iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: III Month of publication: March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78174

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Sheti Mitra - An Interactive System to Predict Crop Yield Along with Profit and Loss to Help Farmers Using Machine Learning

Bangar Sakshi Laxman[1], Bangar Shraddha Prabhakar[2], Chaudhari Sanika Sampat[3], Prof. Thorat Sonam[4]
[1, 2, 3] Student, [4]Assistant Professor, Department of Computer Engineering, Samarth Rural Educational Institute Polytechnic College (MH) India

***Abstract:** Agriculture plays a crucial role in the economic development of many countries, especially where farming is the primary source of livelihood. Farmers often face difficulties in selecting suitable crops, predicting crop yield, identifying plant diseases at an early stage, and estimating financial outcomes such as profit or loss. To address these challenges, this study presents Sheti Mitra, an interactive machine learning–based system designed to assist farmers in making informed agricultural decisions. The proposed system integrates crop recommendation, crop yield prediction, and plant disease detection into a single platform. The system utilizes image processing and deep learning techniques to detect diseases from leaf images using Convolutional Neural Networks (CNN), while crop recommendation and yield prediction are performed using machine learning algorithms such as Random Forest. Environmental parameters including soil nutrients, temperature, humidity, and rainfall are analyzed to determine the most suitable crop and estimate expected yield. Additionally, the system provides an estimation of profit or loss based on predicted yield and crop market factors, helping farmers plan their agricultural activities effectively. A web-based interface built using HTML, CSS, and JavaScript interacts with a Flask-based backend that processes user inputs and generates predictions using trained models. By combining disease detection with crop and yield prediction, the proposed system offers a comprehensive decision-support tool for farmers. The implementation demonstrates that machine learning techniques can significantly improve agricultural productivity and reduce risks associated with crop selection and disease management. This system aims to support smart farming practices and promote sustainable agricultural development.*
***Keywords:** Machine Learning, Crop Yield Prediction, Plant Disease Detection, Random Forest, Convolutional Neural Network, Smart Agriculture, Precision Farming, Agricultural Decision Support System.*

I. INTRODUCTION

Agriculture plays a crucial role in supporting the global economy and ensuring food security for the rapidly growing population. In many developing countries, a large portion of the population depends on agriculture as their primary source of income and livelihood. However, farmers face several challenges such as unpredictable climatic conditions, soil fertility degradation, plant diseases, pest attacks, and unstable market prices. These challenges significantly affect crop productivity and often result in economic losses for farmers. To overcome these issues and improve agricultural efficiency, modern technologies such as machine learning and artificial intelligence are increasingly being integrated into agricultural systems. These technologies enable data-driven decision-making and help farmers adopt more efficient and sustainable farming practices [1].

Machine learning has emerged as an effective tool for solving complex agricultural problems due to its capability to analyze large volumes of data and identify hidden patterns. By using environmental parameters such as temperature, humidity, rainfall, soil nutrients, and historical agricultural data, machine learning algorithms can predict suitable crops and estimate crop yields with considerable accuracy. Algorithms such as Random Forest, Support Vector Machine, and Artificial Neural Networks have been widely applied in agricultural prediction systems due to their ability to handle nonlinear relationships and large datasets [2].

These intelligent models assist farmers in selecting appropriate crops based on environmental conditions and expected productivity.

Another major issue affecting agricultural productivity is plant disease, which can significantly reduce crop yield and quality. Early detection of plant diseases is essential to prevent large-scale crop damage. Traditionally, plant diseases are identified through manual inspection by agricultural experts, which can be time-consuming and not always accessible to farmers in rural areas. With the advancement of deep learning and computer vision techniques, automated disease detection systems have been developed to analyze plant leaf images and identify diseases accurately.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification tasks and are widely used for detecting plant diseases based on visual symptoms such as spots, discoloration, and lesions on leaves [3].

Crop yield prediction is another important application of machine learning in agriculture. Accurate yield prediction helps farmers estimate production levels, manage agricultural resources effectively, and plan future farming activities. Machine learning models analyze multiple factors including soil characteristics, weather conditions, irrigation availability, and crop management practices to forecast crop yield. Ensemble learning techniques such as Random Forest have been found to provide reliable yield predictions because they combine multiple decision trees to improve prediction accuracy and reduce overfitting [4].

In addition to crop yield prediction, farmers often require information about the potential financial outcome of their agricultural activities. Estimating profit and loss based on predicted yield and crop market trends can help farmers make better economic decisions. Integrating crop recommendation, disease detection, yield prediction, and financial analysis into a single intelligent platform can provide a comprehensive decision-support system for farmers. Such systems can improve agricultural productivity, reduce crop losses, and support sustainable farming practices.

