

Mobile Application for Predicting Diseases with Providing Remedies on Guava Plant Leaves with The Help of Deep Learning Techniques and Cloud Computing

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Abstract: *Guava plants are vulnerable to various diseases that can significantly impact their growth and yield. Early detection and treatment of these diseases are critical to prevent their spread and ensure healthy plants. In this study, we propose a mobile application for disease prediction and remedies for guava plant leaves using deep learning techniques and cloud computing. The application takes an image of the guava plant leaves as input from the end-user, which is encoded into base64 and sent to the server. The image is decoded on the server, processed using our trained deep learning model, and the disease name and accuracy are sent back to the end-user. Based on the disease and accuracy, the mobile application provides remedies to the user to prevent the guava plant from this disease. Our experimental results show that the proposed system achieves an accuracy of around 95% in disease prediction on provided testing dataset. The proposed system has the potential to help farmers and growers detect diseases early, leading to improved plant health and higher yields.*

Keywords: Agriculture, Guava disease, Machine learning, Deep Learning, Environment, Mobile Application, CNN.

I. INTRODUCTION

Plants are crucial to the food chain as they provide food for humans and other species. However, plant diseases are increasing rapidly, resulting in poor food quality and significant losses for farmers and communities. Identifying and controlling the spread of plant diseases is a major challenge, and guava plants in particular can experience losses of up to 15.88%. To address this, we propose a system using deep learning to recognize diseases on infected guava plant leaves and provide possible remedies. The system will be implemented as a mobile application using the Flutter framework, which allows for cross-platform development from a single codebase.

II. LITERATURE SURVEY

Crop disease recognition using deep learning techniques is an active research area. The literature survey of the research paper highlights some of the key findings in this field. [1] A pre-trained ResNet50 model integrated with a custom model can be used to recognize crop diseases. However, a shallow deep learning model with very few layers may produce better results than a large pre-trained model. [2] Adding laboratory images to a field image dataset can improve the accuracy of crop disease recognition, particularly when using the Densenet121 architecture. [3] The transfer learning method can reduce overfitting in deep learning models and is useful for transferring knowledge from general large datasets to professional fields with limited data. Selection of hyper-parameters such as the learning rate and optimizer is critical to obtain better results. [4] In cases where datasets have very few images, it can be useful to create synthetic images through deep convolutional generative adversarial networks (DCGAN). [5] Mobile technology can help with early disease detection, although datasets with very few images can present a challenge for the transfer learning method. Overall, the literature survey provides valuable insights into the different techniques and approaches that can be used to recognize crop diseases using deep learning methods.

III. METHODOLOGY

- [1] Data Collection: Collect a large dataset of images of guava plant leaves, with a focus on the various diseases that affect the plant mostly.
- [2] Data Pre-processing: Pre-process the dataset by resizing images to a uniform size, normalizing the pixel values, and splitting the dataset into training and testing sets.
- [3] Model Selection: Experiment with various deep learning architectures such as VGG, ResNet, and DenseNet, and select the one with the best performance on the testing set. A custom model is selected for training purposes.

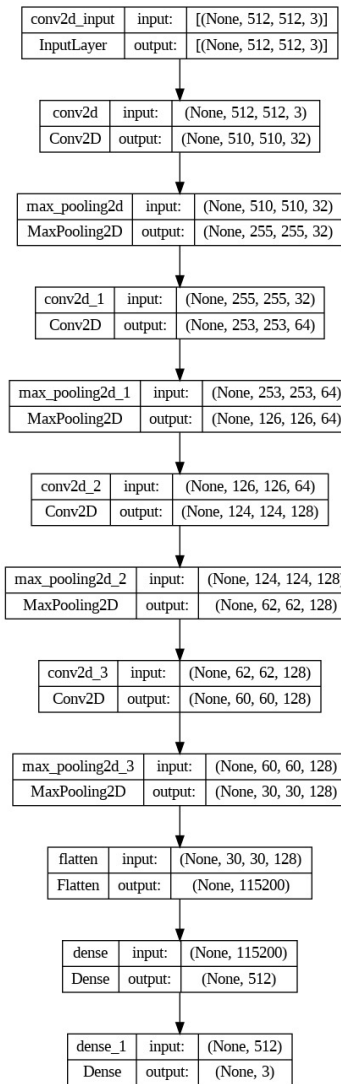


Figure 1: Model Architecture Diagram

- [4] Model Training: Train the selected model on the training set using techniques such as data augmentation, dropout regularization, and learning rate scheduling. Google Colab is used for all training needs of model.
- [5] Model Evaluation: Evaluate the trained model on the testing set using evaluation metrics such as accuracy, precision, recall, and F1-score.

