AgroAI: Smart Crop Protection for Indian Farmers

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Abstract. In India's vital agricultural sector, where crop yield growth and agroindustry products are paramount. The aim is to develop a transformative application, the innovative app enables farmers to combat plant diseases and crop infestations by making informed decisions recommended by our system. The app harnesses image recognition technology, allowing users to capture and submit photos of crops in real-time. These images are processed by a model capable of identifying the specific disease or pest affecting the crops. Once the issue is identified, the app seamlessly integrates it with a recommendation system, by using a new dataset for crop identification and self-developed recommendation dataset we aim to provide tailored suggestions for fungicides or pesticides, considering the identified problem, crop type, and local environmental conditions, it combines image recognition and a recommendation system and empowers farmers with actionable insights, enabling them to protect their crops as well as educate them on ways to tackle crop diseases, this not only reduces crop losses but also enhances overall agricultural productivity, contributing to increased farmer income. A multi-stage approach was employed by utilizing a RESNET-50 architecture for plant disease identification. A newly published crop pests/disease dataset sourced from local farms in Ghana was used for training, comprising images of cashew, cassava, maize, and tomato plants. The model demonstrated high accuracy in classifying crop types, with training accuracies ranging from 94% to 98% and validation accuracies ranging from 84% to 94%. The recommendation phase of the model provided practical guidance on addressing and managing identified plant diseases effectively, considering factors such as disease severity and environmental impact. The comprehensive analysis ensured precise disease identification and pesticide recommendation, benefiting both agricultural experts and enthusiasts. The mission is to equip farmers with the tools they need to make informed decisions and optimize crop management practices.

Keywords: Agriculture, Crop yield, pest recommendation, fertilizers, deep learning, RESNET

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1 Introduction

In India, ensuring food security is of utmost importance due to the country's high population density and the unpredictable nature of its climatic conditions. Indian farmers face significant challenges related to crop diseases and pest infestations, which can have detrimental effects on agricultural productivity. Moreover, the type of soil and the availability of water resources play crucial roles in determining crop yields. To address these challenges and assist farmers in making informed decisions, an application has been developed that leverages a dataset that hasn’t been used before for identifying crops via images. These images are subsequently processed through an advanced model such as RESNET-50, allowing for precise identification of the specific disease or pest issue affecting the crops. Identification and Recommendations: The application goes beyond mere identification. Once a crop health issue is identified, the output seamlessly integrates with a recommendation system that employs an algorithm which provides tailored suggestions for the most appropriate fungicides or pesticides to effectively combat the identified problem. Recommendations are customized based on factors such as the type of disease or pest, the crop variety, and local environmental conditions. By combining image recognition technology with Algorithm-driven recommendations, the app empowers farmers to make informed decisions, thereby enabling them to protect their crops efficiently. This not only reduces crop losses but also enhances overall agricultural productivity, ultimately contributing to increased food security.

2 Literature Review

Tawsifur Rahman et al.[1], in their paper titled "Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques, they proposed the effectiveness of various CNN architectures which is determined for a variety of classification tasks, including binary classification (healthy vs. diseased leaves), multi- class classification (healthy vs. distinct subgroups of sick leaves), and ten-class classification (healthy vs. different categories of unhealthy leaves). In particular, the updated U-net segmentation model segments leaf pictures with impressive accuracy, IoU, and Dice scores of 98.66%, 98.5%, and 98.73%, respectively.

Palaniraj et al.[2] in their paper titled” Crop and Fertilizer Recommendation System using Machine Learning”, they proposed Crop and Fertilizer Recommendation System . It empowers farmers with precise recommendations for suitable crops and optimal fertilizer applications, leading it to increased crop yield and profitability. The paper leverages historical and real-time data, optimizes resource utilization, mitigates environmental impact and promotes sustainable farming practices. It employs a comprehensive range of machine learning models to achieve accurate crop and fertilizer recommendations. Decision trees, support vector machines, and neural networks are harnessed to predict crop yield based on factors such as soil composition, weather patterns, and historical data. Additionally, clustering techniques are employed to segment land regions and tailored recommendations to specific agro-climatic zones. The Support Vector Machine used in this project gives the accuracy over 90.01%.

Prajakta Prashant et al.[3] in their paper titled " Improved Crop Yield prediction Using Neural Network" explored the application of data mining in agriculture, aiming to develop a system that assists farmers in choosing suitable crops using various parameters. Data mining is introduced as a technology for extracting meaningful patterns from databases. It's highlighted how data mining is gaining importance in agriculture research, aiding in tasks like wine fermentation prediction, mushroom sorting, rainfall forecasting, and humidity prediction.

