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AI-based Smart Crop Management System

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A B S T R A C T

Agriculture plays a key role for human survival and serves as the foundation of the global economy.However, crops like Soybean, Tomato, Sugarcane, Wheat, and Rice are vulnerable to insect infestations and diseases, leading to considerable yield losses if left unmanaged. Traditional threat detection methods are time-consuming, labor-intensive, and lack real-time capabilities. This project proposes a deep learning (DL)-based solution utilizing the RESNET9 network model for accurate, real-time insect detection and identification across multiple crops. A diverse data set of insect images from various devices improves model robustness and classification accuracy.In addition to detection, the project integrates AI-driven systems to analyze environmental data, enabling crop disease prediction and early alerts to prevent outbreaks. The platform also provides fertilizer recommendations based on soil such as nitrogen (N), phosphorus (P), potassium (K) content, and pH levels. Crop recommendations are tailored to the soil's nutrient profile to optimize yield. Farmers receive step-by-step guidelines for safe and effective fertilizer usage to enhance productivity and reduce wastage.The final solution will be accessible through mobile and web-based platforms, empowering farmers to monitor crop health in real-time, reduce operational costs, and make timely interventions. This approach fosters sustainable agriculture by mitigating crop losses, ensuring optimal fertilizer use, and promoting soil health management.

Keywords: RESNET9,Crop Disease Prediction, Fertilizer & Crop Recommendation, Neural Networks, Soil pH, Real-time Crop Monitoring.

1. Introduction

Agriculture is the science and practice of cultivating crops, rearing livestock, and managing natural resources to produce food, fiber, and other essential products that sustain human life. Beyond providing sustenance, agriculture is the backbone of the global economy, contributing significantly to employment and trade. However, despite advancements in farming techniques, crops like Soybean, Tomato, Sugarcane, Wheat, and Rice remain vulnerable to insects, pests, and diseases. If left un managed, these threats can cause severe yield losses, compromising food security and farmer livelihoods. Traditional pest and disease detection methods are time-consuming, labor-intensive, and prone to human error, lacking real-time responsiveness. To address these challenges, this project proposes a deep learning-based (DL) approach for real-time insect detection and crop health monitoring using ResNet9. The goal is to provide farmers with an intelligent, reliable system that enables early pest detection and disease prediction, facilitating timely interventions to reduce crop losses.

The system employs neural networks, specifically ResNet9, for real-time insect detection. Transfer learning is used to fine-tune the model with a diverse data set of insect images, ensuring robustness across species and environmental conditions. This allows the model to accurately classify insects, enabling farmers to take immediate corrective actions. Additionally, machine learning algorithms analyze environmental data and crop attributes such as soil nutrients and weather conditions to predict disease outbreaks and recommend preventive measures. Predictive analytics helps farmers proactively address threats, minimizing yield losses and enhancing productivity.Beyond insect detection, the system provides fertilizer recommendations based on soil properties like Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, humidity, and rainfall, ensuring optimal crop health and yield. Recommendations are tailored to crops such as grains (e.g., rice, maize, wheat), pulses (chickpeas, kidney beans, pigeon peas), and cash crops (cotton, jute, coffee). Fruits like mango, banana, grapes, watermelon, muskmelon, apple, papaya, coconut, and orange are also included, offering comprehensive crop suggestions.

The system uses Gaussian Naive Bayes for fast probabilistic classification, assuming feature independence. Decision Trees provide interpretable models by splitting data based on environmental factors to suggest appropriate crops and fertilizers. XGBoost boosts predictive accuracy by combining weak learners, suitable for large datasets. Support Vector Machines (SVMs) identify optimal hyperplane for non-linear crop classification. Logistic Regression predicts probabilities for multi-class outputs, like crop types. Random Forests aggregate multiple decision trees to enhance accuracy and handle missing data, ensuring robust predictions for crop and disease management.

Performance is evaluated using metrics such as precision,recall,F1 Score ,and Accuracy.Precision measures the correctness of positive predictions by calculating the proportion of correctly predicted positive cases (e.g., recommending the right crop) from all predicted positive cases. Recall measures how effectively the model identifies positive instances, ensuring critical warnings, such as disease alerts, are not missed. F1-score balances precision and recall, particularly useful for imbalanced datasets. Accuracy represents the proportion of correct predictions out of all instances but may be limited with uneven class distributions.

2.LITERATURE SURVEY:

Here we have gathered several journals that have conducted research on our connected work, and we have separately summarized each work as shown below. To date, many authors have proposed various approaches to address these issues, each presenting their own methodologies. In the following chapter, we review existing methodologies and evaluate their effectiveness in addressing these challenges.