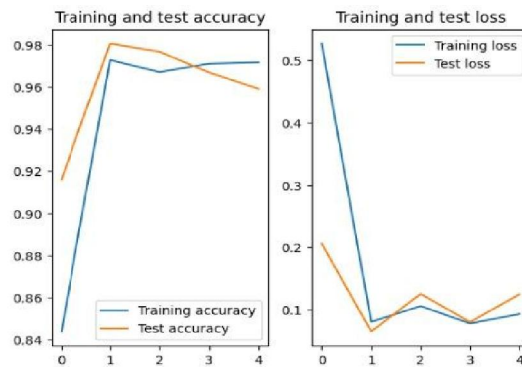


Figure 2: Training – Test accuracy & loss

[6] Hyperparameter Tuning: Experiment with various hyperparameters such as learning rate, batch size, and optimizer, and select the combination that yields the best performance on the testing set.

[7] Deployment: Deploy the trained model on a server, and provide an API that accepts images of guava plant leaves and returns the predicted disease.

[8] Integration with Mobile App: Integrate the deployed model with the mobile app by sending images to the API and displaying the predicted disease and its symptoms to the user.

[9] User Feedback and Improvement: Gather user feedback on the accuracy and usability of the app, and use it to further improve the model and the app.

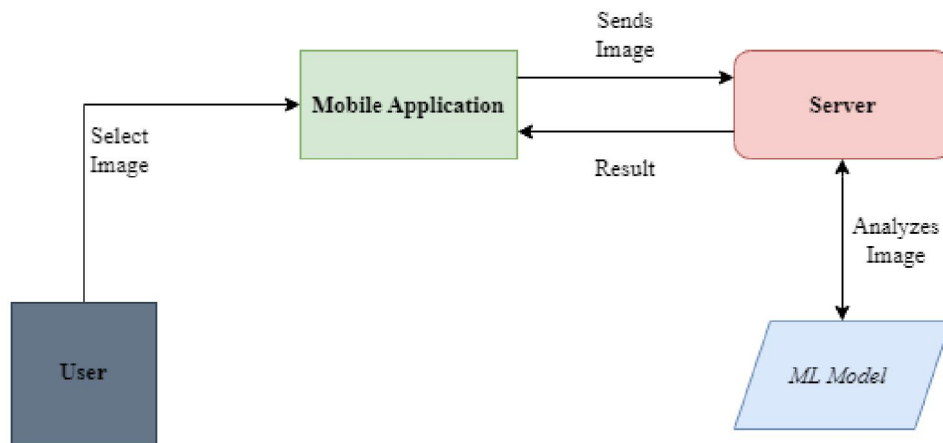


Figure 3: Data flow diagram

III. DATASET DESCRIPTION

In our study, we have utilized a combination of the Plant Village dataset and additional data collected from the internet to train custom models for the purpose of predicting diseases in guava plant leaves. The dataset has been meticulously organized to cater to the specific classes required for this study.

No.	Class	No of training images	No of validation images
1	Red Rust	923	231
2	Mummification	165	110
3	Healthy	700	176

Table 1: Dataset Description

IV. MOBILE APPLICATION

First, the user uploads or captures a guava plant leaf image using the mobile application. The image is then sent to the server using base64 encoding as a string. At the server end, the image is regenerated using base64 decoding so that the trained model can recognize the disease or class of the uploaded image.

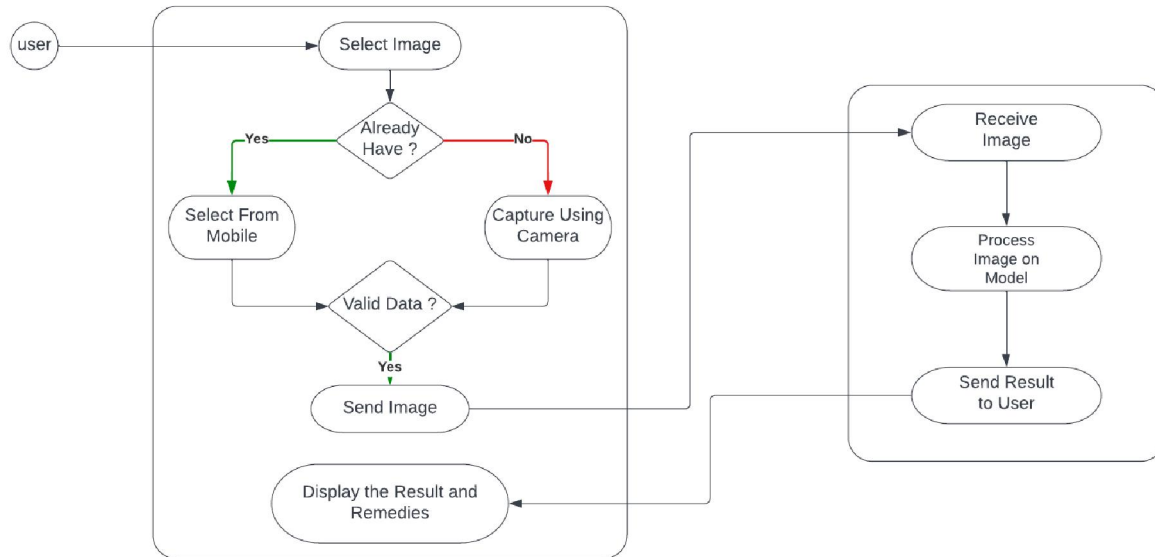
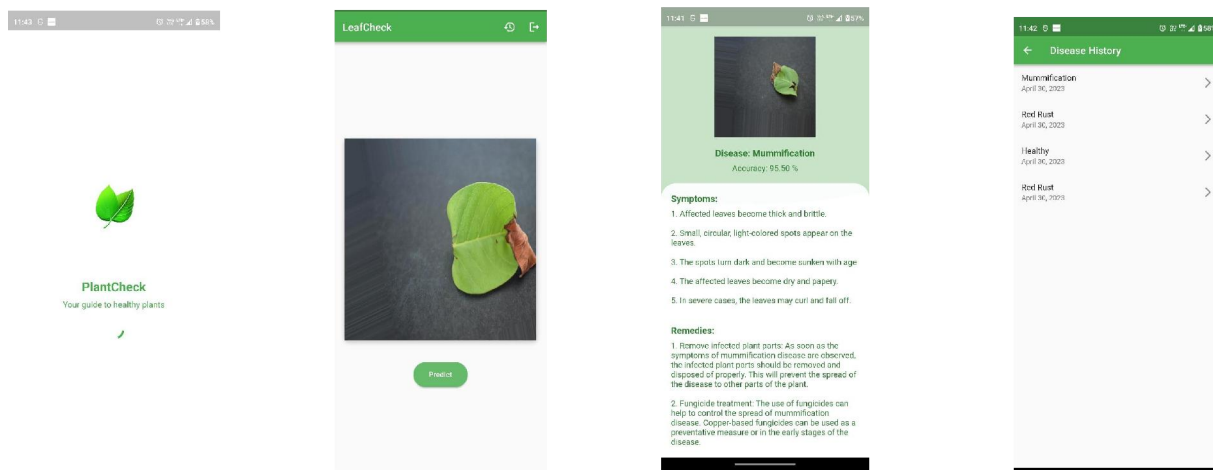