Dr.Prof. Deepali et al.[4] in their paper titled "Intelligent Crop and Pesticide Recommendation Portal using ML and AI", introduces a proposed methodology encompasses two primary modules: crop recommendation and pesticide recommendation. Crop recommendation includes user-input soil characteristics and environmental conditions, including temperature, humidity, and rainfall. A voting classifier model is trained using various machine learning algorithms such as SVC, SVM, Random Forest, GNB, and KNN. These model processes the input data to suggest appropriate crops that align with the given parameters. The pesticide recommendation module involves image analysis. Users upload images of pests found on their crops, which are processed using a Convolutional Neural Network (CNN). The CNN model identifies the pest and recommends suitable pesticides based on the pest's classification. Additionally, the model employs both machine learning and image analysis techniques, enhancing its versatility and accuracy across different scenarios and user requirements.

Krupa Patel et al.[5] , in their paper titled "Multi-criteria Agriculture Recommendation System using Machine Learning for Crop and Fertilizers Prediction", AgriRec algorithm is a machine learning-based recommendation system that automates crop selection and fertilizer recommendations. The algorithm encompasses two phases: the Multi-Criteria Crop Recommendation System (multi-criteria CRS) and the Fertilizer Recommendation System (FRS). Multi-criteria CRS employs parameters like soil type, properties, land area, water level, and minimum support price to suggest crops for autumn and spring seasons. FRS recommends fertilizer combinations and proportions based on crop and soil quality, enhancing resource efficiency. AgriRec emerges as a promising solution to revolutionize agriculture by harnessing the power of machine learning.

Md et al.[6] in their paper titled "IoT Based Smart Soil Fertilizer Monitoring And ML Based Crop Recommendation System", they introduced an innovative solution for improving agricultural yield by addressing the challenges faced by farmers in measuring soil nutrients and selecting the right amount of fertilizers. The proposed system utilizes IoT-based soil nutrient monitoring, deploying various sensors to continuously collect data on soil nutrients from the farm field and transmit it to a cloud database. Machine learning algorithms are employed to analyze the collected data and recommend the types of crops that have the best production potential for the specific land, based on soil and weather attributes. It aims to provide farmers with crop-related details and recommendations based on different soil and weather attributes, ultimately leading to improved agricultural production.

Thendral et al.[7] in their paper titled" Crop And Fertilizer Recommendation to Improve Crop Yield using Deep Learning" they focused on the development of crop and fertilizer recommendations using deep learning algorithms to improve agricultural production and meet the global food demand. The goal is to assist farmers in increasing crop yields by providing suggestions for crops and fertilizers based on input data such as crop yields, soil properties, and fertilizer consumption. The deep learning model is created using methods like CNNs, RNNs, or LSTM networks, and its accuracy is tested to improve outcomes over time. The use of deep learning in crop and fertilizer recommendations can enhance agricultural sustainability and contribute to meeting the global demand for food. The accuracy of the model is tested to improve outcomes over time. Collaborations with agricultural experts and organizations can be pursued to gather more diverse and extensive datasets for training the deep learning models.

3 Proposed Methodology

Methodology for the plant disease identification involves a multi-stage approach, utilizing a RESNET-50 architecture (Fig.1) and specialized disease detection models for different plant categories. Here's a detailed explanation of the methodology:

3.1 Dataset Description

The work presents a newly published crop pests/disease datasets sourced from local farms in Ghana [8]. The dataset is presented in images which consists of 24,881 images (6,549-Cashew, 7,508-Cassava, 5,389-Maize, and 5,435-Tomato) having 21 classes. For the first phase of classification, the dataset is combined in 4 folders based on the crop name irrespective of the diseases. This part-1 dataset is used for training of crop identification model. The part-2 dataset consists of crop-disease wise segmented folders for each crop.

Figure 1 shows sample images of plants in the dataset, illustrating visual characteristics for plant classification.

Fig 1. Sample dataset images of plants

3.2 Model Description

ResNet-50 is a deep neural network architecture designed for image recognition tasks. It's part of the ResNet family, known for its use of residual learning, which introduces shortcut connections to facilitate the training of very deep networks. ResNet-50 consists of 50 layers, utilizing residual blocks with a bottleneck structure. These blocks incorporate 1x1 and 3x3 convolutions, and shortcut connections pass the original input to deeper layers, aiding in training. The network employs global average pooling to reduce spatial dimensions and ends with a fully connected layer for classification as shown in Fig 2. ResNet-50 has been successful in various computer vision applications due to its ability to effectively train deep models.