Therefore, this research proposes "Sheti Mitra – An Interactive System to Predict Crop Yield Along with Profit and Loss to Help Farmers Using Machine Learning." The proposed system integrates machine learning and deep learning techniques to provide crop recommendation, crop yield prediction, and plant disease detection through a unified web-based platform. The system utilizes Convolutional Neural Networks for identifying plant diseases from leaf images and Random Forest algorithms for crop recommendation and yield prediction. A web interface developed using HTML, CSS, and JavaScript interacts with a Flask-based backend that processes user inputs and generates predictions using trained machine learning models. By providing accurate agricultural insights and financial estimations, the proposed system aims to support farmers in making informed decisions and improving overall farming productivity.

II. PROBLEM STATEMENT

Agriculture remains highly dependent on environmental conditions, soil quality, and proper crop management practices, yet many farmers still rely on traditional knowledge and manual observation to make important farming decisions. This lack of technological support makes it difficult for farmers to accurately select suitable crops based on soil nutrients, rainfall, temperature, and humidity, which often leads to poor crop productivity. In addition, early identification of plant diseases is a major challenge because farmers may not have access to agricultural experts or advanced diagnostic tools, causing diseases to spread rapidly and damage crops before preventive measures can be taken. Another critical problem is the inability to accurately predict crop yield and estimate the potential profit or loss associated with agricultural production. Farmers frequently depend on rough estimations rather than data-driven analysis, which increases the risk of financial loss due to uncertain market conditions and varying environmental factors. Existing agricultural support systems generally address only individual aspects such as crop recommendation, yield prediction, or disease detection, but they rarely provide a unified platform that integrates all these functionalities. Therefore, there is a strong need for an intelligent, integrated system that can assist farmers in identifying crop diseases, recommending suitable crops, predicting expected yield, and estimating profit or loss using machine learning techniques. Such a system can support informed decision-making, improve agricultural productivity, and reduce financial risks for farmers.

III. OBJECTIVE

1) To develop an intelligent machine learning–based system that assists farmers in making accurate agricultural decisions.
2) To recommend the most suitable crop for cultivation based on environmental factors such as soil nutrients, temperature, rainfall, and humidity.
3) To predict crop yield using machine learning algorithms in order to estimate agricultural production in advance.
4) To detect plant diseases at an early stage by analyzing leaf images using deep learning techniques such as Convolutional Neural Networks (CNN).
5) To estimate the potential profit or loss associated with crop production to help farmers plan their resources and investments effectively.

IV. LITERATURE SURVEY

Paper Name: Using Deep Learning for Image-Based Plant Disease Detection
Year: 2016
Author: Sharada P. Mohanty, David P. Hughes, Marcel Salathé
Publication: Frontiers in Plant Science

Journal: Frontiers Media

This research presented one of the earliest large-scale applications of deep learning for plant disease detection using image analysis. The authors utilized a deep convolutional neural network to identify diseases from plant leaf images. A publicly available dataset containing more than 54,000 images from 14 crop species and 26 diseases was used for training and testing the model. The CNN model was capable of automatically learning visual features from the images without requiring manual feature extraction, demonstrating the capability of deep learning in agricultural image classification tasks.

The experimental results showed that the trained deep learning model achieved an accuracy of approximately 99.35% in identifying plant species and disease types, proving that automated disease detection is technically feasible. The study also highlighted the importance of large and diverse datasets for improving model generalization in real-world conditions. This work laid the foundation for many subsequent studies in agricultural image processing and smart farming applications using machine learning techniques.

Paper Name: Deep Learning Models for Plant Disease Detection and Diagnosis

Year: 2018

Author: Konstantinos P. Ferentinos

Publication: Computers and Electronics in Agriculture

Journal: Elsevier

In this study, the author developed deep learning models for detecting and diagnosing plant diseases from leaf images. The research employed convolutional neural networks trained on a large dataset containing 87,848 images representing 25 plant species and 58 disease categories. Several CNN architectures were evaluated to determine the most effective model for accurate disease classification. The approach demonstrated that deep learning models can automatically learn discriminative visual patterns from plant images.

The results indicated that the CNN-based system achieved an accuracy of about 99.53% on previously unseen images, showing the effectiveness of deep learning in identifying plant diseases. The research also emphasized the importance of combining large datasets with powerful neural network architectures to achieve high classification performance. This work significantly contributed to the advancement of automated plant disease detection systems for smart agriculture applications.

Paper Name: Automated Detection of Plant Diseases: A Review

Year: 2016

Author: S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, D. Stefanovic

Publication: IEEE International Symposium on Intelligent Systems and Informatics (SISY)

Journal: IEEE

This research focused on developing an automated system for detecting plant diseases using image processing and machine learning techniques. The authors analyzed different approaches used for disease detection, including color analysis, texture extraction, and classification algorithms. The proposed method used convolutional neural networks to identify disease symptoms from plant leaf images, eliminating the need for manual inspection and feature engineering.

The study demonstrated that machine learning techniques can significantly improve the speed and accuracy of plant disease detection. The authors also highlighted the potential of integrating automated disease detection systems with mobile or web platforms to assist farmers in identifying crop diseases. The research emphasized the importance of computer vision technologies in improving agricultural productivity and supporting precision farming practices.

