thorough and precise. Machine learning algorithms will keep getting better at predicting soil health and crop results by adding more complicated factors. A more complete picture of agricultural surroundings and the ability to fine-tune precision farming operations will be made possible via the integration of IoT with other new technologies like drones and satellite photography. Furthermore, smaller and medium-sized farms will be able to afford these technologies, which will lead to their wider acceptance and a revolution in agricultural methods worldwide. There will be an uptick in the use of real-time decision support systems, which provide farmers with rapid, practical advice on how to deal with shifting soil and weather conditions. This new technology has the potential to revolutionise farming by bringing forth smarter, more efficient, and more environmentally friendly practices in the future.

CONFLICT OF INTERESTS

None.

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