Figure 4: User flow in mobile application

Once the model recognizes the disease or class, it sends back the class name to the application. The application then provides the user with information about the symptoms and diagnosis of the predicted disease, which can help them cure the disease.

Overall, this process provides a user-friendly and efficient way for guava plant growers to diagnose and treat diseases in their crops. By utilizing modern technology and machine learning algorithms, your application can help increase crop yields and reduce waste caused by disease-infected plants.

User interface for the application is given below :



V. MATHEMATICAL MODEL

Let S be the entire system, which comprises the following components:

$$S = \{IP, Proc, OP\}$$

Where, IP represents the input to the system,

Proc represents the procedures applied to the input, and

OP represents the output generated by the system after processing the input.

A) Input:

$$IP = I.$$

Where, I represents the image of the leaf.

B) Process:

Proc involves the following steps:

1. Upload the input to the server.
2. Process the image file
3. Predict the names of diseases

C) Output:

$$OP = y, D.$$

Where, y represents the predicted disease name,

D represents the accuracy score.

VI. CONCLUSION

The present study has aimed to address the challenge of plant disease detection and provide remedies for guava plants using deep learning models. The traditional methods of plant disease detection are often subjective and prone to human errors, which can lead to unnecessary pesticide application, increased cost, and environmental pollution. With the proposed mobile application, farmers and gardeners can easily and accurately detect the diseases on guava plants by simply taking a photo of the affected leaves. The deep learning models, trained on a large dataset of guava leaf images, can recognize and diagnose the diseases with high accuracy, thus helping farmers to decide on the specific quantity of pesticide application required. Furthermore, the mobile application also provides suggestions for remedies to prevent the spread of the disease, which is essential in reducing crop loss and maintaining the quality of the food supply chain. The proposed solution offers a simple and effective method for guava plant disease recognition and provides an important contribution towards sustainable agriculture and food security.

VII. FUTURE WORK

The proposed method for plant disease detection using deep learning models and a mobile application has shown promising results for guava plants. However, there are still many possibilities for improvement and expansion in future work. One possibility is to utilize the existing algorithms in outdoor conditions where the lighting and environmental conditions may be different than the controlled laboratory conditions. In this case, it may be necessary to combine both leaf front and back images to create a more comprehensive dataset.

Another area of future research could be focused on improving the automatic estimation of disease severity. Currently, the proposed method is focused on disease detection and recognition, but it may be possible to incorporate additional data to estimate the severity of the detected diseases. This would provide farmers and gardeners with more detailed information about the extent of the disease, and could help them make more informed decisions about the appropriate course of action.

Additionally, the methodological design of this project can be applied to predict disease for various plant types and species across the globe. By collecting and analyzing data from different plant types and species, it may be possible to create a comprehensive database of plant diseases and their corresponding symptoms. This would be an important resource for farmers and gardeners worldwide, as they could use this information to identify and treat diseases in their

crops. Overall, the proposed method for plant disease detection has the potential to significantly improve crop yields and reduce the negative impacts of plant diseases on food security and the environment.

VIII. ACKNOWLEDGMENT

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