Paper Name: Deep Neural Networks for Plant Disease Detection

Year: 2018

Author: A. K. Singh, B. Ganapathysubramanian, A. Singh Publication: Computers and Electronics in Agriculture Journal: Elsevier

This study explored the use of deep neural networks for recognizing plant diseases from leaf images. The authors proposed a deep learning model that utilized convolutional layers to extract features such as color patterns, shape, and texture from plant leaves. The model was trained on a large dataset of plant disease images and was capable of classifying multiple disease types with high precision. The experimental results showed that deep neural networks outperform traditional machine learning techniques in disease detection tasks. The authors also discussed the advantages of using deep learning methods for agricultural monitoring systems, including automated feature extraction and improved classification accuracy. The research demonstrated the potential of deep neural networks for developing intelligent crop monitoring systems in modern agriculture.

Paper Name: Plant Disease Recognition Using a Convolutional Neural Network
Year: 2018
Author: C. Zhang, X. Liu, Y. Ma
Publication: International Conference on Image and Video Processing and Artificial Intelligence
Journal: IEEE
This research proposed a convolutional neural network model designed specifically for plant disease recognition using leaf images. The model was trained to classify various disease categories by analyzing visual characteristics present in plant leaves. Image preprocessing techniques such as resizing, normalization, and noise reduction were applied to improve model performance and ensure consistent input for the neural network.

The results demonstrated that CNN-based approaches can achieve high accuracy in plant disease classification while reducing the need for manual feature engineering. The authors concluded that automated disease recognition systems can assist farmers in detecting crop diseases at early stages, enabling timely intervention and reducing agricultural losses. This study further confirmed the importance of deep learning in smart agriculture and crop health monitoring systems.

Paper Name: Plant Disease Detection Model for Edge Computing Devices
Year: 2023
Author: A. T. Khan et al. Publication: Frontiers in Plant Science Journal: Frontiers Media
This study investigated the development of deep learning models for plant disease detection that can operate efficiently on edge computing devices. The research addressed the challenge of deploying computationally intensive deep learning models in real-world agricultural environments where resources such as processing power and memory may be limited. The authors proposed an optimized deep learning framework capable of achieving high accuracy while maintaining low computational requirements.

The results demonstrated that lightweight deep learning architectures can effectively detect plant diseases while operating on resource-constrained devices. The study highlighted the potential of integrating edge computing with artificial intelligence to develop real-time agricultural monitoring systems. Such systems can assist farmers by providing instant disease diagnosis directly in the field, improving crop management and supporting sustainable agricultural practices.

V. PROPOSED SYSTEM

The proposed system “Sheti Mitra – An Interactive System to Predict Crop Yield Along with Profit and Loss to Help Farmers Using Machine Learning” is designed as an intelligent decision-support platform that assists farmers in improving agricultural productivity and reducing financial risk.

The system integrates machine learning and deep learning techniques to provide crop recommendation, plant disease detection, crop yield prediction, and profit–loss estimation through a single web-based application. The system architecture consists of multiple interconnected modules that process user inputs, analyze agricultural data, and generate accurate predictions. The following sections describe the major components of the proposed system.

A. User Interaction and Data Input

The system begins with user interaction through a web- based interface that allows farmers to access the platform easily. The interface is developed using HTML, CSS, and JavaScript to provide a simple and user-friendly environment for farmers. Through this interface, users can enter important agricultural parameters such as soil nutrients (Nitrogen, Phosphorus, and Potassium), temperature, humidity, rainfall, and pH value of the soil.

These environmental factors play a significant role in determining the suitability of crops and the potential yield. In addition to numerical inputs, the system also allows users to upload leaf images of crops for disease detection. The interface ensures that the system is accessible even to users with limited technical knowledge, enabling farmers to obtain agricultural predictions quickly and efficiently.

B. Data Preprocessing and Feature Scaling

After the user submits input data, the system performs preprocessing to prepare the data for machine learning models. Data preprocessing is an essential step that improves the accuracy and efficiency of prediction models. In this stage, input values are cleaned and standardized to remove inconsistencies or errors.

The system uses StandardScaler to normalize the numerical values of environmental parameters such as temperature, humidity, rainfall, and soil nutrients. Feature scaling ensures that all parameters are converted into a common scale so that no single feature dominates the machine learning model during prediction. This step enhances the performance of the prediction algorithms and ensures reliable output results.

C. Crop Recommendation Module

The crop recommendation module is responsible for suggesting the most suitable crop based on environmental conditions and soil parameters provided by the user.

The system uses the Random Forest Classification algorithm, which is an ensemble machine learning technique that combines multiple decision trees to generate accurate predictions. The model is trained using agricultural datasets containing information about soil nutrients, climate conditions, and crop suitability. When the user enters the required parameters, the trained model analyzes the data and recommends the crop that is most appropriate for the given conditions. This module helps farmers select crops that are likely to grow successfully in their region, thereby improving agricultural productivity.

