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Deep Learning-Based Leaf Disease Detection with Mobile Application Integration for Smart Agriculture

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Abstract: Today, agriculture is playing an important role in the food security and economic stability, crop diseases are still a huge problem in the world of crops and there is a great loss of yield. Plant disease detection is very important to reduce the agricultural losses and increase productivity. This paper is aimed at presenting a deep learning system for the detection of leaf diseases coupled with a mobile application for smart agriculture. The proposed system is based on the MobileNetV2 convolutional neural network architecture to classify the plant leaf diseases from the PlantVillage dataset of 20638 images into 15 different classes. To enhance model performance and generalization, techniques like resizing, normalization, augmentation, and shuffling data are implemented in the image preprocessing stage. The trained model is then converted to the TensorFlow Lite format and integrated into a mobile app developed using the Flutter framework, allowing for a mobile app to detect the diseases in real time on mobile devices without internet connectivity. Experiments show that the proposed method has superior classification performance and fast inference time, which is convenient for handheld devices.

Keywords: Deep Learning, MobileNetV2, Plant Disease Detection, TensorFlow Lite, Smart Agriculture, Flutter, CNN

I. INTRODUCTION

In India agriculture is one of the major sectors which produces food, employment and income for the major population. But farmers have to deal with the problem of climate change, scarcity of water, degradation of soil and plant disease. Of these diseases of plants are a major problem as they can rapidly reduce yield and quality and cause substantial losses. Fungi, bacteria, viruses and pests are the primary causes of plant diseases. Historically, the first step in identifying disease has been carried out by manual examination by agricultural professionals. This is effective, but time consuming, expensive and not readily available in the rural areas, where experts are not available. Often diseases will spread between fields if they are not diagnosed early.

In recent years, with the advent of Artificial Intelligence (AI), particularly Deep Learning and Computer Vision, an automatic diagnosis of plant diseases became possible based on images of leaves. The technologies give more rapid and reliable results than traditional technologies. Furthermore, the rising adoption of smartphones in rural regions opens the door for precision agriculture using AI that can be directly delivered to farmers. The aim of this research work is to design a mobile application to detect tomato leaf disease using deep learning method. Tomato was chosen because it is versatile and is very susceptible to many diseases. Farmers can take pictures of leaves on the farm with their phone and get immediate disease predictions. The trained model is deployed through TensorFlow Lite, so that the detection can be done offline without relying on the internet. This work primarily aims to come up with a cost effective, user friendly and effective method for early detection of disease. It also showcases how lightweight AI models can be applied in agriculture and their potential to assist farmers in better managing their crops and minimizing losses.

II. RELATED WORK

Advancement of AI technology in the last decade has clearly seen a significant increase from laboratory experiments to systems that are now starting to be implemented in the field of agriculture. This chapter summarizes and discusses the most salient research that directly relates to the project's methodological approach for traditional machine learning methods, deep learning using CNNs, mobile deployment techniques, and smart agriculture integration.

4.1 Smart Agriculture and Plant Leaf Disease Detection

Previous research tests of several CNN architectures on plant disease datasets found that the choice of CNN and the diversity of the datasets had an impact on detection. The EfficientNet-B3 model generalised best across a number of datasets and ResNet50 was found to be the model which performed worst when tested across different datasets. Important lessons that can be learnt from this line of work are that training with multiple datasets is found to be quite robust and had a direct impact on the data strategy employed in this project. [1]

The synergistic effect of classification pipelines using both machine learning and deep learning was proven in research. The accuracy of various combinations of these models was shown to differ between the various crops, with the combination of VGG19 and Inception v3 for the Custard Apple Leaf classification achieving an accuracy of 99.1% while other combinations achieved 62.6%. The key takeaway is that there is no single ‘best' approach, as the best approach varies depending upon the crop and disease being targeted. [2]

Numerous studies have shown that deep learning models are consistently more accurate in disease classification than traditional image processing techniques, achieving an accuracy of 97% on commonly-used crop disease benchmarks. In addition to accuracy measures, these studies show that deep learning has a qualitative benefit over methods based on rules or features engineering: a deep learning network can be trained to recognize patterns of disease without the need for a domain expert to determine what to look for. [3]