The paper presents a personalized Crop and Fertilizer Recommendation System (CFRS) tailored to Rwanda's agricultural landscape. It uses machine learning and data analysis to guide farmers in making informed decisions about crop selection and fertilizer application. The project employs a neural network model trained on key growth parameters, including nitrogen, phosphorus, potassium (NPK) levels, and soil pH, achieving 97% prediction accuracy. Effective data modeling and feature extraction ensure the dataset's quality, which is essential for training the model efficiently.The datasets are compiled from multiple sources, including soil fertility data and crop recommendation datasets. Sophisticated data profiling techniques are used to harmonize the data, ensuring consistency and reliability.The proposed CFRS has the potential to improve crop yield and quality while promoting cost-effective farming practices and reducing environmental impact. However, the study suggests further improvements by incorporating additional environmental and geographical factors in future iterations of the system.This work highlights the importance of data-driven agricultural practices in enhancing productivity and sustainability in Rwanda. [1]

The main objective of the paper is to enhance crop prediction and analysis through the application of machine learning algorithms, aiming to optimize agricultural practices and improve crop yields.The study utilizes various datasets, including those collected from IoT devices, to analyze crop types and their features, focusing on factors like water requirements and harvest methods Techniques employed include supervised machine learning algorithms such as Random Forest, Support Vector Machine, Decision Tree, K-Nearest Neighbor, and Naïve Bayes, which are used to classify and predict crop types.This paper is unique as it introduces a new feature combination scheme-enhanced algorithm, which significantly improves classification accuracy, achieving up to 99.59% with the Bayes Net algorithm .Unlike other studies, this research emphasizes the integration of real-time IoT sensor data, allowing for more informed decision-making in crop management.The findings suggest that the proposed methodologies can help farmers detect diseases early, increase production efficiency, and reduce costs, especially during food shortages.In conclusion, the paper highlights the transformative potential of machine learning in agriculture, advocating for its adoption to create more resilient and sustainable farming practices. [2]

The main objective of the paper is to propose a cloud-based machine learning (ML) platform that assists farmers in making informed decisions about crop selection based on various environmental parameters .The study emphasizes the integration of artificial intelligence (AI) in precision farming, specifically focusing on the ML aspect to enhance agricultural productivity .Techniques used in the research include data preparation, exploratory data analysis, and the application of various classification algorithms such as K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Support Vector Machine (SVM).This paper is unique as it combines a cloud-enabled platform with real-time data processing, allowing farmers to access crop recommendations from anywhere, thus enhancing convenience and accessibility.Unlike other studies, this research focuses on a dataset specifically tailored for Indian agricultural conditions, which may differ significantly from datasets used in other regions, highlighting the need for localized solutions.The best conclusion drawn from the study is that the Random Forest algorithm outperformed other models in terms of performance metrics, making it the most suitable choice for the crop recommendation platform.Overall, the paper contributes to the field of precision farming by providing a scalable, cloud-based solution that can evolve with additional data from various geographic locations, ultimately aiming to improve global agricultural practices.[3]

The paper aims to develop crop recommendation models using machine learning techniques to help farmers select the most suitable crops based on environmental factors. Datasets used include key features such as soil content, pH value, temperature, humidity, and rainfall, which were collected and preprocessed to ensure high-quality input. Feature engineering was applied to enhance the dataset's utility, playing a crucial role in improving the model’s performance. The paper addresses gaps in previous research by providing detailed implementation steps, including data sources and model training processes, which are often missing in earlier studies.This detailed approach ensures that the research aligns with real-world agricultural challenges, making it more applicable. Additionally, the study emphasizes the importance of integrating machine learning into agriculture, focusing on practical needs to support farmers effectively. The crop recommendation models are designed to be scalable and adaptable, allowing them to incorporate new data and perform across different regions. This flexibility makes them suitable for widespread application. The paper’s uniqueness lies in combining advanced machine learning techniques with practical agricultural insights, providing farmers with actionable solutions to enhance productivity. Ultimately, the research aims to promote sustainable crop management, offering both economic and environmental benefits to farmers and improving agricultural practices. [4]