Figure 2 depicts the architecture of the ResNet-50 model, illustrating the structure and flow of data through different layers or components, typically used for machine learning or neural networks.

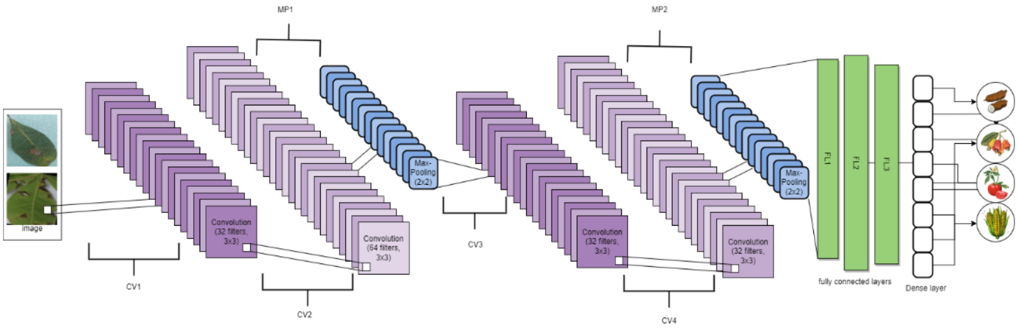


Fig 2. Model Architecture

3.3 Initial Plant Classification

The first phase of the model pipeline involves the initial plant classification, where the provided image is classified into one of the four plant categories. This phase determines the type of plant depicted in the image using a RESNET-50 architecture(Fig 2).

3.4 Disease Detection Phase

After the initial plant classification, the first model passes the output to the next phase model based on the crop type. This phase utilizes the distinctive characteristics of each plant type to accurately identify and diagnose potential diseases. The goal is to reduce the bias and inaccuracy in classification by developing specialized disease detection models for each crop type as shown in Fig 3.

3.5 Recommendation Phase:

In this phase, once a disease is accurately identified in the previous Disease Detection Phase, the model proceeds to recommend suitable pesticides or treatments for the detected disease. The recommendations are based on the disease type and the specific plant category.

Different diseases may require different treatments, and these are tailored to the identified plant type. The recommendations system was custom developed based on the diseases in our dataset which aims to provide users with actionable steps to effectively manage and mitigate the identified diseases in their crops. The choice of pesticides or treatments takes into consideration factors such as the severity of the disease, local regulations, and environmental impact.

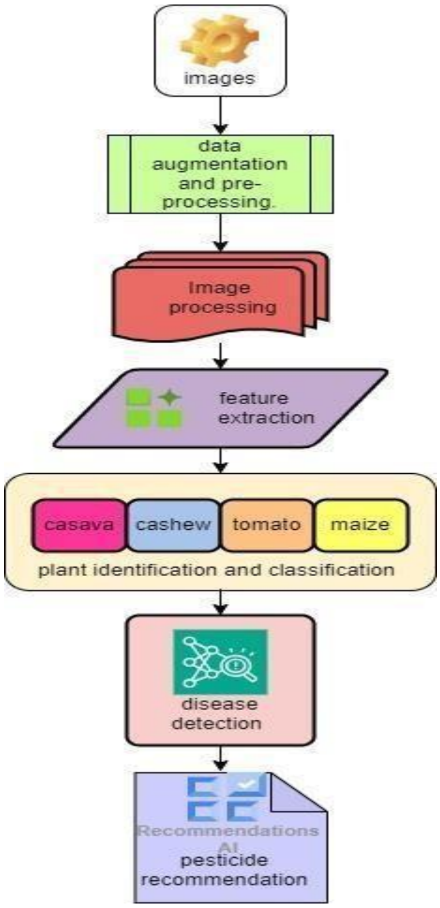


Fig 3. Flow chart of the process

3.6 Comprehensive Analysis:

The multi-stage approach ensures a comprehensive and precise analysis of the plant's condition and pesticide recommendation. This approach offers valuable insights into plant health, aiding both experts and enthusiasts in agriculture and plant health management.

The methodology is designed to improve the accuracy and efficiency of plant disease identification by customizing disease detection models for specific plant categories.