D. Crop Yield Prediction Module

Once the crop recommendation is generated, the system predicts the expected crop yield using a Random Forest Regression model. Crop yield prediction is important for estimating agricultural production before the harvesting stage. The model analyzes various environmental and soil- related factors such as rainfall, temperature, humidity, and nutrient levels to estimate the expected output of the selected crop.

By providing yield predictions in advance, the system helps farmers plan their agricultural activities, manage resources efficiently, and make informed decisions regarding fertilizer usage, irrigation planning, and harvesting strategies.

E. Plant Disease Detection Module

Plant diseases are one of the major causes of crop loss in agriculture. To address this issue, the proposed system includes a plant disease detection module that analyzes crop leaf images uploaded by the user. This module uses Convolutional Neural Networks (CNN) to detect and classify plant diseases based on visual features present in the leaf images. The deep learning model is trained on a large dataset of plant leaf images containing both healthy and diseased samples. The CNN automatically extracts important features such as color variations, spots, and texture patterns from the images to identify specific diseases. Early detection of plant diseases enables farmers to apply appropriate treatment methods and reduce the risk of large-scale crop damage.

F. Profit and Loss Estimation Module

In addition to predicting crop yield, the system also estimates the potential **profit or loss** associated with crop production. This module calculates the expected financial outcome by considering predicted yield and agricultural cost factors. By providing an estimation of economic returns, the system helps farmers understand the financial feasibility of cultivating a particular crop. This information allows farmers to make better investment decisions and reduce financial uncertainty in agricultural activities.

G. Backend Processing and Model Integration

The backend of the system is implemented using the Flask web framework in Python, which acts as the communication layer between the user interface and machine learning models. Flask handles user requests, processes input data, and interacts with the trained models for prediction. Machine learning models such as Random Forest and CNN are stored in trained model files and are loaded when required for prediction tasks. The backend system ensures efficient processing of user inputs and generates prediction results that are returned to the frontend interface.

H. Result Generation and Visualization

After completing all prediction processes, the system displays the results to the user through the web interface. The results include recommended crops, predicted crop yield, detected plant diseases, and estimated profit or loss. These outputs are presented in a clear and understandable format so that farmers can easily interpret the results and take appropriate actions. By providing comprehensive agricultural insights in a single platform, the system supports farmers in improving productivity, reducing crop losses, and adopting modern data-driven farming practices.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

VI. SYSTEM DESIGN

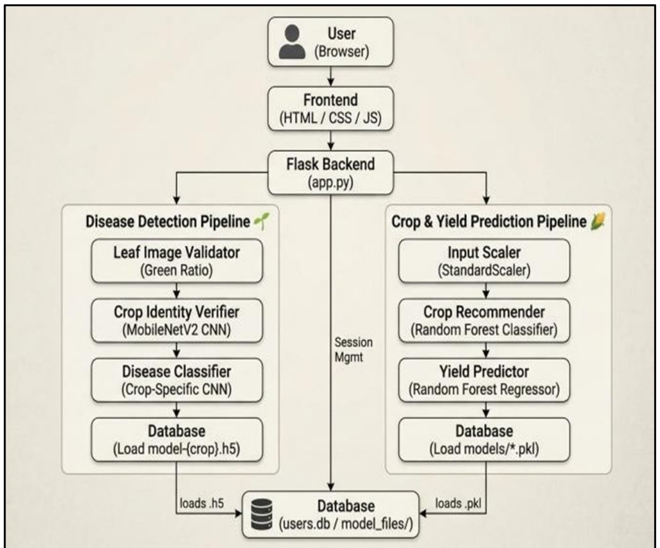


Fig 1: System architecture

The architecture of the proposed system “Sheti Mitra – An Interactive System to Predict Crop Yield Along with Profit and Loss to Help Farmers Using Machine Learning” illustrates the workflow of the entire system from user input to prediction output. The diagram represents the interaction between the user interface, backend server, machine learning models, and database components. The system is divided into multiple modules that work together to process agricultural data, detect plant diseases, recommend suitable crops, and predict crop yield along with financial outcomes. The following sections explain each component of the architecture in detail.

A. User Interface (Web Browser)

The system begins with the user interface, where farmers interact with the application through a web browser. This interface is designed to be simple and user-friendly so that farmers can easily access the system without requiring technical expertise. Through this interface, users can enter environmental parameters such as soil nutrients (Nitrogen, Phosphorus, Potassium), temperature, humidity, rainfall, and soil pH. In addition to numerical inputs, the interface also allows users to upload leaf images of crops to identify plant diseases. The web interface acts as the communication layer between the user and the backend processing system.

B. Frontend Development (HTML, CSS, JavaScript)

The frontend of the system is developed using HTML, CSS, and JavaScript, which together create an interactive and responsive web application. HTML is used to design the structure of the webpages and provide input forms for agricultural data. CSS improves the visual appearance and layout of the application to make it easy for users to understand and navigate. JavaScript is responsible for handling dynamic functionalities such as form validation, image upload handling, and sending user requests to the backend server. This frontend layer ensures smooth communication between the user interface and the server-side processing modules.