The paper aims to develop a mobile-based system that automates the diagnosis of plant leaf diseases using deep learning techniques, specifically Convolutional Neural Networks (CNN). The goal is to assist farmers in quickly and accuartely identifying diseases in their crops, reducing agricultural losses. The CNN model is trained on a dataset of over 96,000 images of healthy and diseased plant leaves from sources like Kaggle and Plant Village. Data augmentation techniques, including rotations, scaling, and cropping, were applied to enhance the dataset and prevent overfitting.A key feature of the system is its mobile deployment, allowing farmers to diagnose diseases directly in the field through a user-friendly interface. The system also focuses on real-time processing and visualization of agricultural data, making it applicable beyond agriculture, such as in transportation. The model achieves a classification accuracy of 94% across 38 disease classes, demonstrating its effectiveness in crop health management.The paper contributes to the opensource community by making the code and dataset publicly available to foster further advancements. Future work includes expanding the approach for use with UAVs for aerial crop monitoring and improving model accuracy by utilizing larger datasets, especially for rare diseases.This research offers a practical tool for farmers to enhance crop management and reduce lossess.[5]

The primary objective of this paper is to develop a two-stage ensemble deep learning model for the precise detection of leaf abnormalities in Centella asiatica (CAU), which is crucial for maintaining agricultural productivity and quality.The model employs advanced techniques, including U-net, Mask-R-CNN, and DeepNetV3++ for image segmentation in the first stage, followed by robust CNN architectures like ShuffleNetV2, SqueezeNetV2, and MobileNetV3 for classification in the second stage. A unique feature of this study is the integration of a parallel-Variable Neighborhood Strategy Adaptive Search (parallel-VaNSAS) for decision fusion, which enhances the model's performance significantly compared to traditional methods.The dataset used comprises 14,860 images representing eight types of leaf abnormalities, ensuring a comprehensive evaluation of the model's effectiveness.This paper stands out from others by demonstrating a substantial improvement in accuracy through the combination of ensemble segmentation and diverse CNN models, achieving an 8.43% enhancement over homogeneous ensemble models.The findings indicate that the proposed model not only excels in accuracy but also maintains a relatively small size, making it efficient for practical applications in agricultural management. In conclusion, the novel approach presented in this paper promises significant advancements in the early detection of leaf diseases, ultimately contributing to better crop health and productivity in agricultural practices. [6]

The primary objective of the paper is to enhance the identification of leaf diseases and nutrient deficiencies in rice plants, which are critical for improving yield productivity.The study employs a Hybrid Convolutional Neural Network (HCNN) optimized with Improved Tunicate Swarm Optimization (ITSO) to achieve this goal.Two datasets were utilized a field work dataset and a Kaggle dataset, ensuring a comprehensive evaluation of the proposed method across diverse data sources.A unique feature of this paper is the integration of Fuzzy C Means clustering with ITSO, which aids in effectively segmenting lesions on rice leaves.The proposed model achieved impressive performance metrics, with accuracies of 98.8% and 99.01% on the respective datasets, outperforming previous methods.This paper stands out due to its robust validation process and the combination of advanced optimization techniques, which enhances the model's generalizability and effectiveness.In conclusion, the study demonstrates that the HCNN-ITSO model not only accurately classifies leaf diseases and nutrient deficiencies but also provides a scalable solution for agricultural applications, thereby contributing significantly to rice cultivation practices. [7]

The main objective of the paper is to develop a context-aware fertilizer recommendation system that utilizes real-time soil fertility data captured through IoT technology. This aims to enhance precision agriculture by improving fertilizer application efficiency and crop yield. The techniques employed in this study include machine learning models such as Logistic Regression (LR), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), and K-Nearest Neighbor (KNN) to analyze soil fertility data and recommend appropriate fertilizer amounts .A unique feature of this paper is its integration of IoT-assisted soil fertility mapping, which allows for real-time monitoring and assessment of soil nutrient levels, making it more practical for farmers compared to traditional methods that are often costly and time-consuming.The paper stands out from others by focusing on the real-time context of soil fertility, which is often overlooked in existing fertilizer recommendation systems.This real-time approach ensures that recommendations are tailored to current soil conditions, enhancing their effectiveness.The results indicate that the proposed IoT-assisted system provides accurate soil fertility mapping, with mean differences of 0.34 for Nitrogen (N), 0.36 for Phosphorous (P), and -0.13 for Potassium (K) when compared to standard chemical analysis methods.The conclusion emphasizes that the GNB model outperformed other machine learning models, achieving accuracies of 96% and 94% for training and testing datasets, respectively, showcasing the effectiveness of the proposed system.Overall, this paper contributes significantly to the field of precision agriculture by providing a practical, efficient, and accurate method for fertilizer recommendations, ultimately promoting sustainable farming practices.[8]