The Recommendation Phase enhances the utility of the plant disease identification system by not only diagnosing diseases accurately but also providing practical guidance on how to address and manage the identified plant diseases effectively. It helps users, whether they are agricultural experts or enthusiasts, take informed actions to protect their crops and maintain plant health.

4 Experiments and Results

The following are precision, recall, F1 score, accuracy and loss of testing, training, validation for cashew, maize and tomato plants with its overall model confusion matrix presented below in figures 4 to 11. Each model was trained on 10 epochs using a RESNET-50 model. Apart from this a RESNET-50 model with 10 epochs was also trained on the entire dataset with 21 classes as shown in fig 8.

4.1 Final results

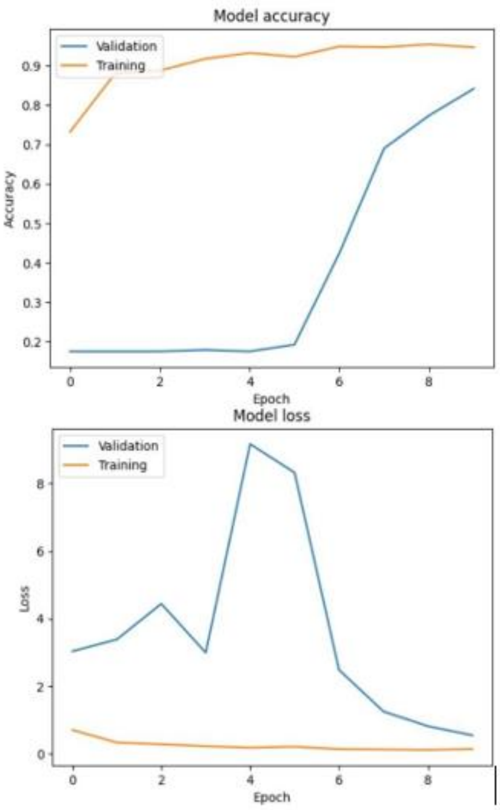
The RESNET-50 model demonstrated high accuracy in classifying crop types, with training accuracies ranging from 94% to 98% and validation accuracies ranging from 84% to 94%. Additionally, specialized disease detection models for each crop type showed promising results, significantly outperforming traditional approaches that trained models on the entire dataset. This two-step approach led to improved precision, recall, F1 score, and accuracy metrics, as evidenced by the confusion matrices in Fig 6.

Table 1 displays the performance metrics of ResNetmodel, providing a comparison of their effectiveness in classifying crop types.

Table 1. Metrics of special models

Plant Name	**Training Accuracy**	**Validation Accuracy**	**Training Loss**	**Validation Loss**
Cassava	98%	94%	0.04	0.21
Maize	94%	85%	0.13	0.94
Tomato	97%	84%	0.06	0.81
Cashew	98%	93%	0.02	0.30