C. Backend Server (Flask Application)

The backend processing of the system is handled using the Flask framework in Python, which acts as the central controller of the application. The Flask server receives user requests from the frontend interface and processes them accordingly. When a farmer submits environmental data or uploads a leaf image, the request is sent to the Flask application where it is analyzed and forwarded to the appropriate machine learning module. Flask also manages communication between different components of the system, including machine learning models, databases, and result generation modules. Once predictions are generated, the Flask server sends the results back to the frontend for display.

D. Leaf Image Validation Module
Before performing plant disease detection, the system verifies whether the uploaded image contains a valid plant leaf. This validation is performed using a green ratio technique, which calculates the proportion of green pixels in the image. Since plant leaves typically contain a significant amount of green color, this method helps determine whether the uploaded image is suitable for analysis.
If the image does not meet the required threshold, the system prompts the user to upload another valid image. This step ensures that only relevant images are processed for disease detection.

E. Crop Identification Module (MobileNetV2 CNN)
After validating the leaf image, the system identifies the crop type using a MobileNetV2 Convolutional Neural Network model. MobileNetV2 is a lightweight deep learning architecture designed for efficient image classification tasks. The model analyzes visual features of the leaf such as shape, texture, and color patterns to determine the crop species. Identifying the crop type is important because different crops are affected by different diseases, and the correct crop identification ensures accurate disease classification in the next stage.

F. Plant Disease Detection Module
Once the crop type is identified, the system loads a crop-specific Convolutional Neural Network (CNN) **model** to detect plant diseases. Each model is trained on datasets containing images of healthy and diseased leaves. The CNN automatically extracts features from the leaf image and compares them with trained patterns to classify the disease accurately.
This module helps farmers detect plant diseases at an early stage, enabling them to take appropriate preventive measures and minimize crop damage.

G. Crop Recommendation and Yield Prediction Module
The second major pipeline of the system focuses on crop recommendation and yield prediction. The environmental data entered by the user is first normalized using StandardScaler, which standardizes all input values to a common scale. This preprocessing step improves the performance of machine learning models.
The system then uses a Random Forest Classifier to recommend the most suitable crop based on environmental conditions such as soil nutrients, rainfall, humidity, and temperature. After recommending the crop, a Random Forest Regression model predicts the expected crop yield. The predicted yield helps farmers estimate agricultural production before harvesting and plan their farming strategies accordingly.

H. Database and Model Storage
The system uses a database to store user information, prediction results, and trained machine learning models. The database ensures efficient data management and retrieval during system operation. Machine learning models used for crop recommendation and yield prediction are stored in .pkl files, while deep learning models used for disease detection are stored in .h5 format. These models are loaded by the backend server whenever a prediction request is received.

I. Result Generation and Output Display
After processing the input data and running the machine learning models, the system generates prediction results. The results include detected plant disease, recommended crop, predicted crop yield, and estimated profit or loss. These results are sent back to the web interface through the Flask server and displayed to the user in a clear and understandable format. By providing these insights, the system helps farmers make informed agricultural decisions and adopt more efficient farming practices.

VII. RESULT
The results of the proposed system “Sheti Mitra – An Interactive System to Predict Crop Yield Along with Profit and Loss to Help Farmers Using Machine Learning” demonstrate the effective implementation of crop disease detection and crop yield prediction using machine learning and deep learning techniques.
The system provides an interactive web interface that allows farmers to analyze crop conditions, detect plant diseases, and obtain yield predictions based on environmental parameters. The following sequence describes the results obtained from the implemented system.

A. System Home Interface

Fig 2: Interface

The first result screen represents the home interface of the AgriTech Solutions platform, which acts as the entry point for users. The interface clearly displays the title "Multi-Crop Disease & Yield Detection System", indicating that the platform integrates both crop disease detection and yield prediction functionalities. The homepage provides options such as Home, About, Contact, Login, and Register, allowing users to navigate easily within the system. It also highlights key system features including real-time AI processing, high accuracy prediction, and continuous availability. Additional information such as the number of analyzed images, prediction accuracy, and system availability is displayed to build user confidence in the system. This interface ensures that farmers can easily access the application and begin the analysis process.

B. Crop Image Upload and Disease Detection

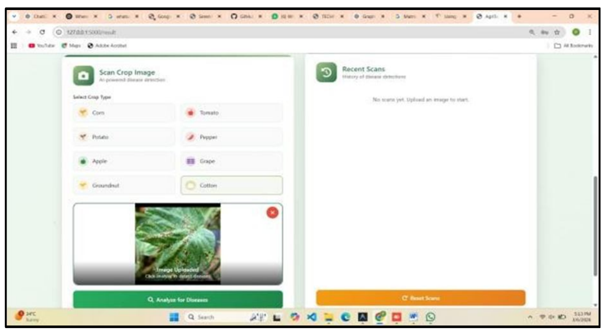


Fig 3: Upload images

The second result screen shows the crop disease detection module, where users can upload images of plant leaves for analysis. The interface allows the user to select the crop type from multiple options such as corn, tomato, potato, pepper, apple, grape, groundnut, and cotton. After selecting the crop type, the user uploads a leaf image that will be analyzed by the deep learning model. The uploaded image is displayed on the interface to confirm that the correct image has been selected. Once the image is uploaded, the user can click the "Analyze for Diseases" button to initiate the disease detection process. The system processes the image using a trained Convolutional Neural Network (CNN) model, which analyzes visual patterns such as leaf color variations, spots, and texture changes. This module enables farmers to quickly identify plant diseases without requiring manual inspection by agricultural experts.