The main objective of the paper "IoT-Driven Artificial Intelligence Technique for Fertilizer Recommendation Model" is to enhance agricultural productivity by developing a smart farming system that integrates IoT and AI technologies. The paper proposes a four-layer architectural model that includes sensor, network, service, and application layers to facilitate effective fertilizer recommendations based on soil nutrient data.The techniques used involve a deep learning approach, specifically a Bi-LSTM (Bidirectional Long Short-Term Memory) model, which processes input data such as temperature, humidity, nitrogen (N), phosphorus (P), and potassium (K). This unique approach allows for real-time data collection and analysis, enabling farmers to optimize fertilizer usage and improve crop yield.This paper stands out from previous research by fully automating the fertilizer recommendation process through the integration of advanced sensor technology and AI, which was lacking in earlier studies .The proposed mobile application serves as a user-friendly interface for farmers, making it easier to access and implement the recommendations.The conclusion emphasizes that the developed system not only aids in providing precise fertilizer recommendations but also enhances overall agricultural efficiency by reducing reliance on expert advice.The study highlights the potential for future integration of more agricultural sensors to create a comprehensive framework for managing farming activities.Ultimately, this research contributes significantly to the digital transformation of agriculture, promoting sustainable practices and increased productivity.[9]

The primary objective of the paper is to explore the integration of the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) to enhance smart agriculture applications, focusing on improving food production and sustainability.The paper employs various techniques, including real-time data collection through wireless application protocols like ZigBee, WiFi, SigFox, and LoRaWAN, to monitor environmental conditions and optimize agricultural practices.A unique feature of this paper is its comprehensive approach, which not only reviews existing literature but also addresses recent challenges and proposes mitigation strategies for IoT-WSN integration in agriculture.Unlike other studies, this paper emphasizes a future-oriented perspective, discussing the evolution of IoT-WSNs and their potential applications in precision agriculture.The paper also highlights the importance of bibliometric analysis to identify trends and influential studies in the field, providing a structured overview of the research landscape.In conclusion, the study advocates for the adoption of advanced technologies in agriculture, aiming to address food scarcity and improve efficiency in agricultural practices through automation and data-driven decision-making.By synthesizing various research findings and proposing clear recommendations, this paper contributes significantly to the ongoing discourse on smart agriculture, making it a valuable resource for future research.[10]

3.METHODOLOGY:

This study proposes a comprehensive agricultural assistance system composed of three interconnected modules: Crop Recommendation, Fertilizer Recommendation, and Crop Disease Detection. Each module is tailored to address specific challenges faced by farmers, leveraging machine learning and deep learning to provide actionable insights. The methodology for each module is described below.