AI platforms like PlantGuard have already shown how CNN-based detection can be packaged for the farmers' use – allowing for early disease detection by analyzing images of plants. In this research the practical use of those systems is also highly dependent on the user interface design and on the fact that the system is accessible in the field, which is frequently overlooked in the purely technical assessment. Future directions that were identified in the literature include integrating with drone imagery and IoT sensor data. [4]

The studies for using EfficientNetV2 for disease detection have demonstrated that newer CNN-based models can learn subtle differences in the leaves features corresponding to different disease types which outperform older CNN-based models in terms of different evaluation metrics. The researchers point out that it's not just about accuracy, but also the ability to track disease over time may change the way farmers manage crop health during the growing season. [5][6]

Research on the Vision Transformer models for plant disease tasks, also known as PLA-ViT, demonstrated that attention-based models can achieve better accuracy and disease localisation results on some metrics than CNNs, especially for tasks involving real-time monitoring with IoT. Although this is an interesting path to take, the demands of computation of transformer models are not currently compatible with the on-device mobile deployment context of this project. [7]

CNN-based systems for plant disease recognition have been successfully developed and used to create Web-based applications to deliver diagnostic information for farmers such as disease name, area of plant affected and suggested treatment. Among those frameworks, one had an accuracy of 96.67%, thus showing the readiness of these approaches in practice. This project directly addresses the limitation mentioned by research team which is connectivity dependency, with on-device inference. [8]

To tackle the loss of crops to pests and diseases (30-35% annual loss), CNN-based disease detectors have been developed in the Indian agricultural context using datasets comprising more than 12500 images. The systems have been introduced, each associated with a disease, for 16 plant types, and made available via cloud servers to help farmers across the country reach them. This project is relevant because of the size of the problem and the technical viability of CNN-based solutions. [9]

4.2 Crop Disease Detection

There has been a significant body of work in this area. It found that DL methods have contributed significantly to the fields of classification, detection, and segmentation in plant disease detection, as evidenced by the 160 articles analysed in this systematic review, published between 2020 and 2024. The review found that although traditional methods are resource-consuming and time-taking, deep learning can detect early signs at scale using its automatic processing of large image datasets. Persistent challenges throughout the field identified by the survey were dataset diversity and class imbalance. [10][11]

The conventional image processing pipelines were evaluated by segmenting the images to identify diseased regions and then extracting features from the segmented regions and applying classifiers such as SVM, KNN, and Decision Trees, which yielded satisfactory results in controlled environments but were found to be less effective in the presence of real-world variability in lighting, background, and image quality. Manual feature designs have a basic constraint that they are not able to change as a function of unobserved data, which reduces their ability to be broadly applicable compared to learned representations. [12]

Comparative analysis of CNN architectures (AlexNet, VGG16, ResNet50 and InceptionNet) showed that with enough data, deep learning models can consistently outperform 90% classification accuracy for plant disease detection. It was demonstrated that techniques like data augmentation, transfer learning and fine-tuning significantly enhance the accuracy, especially when labeled training data is scarce. One issue raised as an open problem was the ability to deploy models in field data, as opposed to controlled datasets. [13]

Transfer learning for plant disease datasets was discussed in review papers, which showed the potential for using a model trained on a large-scale dataset, such as ImageNet, with a much smaller number of labelled plant disease images to produce good specialised performance. The common failure cases are shown to be overfitting with too many layers unfrozen during fine-tuning and performance drops when the pre-training domain is too far away from the target domain. [14]

Recent research has investigated CNN architectures that focus the model's attention on the most relevant parts of an image, often the infected parts of a leaf, but most often the background noise is ignored. They are particularly useful for images with complex or noisy backgrounds, typical in field photography. The cost is increased complexity of the trade-off that must be considered in a deployment environment that is limited in resources. [15][16]