C. Disease Detection Result Output

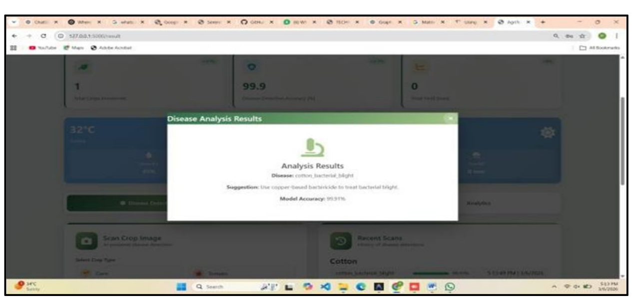


Fig 5: Analysis results

After analyzing the uploaded leaf image, the system displays the disease analysis results through a pop-up window. The output includes the detected disease name, model accuracy, and recommended treatment suggestions. In the presented result, the system identifies the disease as Cotton Bacterial Blight, which is a common disease affecting cotton crops. The system also provides a suggestion recommending the use of copper-based bactericide to control the disease. In addition, the model accuracy is displayed as approximately 99.91%, indicating the high reliability of the deep learning model used for disease detection. This result demonstrates the effectiveness of the CNN model in accurately identifying plant diseases from leaf images, allowing farmers to take early preventive measures.

D. Crop Yield Prediction Interface

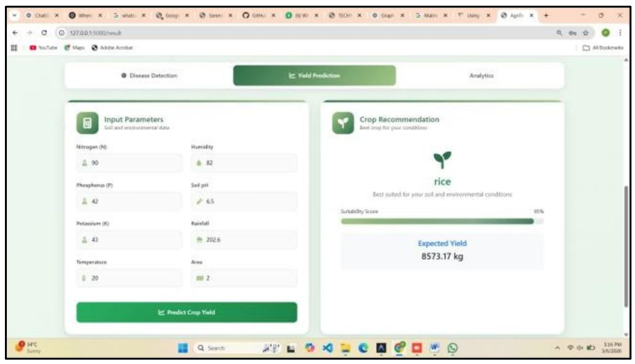


Fig 6: Parameter showing

The next result screen illustrates the crop yield prediction module, where farmers enter environmental and soil-related parameters to obtain yield predictions. The interface allows the user to input values such as Nitrogen (N), Phosphorus (P), Potassium (K), humidity, soil pH, rainfall, temperature, and cultivated area. These parameters represent important agricultural factors that influence crop growth and productivity. After entering the required data, the user clicks the “Predict Crop Yield” button, which sends the data to the machine learning model for analysis. This module uses a Random Forest algorithm to analyze the input features and determine the most suitable crop along with its expected yield.

E. Crop Recommendation and Yield Prediction Result

After processing the input parameters, the system generates the final prediction results. In the displayed output, the system recommends Rice as the most suitable crop based on the provided environmental conditions. The system also displays a suitability score of 95%, indicating that the environmental parameters strongly support the cultivation of rice. Additionally, the predicted crop yield is shown as 8573.17 kilograms, which represents the expected production based on the input conditions and the trained machine learning model. These predictions help farmers plan their cultivation strategies and estimate agricultural output in advance. By providing both crop recommendation and yield estimation, the system supports data-driven decision-making in agriculture.

F. System Performance Observation

The experimental results show that the proposed system successfully integrates plant disease detection and crop yield prediction within a single web-based platform. The disease detection module achieves high accuracy through the use of Convolutional Neural Networks, while the crop recommendation and yield prediction modules utilize Random Forest algorithms to generate reliable predictions. The interactive interface allows farmers to easily upload images, enter environmental parameters, and receive prediction results within a short time. Overall, the system demonstrates the practical applicability of machine learning techniques in modern agriculture and provides valuable insights that can help farmers improve crop productivity and reduce financial risks.

VIII. CONCLUSION

The proposed system “Sheti Mitra – An Interactive System to Predict Crop Yield Along with Profit and Loss to Help Farmers Using Machine Learning” demonstrates how modern machine learning and deep learning technologies can be effectively applied to support smart agricultural practices.