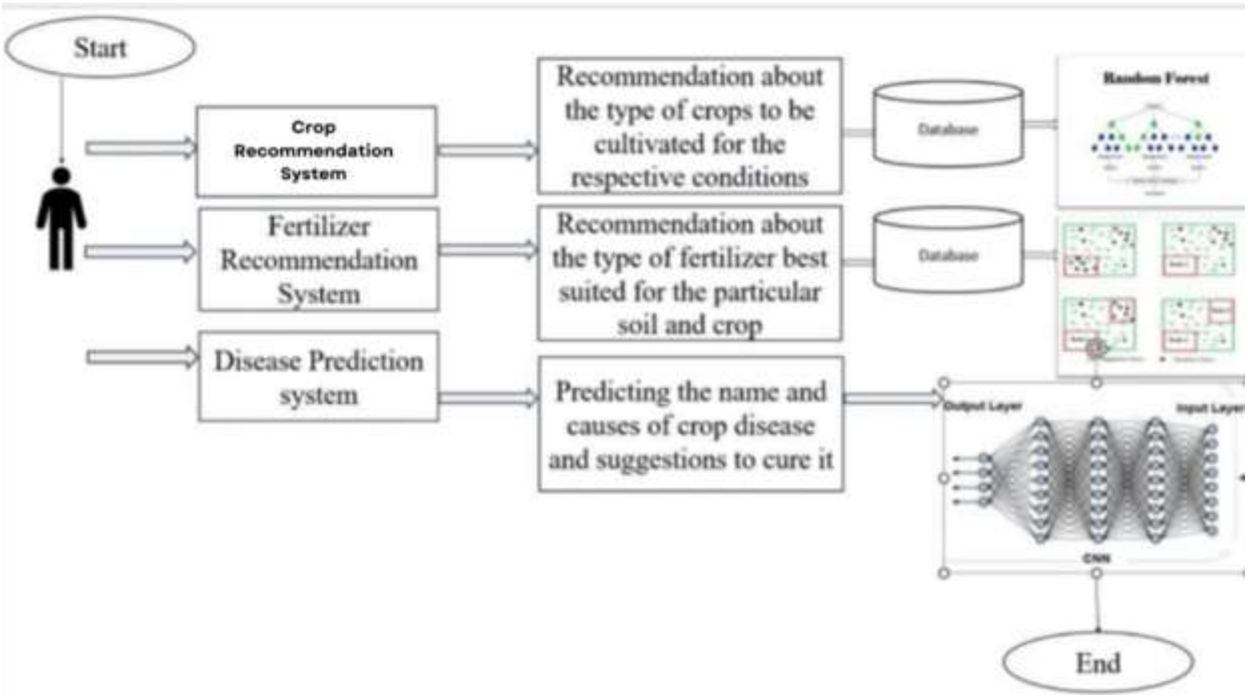


Fig3.1: Architecture of flow diagram

Module 1. Crop Recommendation:

The Crop Recommendation module identifies the most suitable crop to cultivate based on soil composition, environmental factors, and prevailing weather conditions.

Process:

1.Input Data Collection: The system collects essential input parameters such as:

- Soil features: Levels of nitrogen, phosphorus, and potassium (NPK), pH value, and organic matter content.
- Environmental conditions: Local temperature, humidity, and rainfall patterns.

These inputs are either gathered manually by the farmer or through IoT devices such as soil sensors and weather forecasting APIs.

2.Data Preprocessing:

- Raw data from sensors often contain inconsistencies like missing values or noise.To address this, techniques such as median imputation

(for missing values) and outlier removal are applied.

- Numerical attributes are normalized to bring them to a comparable scale, ensuring uniform input for the machine learning model.

3.Model Training and Implementation:

- A supervised machine learning algorithm, such as Random Forest, is employed to classify soil and environmental features into potential

crop categories. Random Forest is selected for its ability to handle complex, non-linear interactions between features.

- The model is trained using a large dataset containing historical agricultural data, which maps soil and climatic conditions to optimal crop types.

The dataset is split into training and testing subsets to validate the model's accuracy.

4.Recommendation System:

When the user provides input data, the model processes the features and predicts the most suitable crop. The system also provides supplementary insights, such as expected yield and specific conditions that enhance crop performance.

Output: The module returns a ranked list of recommended crops, prioritizing the one most compatible with the input conditions.

Module 2. Fertilizer Recommendation:

The Fertilizer Recommendation module ensures that farmers apply the optimal type and quantity of fertilizers to enhance yield and maintain long-term soil health.

Process:

1.Input Data Collection:

- Farmers input the soil test results, particularly the NPK levels, along with details of the selected crop.
- Weather conditions, such as temperature and rainfall forecasts, are also taken into consideration to customize fertilizer suggestions.

2.Logic and Algorithm:

- Rule-based System: The module uses predefined agronomic rules to ensure basic compatibility between soil properties and

fertilizer recommendations. For instance, it avoids fertilizers with high nitrogen levels if the soil already has sufficient nitrogen.

- Machine Learning Integration: A machine learning model trained on historical data refines the recommendations further by considering

crop-specific nutrient demands, seasonal variations, and fertilizer efficiency. Decision Trees or Gradient Boosting algorithms are often used for this purpose due to their interpretability and accuracy.

3.Fertilizer Prescription:

- The system generates fertilizer recommendations, specifying the type (e.g., urea, ammonium phosphate), quantity, and application schedule

(e.g., pre-sowing or post-sowing).

- To promote sustainability, the system suggests alternatives like organic fertilizers and green manures where possible.

Output: A detailed fertilizer plan tailored to the selected crop and soil conditions, with step-by-step application guidance.

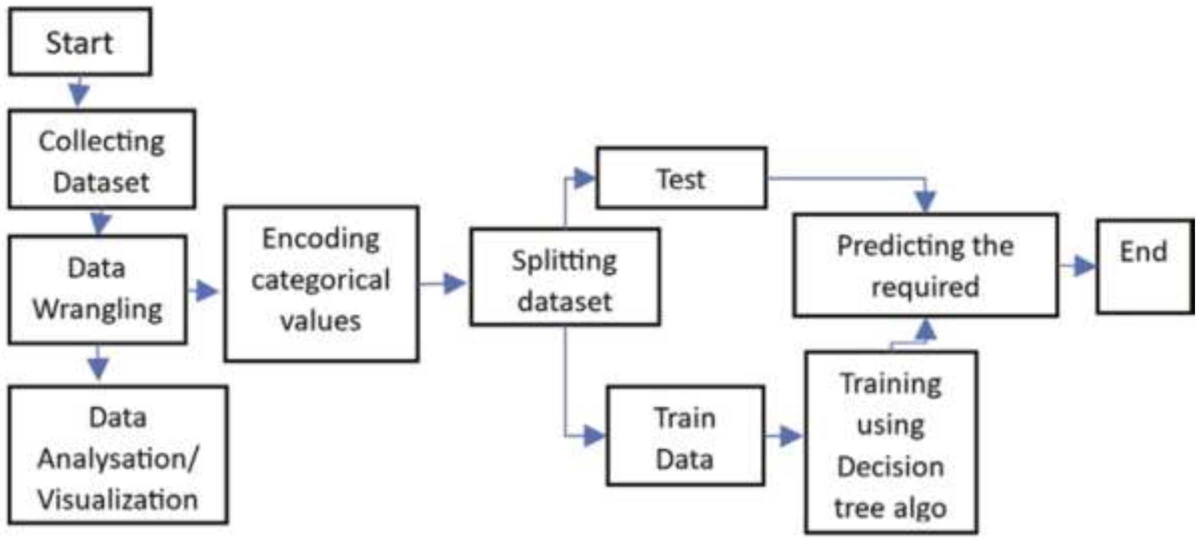


Fig3.2: Fertilizer recommendation System

Module 3. Crop Disease Detection:

The Crop Disease Detection module identifies plant diseases from leaf images and provides remedial measures to minimize crop losses.

Process:

1.Dataset Preparation:

- A curated dataset of leaf images is collected, containing multiple classes of healthy and diseased leaves across various crops. The dataset includes diseases like Powdery Mildew, Bacterial Spot, and Early Blight.

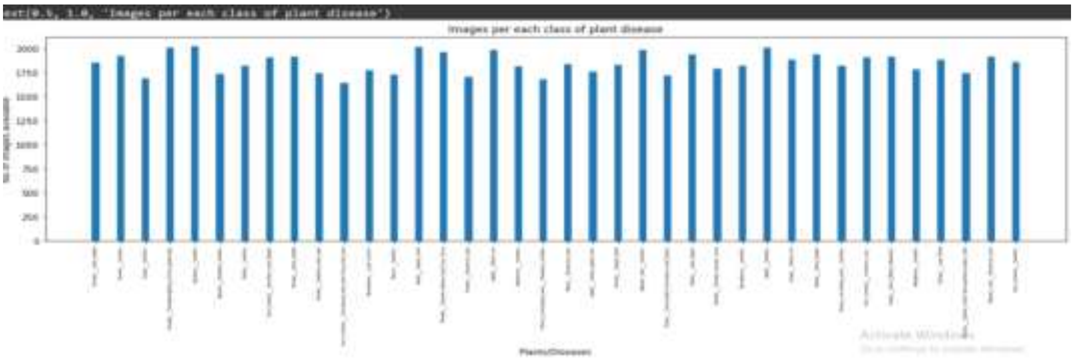


Fig3.3: Number of Images for a particular a particular Plant.

Preprocessing techniques are applied to the images:

- Re-sizing**:** Ensures uniform input dimensions for the model.
- Data Augmentation: Includes transformations like flipping, rotation, and brightness adjustments to improve the model's ability to generalize to unseen data.
- Normalization: Ensures pixel values are scaled for faster convergence during training.

2.Deep Learning Model Design:

- The ResNet-9 architecture is implemented for disease classification. This convolutional neural network (CNN) uses residual connections to enhance the flow of gradients, preventing vanishing gradient issues in deep networks.
- The model comprises multiple convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and fully connected layers for classification. Residual blocks improve efficiency by allowing skip connections, which enable layers to learn identity mappings.
- The output layer of the model maps the extracted features to specific disease classes.

3.Inference and Recommendations:

- When a farmer uploads an image of an affected plant leaf, the model analyzes it and predicts the corresponding disease class.
- Based on the disease classification, the system provides farmers with tailored remedies and preventive measures, such as the application of specific fungicides, maintaining proper plant spacing, and crop rotation practices.

Output: A diagnosis of the crop disease along with actionable treatment and prevention strategies to mitigate its spread.

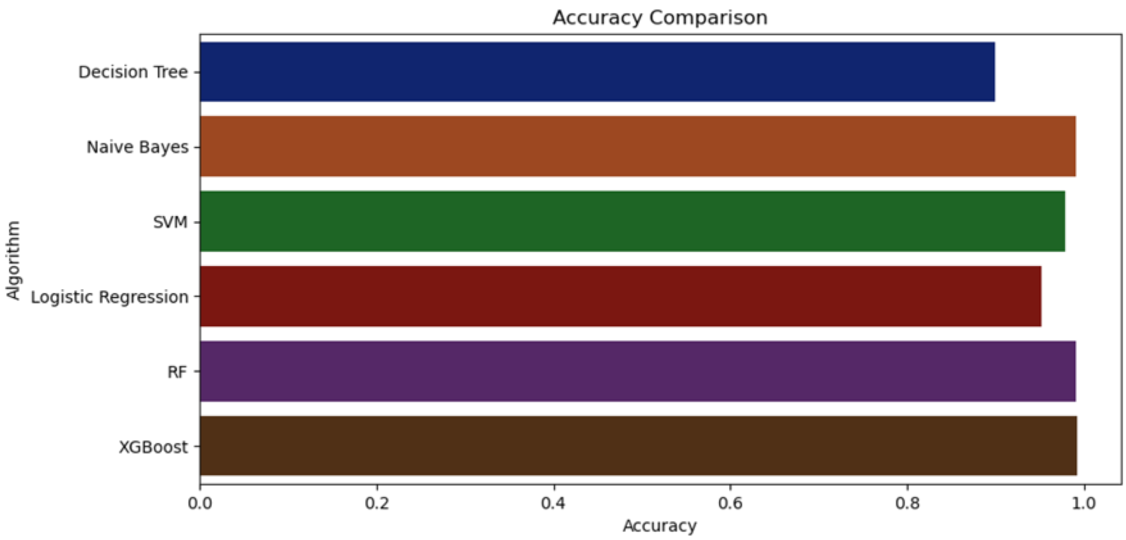


Fig3.4:all models accuracy

Integrated Approach

These three modules are integrated into a single platform to provide a holistic solution for farmers. The Crop Recommendation and Fertilizer Recommendation modules assist in pre-sowing decisions, while the Crop Disease Detection module ensures timely intervention during crop growth. Together, they empower farmers with data-driven insights, enhancing agricultural productivity and sustainability.

4.RESULTS:

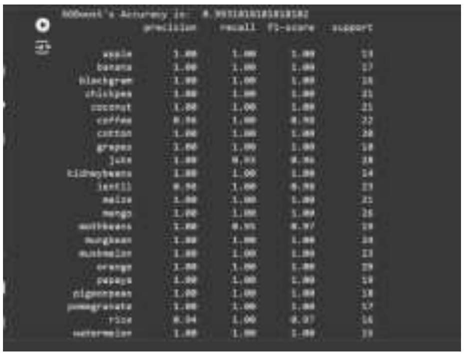
Crop Disease Detection: we have tested several approaches like random forest,logistic regression etc based on tested results XG Boost showcased the higher accuracy of 99.3% the following image shows the metrics for each plant variety tested.

Accuracy Assessment:

Metrics: Accuracy, precision, recall, F1-score.

Strengths: High accuracy, efficient with complex data, handles large datasets well.

Limitations: Computationally intensive and may require parameter tuning for optimal performance.



XGBoost's Accuracy is: 0.9931818181818182

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	1.00	1.00	1.00	16
chickpea	1.00	1.00	1.00	21
coconut	1.00	1.00	1.00	21
coffee	0.96	1.00	0.98	22
cotton	1.00	1.00	1.00	20
grapes	1.00	1.00	1.00	18
jute	1.00	0.93	0.96	28
kidneybeans	1.00	1.00	1.00	14
lentil	0.96	1.00	0.98	23
maize	1.00	1.00	1.00	21
mango	1.00	1.00	1.00	26
mothbeans	1.00	0.95	0.97	19
mungbean	1.00	1.00	1.00	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	1.00	1.00	19
pigeonpeas	1.00	1.00	1.00	18
pomegranate	1.00	1.00	1.00	17
rice	0.94	1.00	0.97	16
watermelon	1.00	1.00	1.00	15

Fig3.5:XG boost accuracy

Visualizing The Graphs Of Resnet-9 Model:

It includes following :

1.Accuracy vs. Epochs

2.Loss vs. Epochs

3.Learning Rate vs. Batch Number

The generated plots provide insights into the training process for the crop disease prediction model:

Accuracy vs. Epochs: This graph shows a steady increase in validation accuracy over the epochs, indicating that the model's performance on the validation set is improving with each epoch.