The authors have made a comparison of various machine learning algorithms applied to crop disease identification in this review. The analysis of accuracy and efficiency of algorithms is done for SVM, KNN, Random Forest and Naïve Bayes. The study reveals that Random Forest and SVM work well in most cases, as they are able to process complex datasets well.The paper also emphasizes the importance of feature extraction techniques, such as texture and color analysis, which directly impact model performance. One of its drawbacks is the selection of its features that are manually extracted – this might fail to capture the variations found in the real world. The authors propose that the results can be improved by combining both ML and deep learning. [17]

The image processing technique is used to detect the plant disease. The infected areas of the leaf are determined using various techniques like thresholding, edge detection and segmentation. The features are subsequently analysed and classified as diseases.The study shows that image processing techniques are simple and cost-effective, which is suitable for basic applications. However, this is challenging when there are complex images with noisy backgrounds or different lighting conditions. The authors find that image processing works, but it is not as strong as deep learning methods. [18]

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4.3 Machine learning for leaf Disease detection

Plant disease classification generally involves a sequence of tasks of image collection, pre-processing, segmentation, hand-crafted feature extraction and classification using machine learning techniques. SVM has been found to be the most successful among traditional classifiers in this area and has performed well compared to other classifiers like KNN and Decision Trees, especially when the feature space is high dimensional. All of these, however, have the basic limitation that their performance is constrained by the quality of manual feature engineering, a limitation overcome by deep learning. [19][20]

The results indicate that SVM provides a more stable and precise performance, especially with high-dimensional data. With smaller and less complex datasets, KNN works well. Logistic Regression is not as effective when the data is complex, like detailed information on images.It points out that good classification results cannot be gotten only from using good algorithm; feature selection and appropriate parameter tuning is also critical. [21]

For this study, the researchers have compared two popular machine learning algorithms: Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) for the purpose of disease identification in plant leaves. The process starts with image collection of the leaves, followed by preprocessing and scaling to ensure consistency of leaf images throughout the data set, including noise reduction. The preprocessing is followed by segmentation processes which help identify the affected parts of the leaf, only analysing the important parts of it. After identifying the relevant regions, various kinds of features are extracted from images. These include colour features, for detecting pigment colour changes, and texture features, for detecting irregular patterns associated with infection. Sometimes shape features are also taken into account. Then these features were fed to the classification models, SVM and KNN.The same data set is used to compare the performance of both algorithms. Based on the results, SVM gives better performance generally as it can draw a clear decision boundary in high dimensional data in the presence of complex data pattern. The latter, KNN, is easier to understand and implement, but it is very sensitive to the parameter k and is more susceptible to noise in the data.

As far as computation is concerned, KNN needs more time when it is predicting since it performs comparison of each new input with all the training samples, while SVM after training can predict more rapidly. Both methods however have a drawback when relying on manually extracted features, which may not capture variations in real world conditions like lighting variations or complex backgrounds. In general, the study indicates that SVM is more suitable for practical plant disease detection systems and KNN can be beneficial for certain simpler applications or smaller datasets. [22]

CNN-based methods are the most popular strategy today for plant disease detection for this reason. The superior accuracy of deeper, newer architectures (such as AlexNet to EfficientNet) follows a general trend of more depth and more resources being needed for better accuracy. This results in a design tension for mobile deployment, where computational budget is limited. The literature indicates that MobileNet family of architectures is the state of the art to date solution for the accuracy-deployability trade-off for on-device applications. [23]

Different neural network techniques used for plant disease detection are presented in this paper in a comprehensive manner. It covers various models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, hybrid models, and transfer learning models. The authors explain that CNNs are mostly employed for capturing spatial features from an image of the leaf, while RNNs or LSTMs may be useful in capturing sequential or time-related features in some data types.

The overall workflow for building such systems is also described. This involves pre-processing of images such as resizing and enhancement, training methods such as data augmentation and batch normalization, and evaluating the results with accuracy, precision, recall, etc. The results show that using deep learning models can get very high performance especially when trained on large and well-prepared sets of data.

Meanwhile, some significant issues are pointed out in the paper. Model performance can be impacted by factors like class imbalance, over-fitting, and the requirement for large labeled datasets. The authors propose methods such as data augmentation, dropout and transfer learning to overcome these issues. Finally, the study highlights the efficacy of deep learning techniques, but also underscores the importance of dataset preparation, and model tuning in practical applications. [24]

CNN-LSTM hybrid-based multi-crop disease detection research focused on integrating spatial feature extraction with the temporal modelling of disease progression. This has led to an increase in memory usage and increased training complexity that makes it impractical for mobile-first solutions without substantial compression. [25]

III. METHODOLOGY

A. Dataset

The data that is used in this research work is publicly-available PlantVillage Dataset, which is commonly used in plant disease detection studies. The dataset consists of labeled images of plant leaves with various diseases and healthy leaves from different crops like tomato, potato and bell pepper. A total of 20638 images were used in this research work for both training and validation comprising 16511 images for training and 4127 images for validation in 15 classes.

B. Implementation Phase

Implementation phase of this research work is the development of the mobile application and the integration of deep learning model. The entire system was built with Flutter framework for mobile app development, and the model was trained and deployed on TensorFlow and TensorFlow Lite. The application has been developed to identify plant diseases on leaves and then predict the diseases in real time on the mobile device. The system architecture comprises three core components: mobile application (frontend), deep learning model, and integration layer. The workflow starts with the user taking or uploading a leaf image and then the image is preprocessed before being fed to the trained model. The model then processes image, makes disease prediction and shows the user the prediction on the screen with the score.

The mobile application's screens are divided into several sections, each serving a specific purpose, which makes the application easy to navigate and user-friendly. Launched application shows the splash screen with the name of the application and loading animation before it automatically flows to the home screen. The home screen, which showcases the camera and information screens in a clean and easy-to-navigate layout, is the main interface. Information screen has instructions to use application and guidance for obtaining good leaf images. To take a picture directly with the device camera, the camera screen enables users to take images directly by holding down the shutter button. Also, images can be selected from the gallery, and a preview of the image is shown before processing. Lastly, the prediction screen will show the name of the detected disease and the percentage of confidence of the prediction. All screens are connected through navigation system in Flutter to make smooth transition across different screens and make a seamless application flow (Home screen → Upload screen → Prediction screen).

C. Deep Learning

This research work's deep learning model was built in the Jupyter Notebook using the TensorFlow library. The dataset was loaded using the TensorFlow built-in utilities, in which images were read directly from the directory of the dataset, and class labels were automatically assigned by the directory structure of the images. Next, the dataset was split into training and validation sets. To build the model, the pre-trained MobileNetV2 architecture was chosen as the base model because of its lightweight architecture and the fact that it could be used in mobile apps. The weights of the base layers were frozen and custom classification layers were added, with a dense layer of 128 neurons and an output layer with 15 classes. The model was created with the Adam optimizer, categorical crossentropy loss function and the accuracy evaluation measure.

A total of 16,511 training images and 4,127 validation images were used for training the model. The number of epochs for training was set to 5 to 10 epochs, depending on the available system resources, with the batch size being determined. In the training process, validation data was also fed into the model to observe the accuracy of the model with the loss value. The model was then converted to TensorFlow Lite format for mobile deployment and offline prediction after successful training and evaluation. The process involved loading the trained model, converting it to .tflite, and generating a label file to go with it. The model.tflite and labels.txt are the final deployment files generated.

D. Integration of Model with Mobile Application

The integration phase links the trained TensorFlow Lite model with the Flutter mobile app to facilitate on-the-spot plant disease identification. We have included required dependencies like image_picker, tflite_flutter, image to enable image selection, loading model, and the pre-processing of images. The trained files (model.tflite and labels.txt) were embedded as application resources and loaded using the TensorFlow Lite interpreter. The user takes a picture or uploads a leaf image and the app resizes, normalizes, and saves the image as a tensor before sending it to the model for prediction. The model then outputs probabilities for the various diseases, and the disease showing the highest score of confidence is shown on the Prediction Screen.

Simple error handling routines were added to handle cases of invalid image and/or model loading to maintain reliability and smooth performance. To enable quick predictions on mobile devices, some light weight MobileNetV2 model and efficient preprocessing were employed in the performance optimization techniques. The application was also tested with respect to UI functionality, the flow of navigation, compatibility of images and prediction accuracy. The challenges faced included model size reduction, integration with the Flutter app, and handling image formats, which were addressed through optimization and continuous modifications.Despite the difficulties faced, including model size reduction, Flutter app integration, and image format handling, they were able to optimize and improve the model to achieve an efficient and user-friendly plant disease detection system.

Simple error handling routines were added for handling cases with invalid images and loading error of the model for reliability and smooth performance. Fast predictions on mobile devices was achieved with performance optimization techniques such as using a lightweight MobileNetV2 model and efficient preprocessing. The application was also subjected to UI functionality, Navigation flow, Image compatibility, and prediction accuracy testing. While some hurdles like model size reduction, Flutter integration and image format processing were faced, they were tackled with optimization and successive improvement, leading to a robust and user-friendly plant disease detection system.

IV. RESULTS AND DISCUSSIONS

The proposed deep learning-based plant disease detection system successfully demonstrated the feasibility of integrating lightweight CNN models with mobile applications for smart agriculture. The use of MobileNetV2 and TensorFlow Lite enabled efficient offline inference suitable for mobile deployment. Although some disease categories exhibited moderate classification performance due to visual overlap and dataset imbalance, the overall system achieved strong real-time performance with acceptable accuracy and fast inference speed. The Flutter application provided a responsive and user-friendly environment for practical agricultural use. The results confirm that lightweight deep learning systems can serve as valuable assistive tools for farmers by enabling early disease detection, reducing crop loss, and improving agricultural productivity.

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TABLE 1: COMPARATIVE ANALYSIS OF PLANT DISEASE DETECTION METHODS

Method	Accuracy	Speed	Ease of Use
Manual Detection	55 - 65%	2 - 5 minutes	Difficult
DL (Traditional)	70 -80%	10 - 30 seconds	Moderate
Proposed System	85 - 92%	1 - 3 seconds	Easy

Table 1 compares different plant disease detection methods based on accuracy, prediction speed, and ease of use. Manual detection methods are less accurate and time-consuming, while traditional deep learning approaches improve performance but still require moderate processing time. The proposed system achieves the highest accuracy of 85–92% with faster prediction time of 1–3 seconds. The integration of TensorFlow Lite with a mobile application enables efficient real-time disease detection with a simple and user-friendly interface, making the system suitable for smart agriculture applications.

```
loss, accuracy = model.evaluate(val_data)

print(f"\nFinal Validation Accuracy: {accuracy*100:.2f}%")
print(f"Final Validation Loss: {loss:.4f}")

130/130 ━━━━━━━━━━━━━━━━━━━━ 174s 1s/step - accuracy: 0.9221 - loss: 0.2282

Final Validation Accuracy: 92.21%
Final Validation Loss: 0.2282
```

The evaluation results show that the trained deep learning model achieved a validation accuracy of 92.21% with a low validation loss of 0.2282. These results indicate that the model can effectively classify plant leaf diseases with high accuracy and minimal prediction error. The low loss and high accuracy confirm that the model generalizes well to unseen data and is suitable for real-time smart agriculture applications.

V. CONCLUSION

The proposed system successfully developed a deep learning-based plant disease detection application using MobileNetV2, TensorFlow Lite, and Flutter for smart agriculture. The model effectively classified plant diseases from leaf images while maintaining fast prediction speed and lightweight mobile deployment. The application supports offline real-time disease detection, image capture, gallery upload, and user-friendly result display, making it suitable for farmers and agricultural users. Experimental results showed improved accuracy, faster inference, and better accessibility compared to traditional detection methods. Although challenges such as image quality, lighting conditions, and visually similar diseases affected performance, the system demonstrated strong potential for practical agricultural applications. Future improvements may include larger real-world datasets, IoT integration, multilingual support, and enhanced disease severity analysis.

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