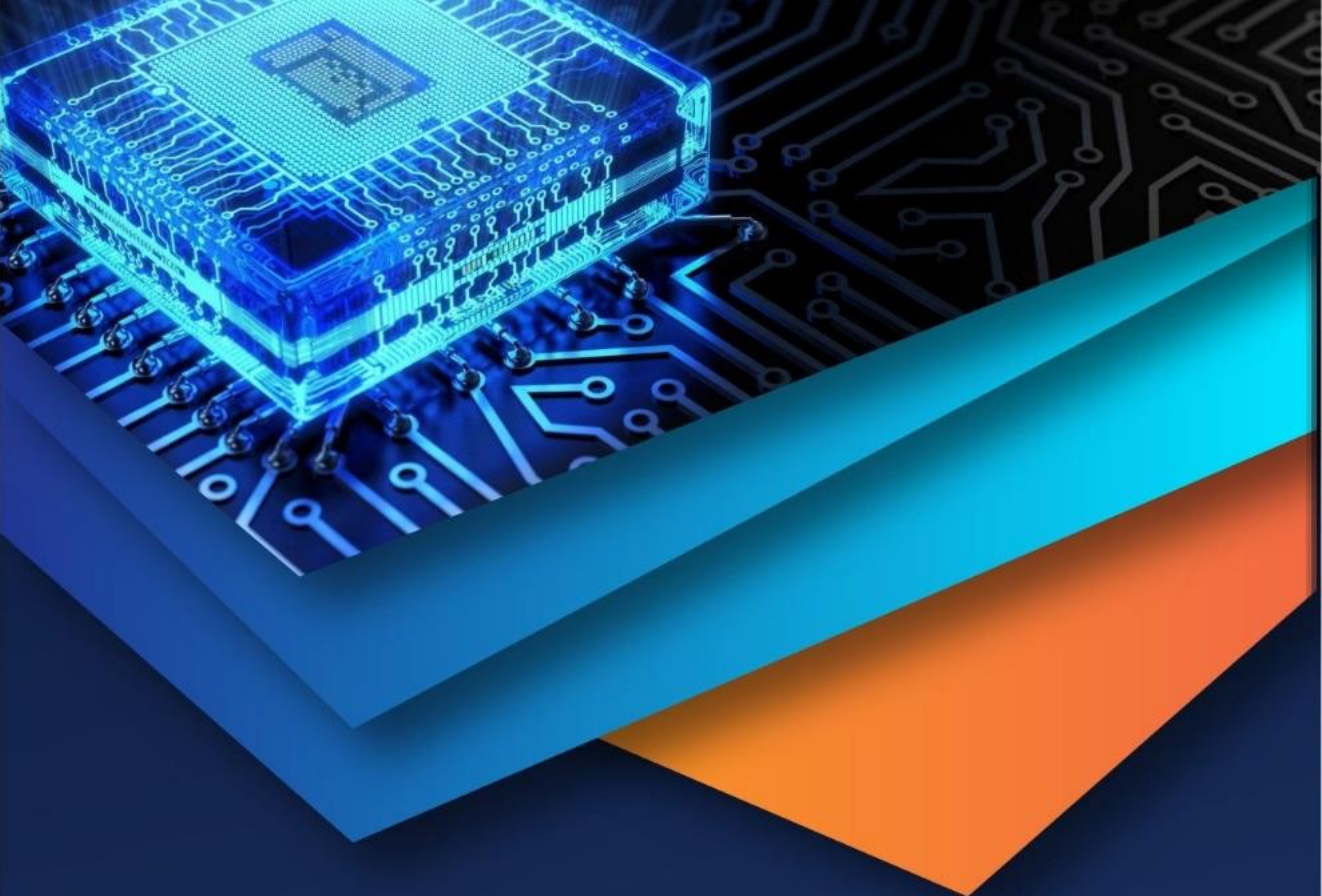
The system integrates multiple functionalities such as crop recommendation, crop yield prediction, and plant disease detection into a single interactive web-based platform. By analyzing environmental parameters including soil nutrients, temperature, humidity, rainfall, and soil pH, the system is capable of recommending the most suitable crop and predicting the expected crop yield using machine learning algorithms such as Random Forest. In addition, the plant disease detection module utilizes Convolutional Neural Networks to accurately identify diseases from leaf images and provide appropriate treatment suggestions to farmers. The implementation results show that the system can provide reliable predictions with high accuracy, enabling farmers to make better agricultural decisions and reduce potential crop losses. Furthermore, the user- friendly interface ensures that farmers can easily access the system and obtain real-time insights without requiring technical expertise. Overall, the proposed system contributes to improving agricultural productivity, supporting data-driven farming practices, and helping farmers estimate potential profit or loss before cultivation, thereby promoting more efficient and sustainable agricultural management.