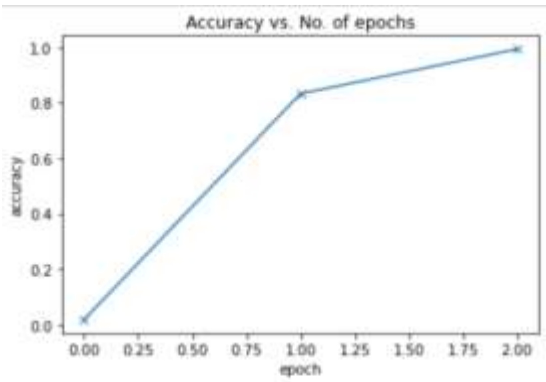


Fig3.6 : Validation Accuracy

Loss vs. Epochs: The training and validation loss curves both show a consistent decrease over the epochs. This trend suggests that the model is learning effectively, with training and validation losses reducing as the epochs progress.

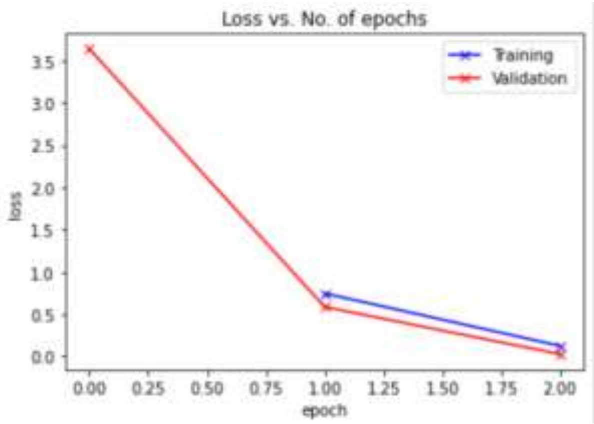


Fig3.7 :Validation loss

The smaller gap between the training and validation losses indicates limited overfitting.

Learning Rate vs. Batch Number: This plot shows the learning rate schedule over the batches in each epoch, following a decreasing trend. This reflects the use of a one-cycle learning rate policy, which starts with a high learning rate and gradually reduces it to help the model converge.

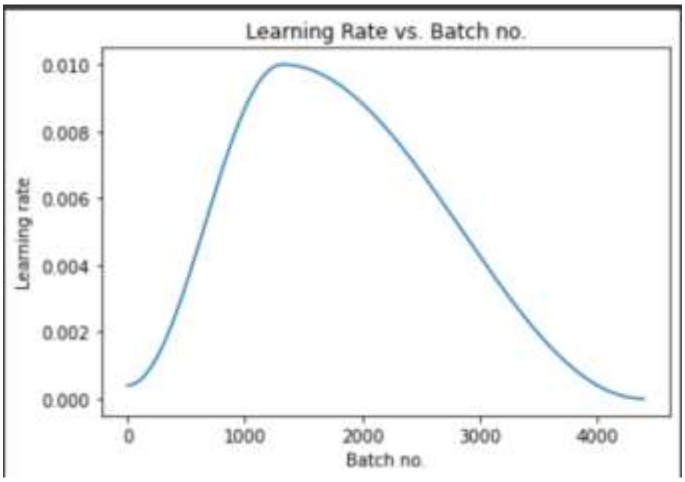


Fig3.8 :Validation Rate Overtime

5.CONCLUSION:

The integration of crop recommendation and disease prediction into a single web-based platform marks a significant step forward in the application of technology in agriculture. By merging raw crop data, fertilizer information, and advanced image-based disease detection powered by Res-Net, this solution addresses critical challenges faced by modern farmers.

The crop recommendation system, driven by soil analysis, environmental data, and fertilizer requirements, empowers farmers to select the most suitable crops for their fields. This ensures optimized resource utilization, improved yields, and long-term soil health management. Meanwhile, the disease prediction system, leveraging the capabilities of Res-Net, offers rapid and accurate diagnosis of crop diseases. Early detection enables farmers to take timely action, reducing crop losses and minimizing the use of harmful pesticides.

The web application serves as a unified platform, providing an intuitive interface where farmers can input data and receive actionable insights. By seamlessly combining these tools, the application simplifies decision-making and makes precision agriculture accessible to a broader audience.

Key Benefits:

Improved Productivity: Farmers can maximize yields through data-driven crop selection and early disease management.

Sustainability: The system encourages the judicious use of fertilizers and pesticides, promoting environmentally responsible farming.

Cost-Effectiveness: Reduced crop losses and optimized resource use lower overall farming costs.

Scalability and Accessibility: The web-based design makes the solution accessible to farmers worldwide, enabling widespread adoption of advanced agricultural practices.This innovative approach showcases how technology can transform agriculture, addressing the dual challenges of increasing food demand and environmental sustainability. As this system evolves, incorporating more data sources and advanced models, it has the potential to revolutionize the way farming decisions are made, ensuring a more sustainable and food-secure future.

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