4.2 Metrics Results



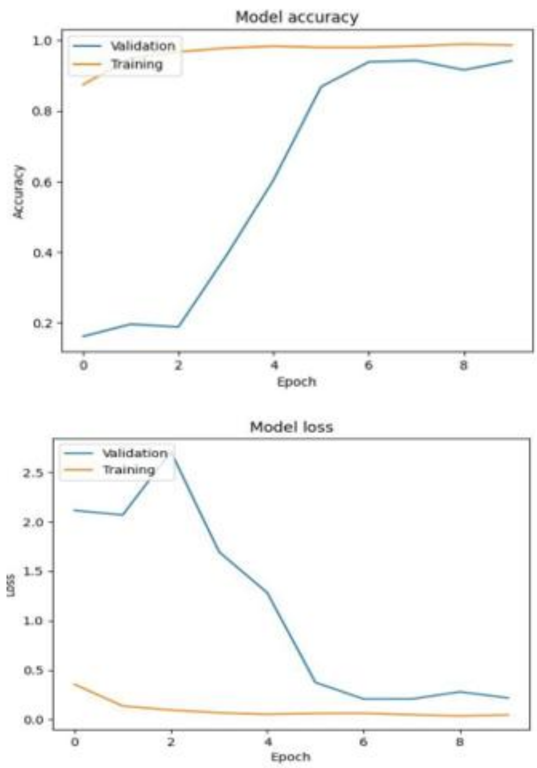


Fig 4. Metrics for cassava plant

Fig 5. Metrics for maize plant

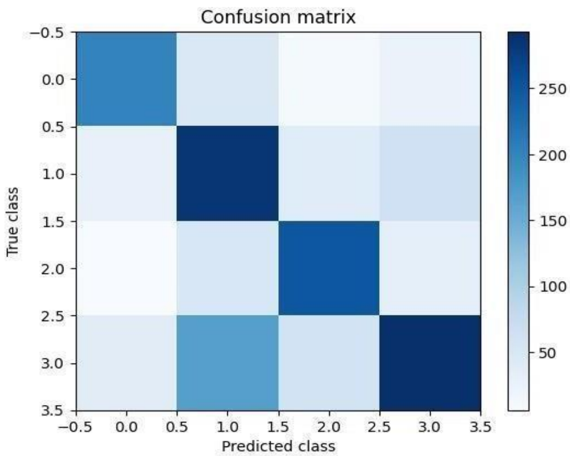


Fig 6. Metrics for crop prediction model

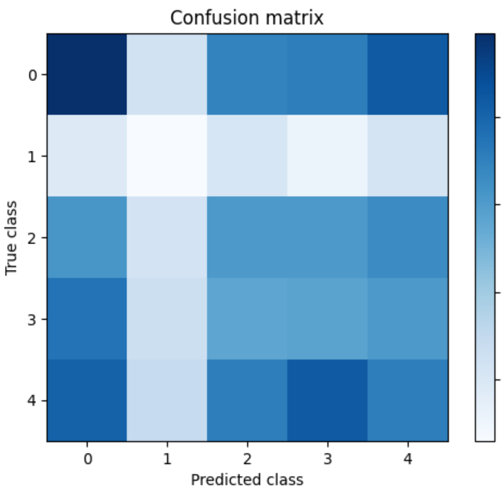


Fig 7. Confusion matrix for cashew model on test data

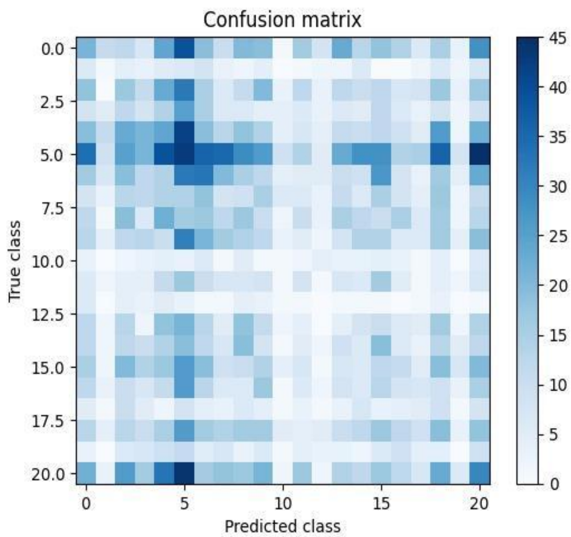


Fig 8. Confusion matrix with 21 classess

Figure 7 shows the confusion matrix for a cashew model on test data, indicating the model's performance in classifying cashew-related categories.

Figure 8 displays a confusion matrix with 21 classes on test data, representing the model's classification accuracy across crop types.

From the above results, the proposed two step approach to provide disease classification significantly outperforms the traditional approach to prepare model on entire dataset. By breaking down the models to first predict the specific crop and then using specialized models trained on diseases of that crop only to predict the disease significantly improves the prediction capabilities of the system. The models approached high accuracy metrics only with 10 epochs of training.

5. Conclusion

In this study, a recommendation system was developed for agricultural purposes, with a specific focus on the classification of crop types and the associated diseases. Utilizing a ResNet-50 model, input images were effectively classified into four distinct categories: maize, tomato, cashew, and their corresponding diseases. Specialized models were then employed for disease detection within each crop category. Consequently, a comprehensive recommendation system was created to provide practical steps for addressing the identified crop diseases.

The results of the study illustrate the effectiveness of the proposed approach in accurately classifying crop types and detecting diseases. This, in turn, leads to tailored recommendations for addressing specific agricultural challenges. The study achieved significant accuracy and efficiency in the identification and management of crop diseases, thereby contributing to the enhancement of crop management practices and overall agricultural productivity.

While the current recommendation system for crop management has shown promise, there exist several opportunities for further enhancement. These opportunities encompass the incorporation of diverse datasets to enhance the model's robustness, Inclusion of advanced models for disease prediction can significantly boost the capabilities of the approach.

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