IX. FUTURE SCOPE

The proposed system can be further enhanced by integrating additional advanced technologies to improve its accuracy, usability, and real-world applicability. In the future, the system can incorporate real-time environmental data obtained from IoT-based sensors to automatically collect information such as soil moisture, temperature, humidity, and rainfall conditions. This integration would allow the system to provide more precise crop recommendations and yield predictions based on real-time field conditions. The disease detection module can also be expanded to support a larger variety of crops and plant diseases by training deep learning models on more extensive datasets. In addition, the system can be developed as a mobile application so that farmers can easily access the platform through smartphones while working in the field. Integration with market price data and government agricultural schemes could further help farmers estimate accurate profit or loss and make better financial decisions. Furthermore, incorporating advanced machine learning techniques such as deep neural networks and real-time image analysis could improve prediction performance and system efficiency, ultimately contributing to the development of a more intelligent and comprehensive smart farming support system.

REFERENCES

[1] Shawon, S. M., et al., “Crop Yield Prediction Using Machine Learning: An Extensive Review,” Smart Agricultural Technology, 2024.
[2] Jabed, M. A., et al., “Crop Yield Prediction in Agriculture Using Machine Learning and Deep Learning: A Systematic Review,” Heliyon, 2024.
[3] Nikhil, U. V., et al., “Machine Learning-Based Crop Yield Prediction Using Weather and Soil Data,” Computers, 2024.
[4] Rastogi, P., et al., “Early Disease Detection in Plants Using Convolutional Neural Networks,” Procedia Computer Science, 2024.
[5] Sajitha, P., et al., “A Review of Machine Learning and Deep Learning Techniques for Plant Disease Detection,” Artificial Intelligence in Agriculture, 2024.
[6] Trivedi, P., et al., “Plant Leaf Disease Detection and Classification Using Deep Learning Models,” Open Agriculture Journal, 2024.
[7] Hukkeri, G. S., et al., “Classification of Various Plant Leaf Diseases Using EfficientNet Architecture,” Open Agriculture Journal, 2024.
[8] Iftikhar, M., et al., “Plant Disease Management Using Enhanced CNN Models,” Artificial Intelligence Review, 2024.
[9] Cho, O. H., “Evaluation of Machine Learning Approaches for Detecting Leaf Diseases in Agriculture,” Legume Research, 2024.
[10] Agarwal, J., et al., “Plant Disease Detection Using Convolutional Neural Networks,” 2024.
[11] Rahman, K. N., et al., “Real-Time Monitoring System for Plant Leaf Disease Detection Using Deep Learning,” Smart Agricultural Systems, 2025.
[12] Lionel, B. M., et al., “Comparative Study of Machine Learning Models for Crop Yield Prediction,” Springer Agriculture Journal, 2025.
[13] Hernández, G. C., et al., “Predictive Models Based on Artificial Intelligence for Crop Yield Estimation,” Agriculture (MDPI), 2025.
[14] Saha, S., et al., “Precision Agriculture for Improving Crop Yield Predictions Using Machine Learning,” Frontiers in Agronomy, 2025.
[15] Fariz, T. K. N., et al., “Hybrid Artificial Intelligence Model for Crop Yield Prediction,” Smart Agriculture Technology, 2025.
[16] Kheir, A. M. S., et al., “Smart Plant Disease Diagnosis Using Multiple Deep Learning Models,” Artificial Intelligence in Agriculture, 2025.
[17] Yasin, K., et al., “Deep Learning Architectures for Plant Disease Detection: A Comprehensive Review,” Plant Science Journal, 2025.
[18] Devarajan, D., et al., “AI-Based Real-Time Plant Disease Diagnosis Using Deep Learning,” Plant Methods, 2026.
[19] Yan, Y., et al., “Crop Yield Time-Series Prediction Using Hybrid Machine Learning Models,” 2025.
[20] Yewle, A. D., et al., “Multi-Modal Data Fusion and Deep Ensemble Learning for Crop Yield Prediction,” 2025.
[21] Gupta, A., et al., “Agri-GNN: Graph Neural Network Framework for Crop Yield Prediction,” 2023.
[22] Mena, F., et al., “Adaptive Fusion of Multi-View Remote Sensing Data for Crop Yield Prediction,” 2024.
[23] Patidar, S., et al., “Crop Yield Prediction Using Machine Learning Techniques,” Agricultural Informatics Journal, 2023.
[24] Mohanty, S. P., Hughes, D., and Salathé, M., “Using Deep Learning for Image-Based Plant Disease Detection,” Frontiers in Plant Science.
[25] Kamilaris, A., and Prenafeta-Boldú, F., “Deep Learning in Agriculture: A Survey,” Computers and Electronics in Agriculture.
[26] Liakos, K. G., et al., “Machine Learning in Agriculture: A Review,” Sensors Journal.
[27] Jeong, J. H., et al., “Random Forest-Based Crop Yield Prediction Model Using Climate Data,” Agricultural Systems.
[28] Zhang, S., et al., “Deep Learning-Based Plant Disease Detection Using Leaf Images,” IEEE Access.
[29] Hossain, M. S., et al., “Deep Convolutional Neural Networks for Plant Disease Recognition,” Computers and Electronics in Agriculture.
[30] Ghosal, S., et al., “Automated Plant Disease Detection Using Deep Learning,” Plant Methods.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY