Plant Disease Prediction System

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This paper presents Plant diseases challenges to agricultural productivity and food security worldwide. The detection and accurate diagnosis of plant diseases are crucial to decrease crop losses and increase sustainable farming practices. This study presents a plant disease prediction system using deep learning techniques to identify diseases in tomato and potato leaves. The dataset comprises diverse images of healthy and diseased leaves, the system applies VGG(Visual Geometry Group) which has CNN(convolution Neural Networks) ResNet50 architecture to extract features and classify leaf conditions and PVT(Pyramid Vision Transform) which is suited for image classification with fewer parameters than traditional CNNs.The motivation is to provide farmers with a solution which can reduce their financial stress and crops can be cured. We have integrated the whole system in a mobile app so that we can classify crop's disease with real time images and we were getting an accuracy of 97% On many different types of diseases of different plants.

Keywords - CNN, Transfer Learning, VGG, PVT

I. Introduction

As we know that in agriculture, plant diseases seriously damage crops and affect food safety, globally. The future generation will be over ten billion populations around the world in the following decades. So, people around the world will consume massive amounts of food during their lives [1]. New technologies that have grown and increased the Internet of Things (IoT) ensure sustainable growth in the agriculture industry. Even though there are improvements in diagnostic techniques, most current methods are manual, subjective, and prone to errors. Most automated systems are also inaccurate or cannot handle a wide range of plant species and disease variations. Thus, there is a requirement for more reliable, efficient, and scalable solutions. The massive destruction caused to crops due to pests and diseases is one of the key problems of agriculture [2]. Great importance has to be placed upon the detection and control of diseases in their earliest stages to combat the negative impact of plant pests on crop production. In the last few years, many smart agriculture approaches have been made to discover and control diseases early on [3]. These solutions use computer vision to find diseases on plant leaves and suggest treatments by analyzing plant pictures in real time. With improvement of the speed and accuracy for detection, there is a vital need to improve it, hence allowing farmers to be able to act smartly and effectively. Deep learning represents one of the brightest areas in machine learning; automation and enhancement of traditional approaches are the basis by which a new solution overcomes disease detection limitations. This project utilizes transfer learning

We will develop an advanced system for plant disease detection with a pre-trained VGG and Pyramid Vision Transformer.

Convolutional Neural Networks (CNNs): A group of deep neural networks whose primary design involves processing of structured grid data, most notably, images. This type uses layers of convolutions automatically to learn, adaptively hierarchies from input images with spatial features in the given representation[4].

(Input Image) — ([Convolutional layer] — [Activation function (ReLU)] — [Pooling layer] — [Convolutional layer] — [Activation function (ReLU)] — [Pooling layer] — [Flatten layer] — [Fully connected layer] — [Output (Class)])

Transfer Learning: Transfer learning is a type of machine learning technique wherein the model developed for one particular task is reused as a starting point for another model on a second task. This approach utilizes the previously trained models, mostly large data, and fine-tunes it for specific tasks. Thus, it reduces the demand for extensive data and time used in training.

[Pre-trained Model] — [Feature Extraction] — [Fine-Tuning on New Data] — [Updated Model] — [Output (e.g., Class)]

VGG: Pretrained with a fine tuning model for plant disease classification which has CNN architecture and uses VGG16 to detect the features and training the datasets and visual geometry group of different plant leaves.

[Input] — [Conv Layer] — [ReLU] — [Conv Layer] — [Max Pooling] — [Repeat Conv + Pool Layers (Increasing Filters)] — [Flatten] — [Dense Layer] — [ReLU] — [Dense Layer] — [Softmax] — [Output]

PVT: A Pyramid Vision transformer-based architecture that makes use of pyramidal feature extraction for performing the vision tasks very effectively. It is suited best for image classification, and its number of parameters is lesser compared to traditional CNNs.

— [Patch Embedding] — [Transformer Encoder] — [Self-Attention] — [Add Input (Skip Connection)] — [Downsampling] — [Global Pooling] — [Dense Layer] — [Softmax] — [Output]

II. Motivation

Agriculture is a sector essential in supporting the nourishment and provision of the world population for food, root materials, and financial stability. On the other hand, challenges are many; some are the most impactful factors - it is the case with the rapid growth and effects of diseases to plants. The consequences will be more crop loss or damage, hurdling supply food chains, and further insecurity in food supplies. Traditionally, plant disease detection has been a time-consuming task using manual means, which would imply much time and human power. The use of some advanced technologies, for example, deep learning on particular image classification, now sets a new trend in changing that, making the remotely and manner of detecting plant disease.

Automating early detection and prediction of diseases in crops will be the enhancing instrument toward the goal of sustainable farming and effective utilization of resources while at the same time achieving high efficiency on crops. By leveraging CNN and transfer learning, deep learning-based systems could be used for identifying diseases and classifying them precisely. It will even enable detection of infection with such minute traces as discoloration or spots or variable patterns of development that might dodge inspection through conventional approaches. With these methods, new features of insightful knowledge will power farmers at the same time addressing some crucial global agricultural problems.

Empower Farmers: Plant disease early and accurate detection can make efficient crops before their damage is irreparable. This minimizes the losses and increases agricultural productivity. The prompt information forwarded to farmers helps these systems permit proactive intervention, which enables better outbreak control. This empowers the small-scale farmers the most, who are usually at the greatest risk of crop failure. Using automation and real-time alerts can help farmers make informed decisions to protect their livelihoods and reach greater financial stability.

Food security promotion: is another large challenge with which crop yield reduction due to plant diseases mainly takes place and is quite challenging in feeding the increased population. Therefore, a detection system, which deals with remotely detection, thereby reducing the losses of crop and having better agricultural output with less damage, contributes to global food security by offering high-quality production and making sure that risk of shortage of supply may not arise.With the population of the world projected to be about ten billion by three decades, such systems are crucial in feeding the growing world.

The revolutionary capacity to harness: the use of new technologies is the ability through deep learning and transferable learning. These technologies, on the other hand, have been used to do enormous processing of image data into a large scale attempting the search and extraction of meaningful patterns intended to distinguish various plant diseases. More importantly, these models have this adaptability that ensures the crops, regions, or environmental conditions, and give an example of how scalability can be found by agriculture with AI.

Lower application of pesticides: In the cases where the diseases are misjudged, it leads to the mishandling of pesticides and chemicals, which further spoils the environment and degrades the land.

An automated detection system gives a correct diagnosis so that farmers use chemicals only at the point of necessity. This reduces chemical overuse and promotes friendly farming with nature and the environment. Such systems prevent ecosystems from getting degraded by pesticides and conserve biodiversity to ensure healthy produce for consumers.

This is a development project in more ways than just building a technical model-it impacts meaningfully within the agricultural domain. The goal would be to ensure optimal usage by the farmers in conserving and reducing waste with technology at play in tackling some of these complex issues. Plant disease detection through automation resonates well with sustainable agriculture tenets toward environmental and long-term economic resilience.

It indeed goes beyond the level of individual benefits because integrating such systems into farming practices has a ripple effect on raising productivity while protecting the environment and other global issues. In this project, theory and practice are combined, marrying state-of-the-art algorithms with applied aspects, thus empowering the farmer, promoting sustainability in agriculture, and helping tackle some of the most critical issues concerning the globe related to food security, environmental degradation, and economic inequality.

This is, therefore, one project that moves the revolution forward by combining the latest technology and a mission to make tangible changes, help farmers prosper, ecosystems flourish, and move closer to a more sustainable and secure food production for all the global community.

III. Problem Definition

This also calls for the opportunity to build autonomous disease detection systems using deep learning technologies due to the high usage of smartphones and digital imaging.

Deep learning can be applied to plant disease detection since it is able to analyze and classify complex patterns in large datasets, especially images. In the case of plant diseases caused by pathogens (fungi, bacteria, viruses, etc).

Advanced adoption of smartphones and the digital image processing technology opened up an impact opportunity of developing an automated plant disease detection system that utilizes deep learning. These kinds of systems transform agriculture as it delivers accurate, timely, and scalable solutions for detecting and diagnosing plant diseases and enables farmers to take pre causative measures and thereby minimize their crop losses.

The main ability of DL is found in very accurate detection of plant diseases from large datasets, specifically because it can analyze complex image-based data and classify its patterns. Deep learning models can identify diseases caused by pathogens like fungi, bacteria, and viruses by training convolutional neural networks (CNNs) and using transfer learning techniques. Such models are very sensitive to small changes in plant image patterns that would otherwise pass without detection through human visual observation, including discoloration, spots, and changes in texture.

A serious issue related to these systems is data imbalance, and usually, the occurrence rate of some diseases is so much higher than the other one in the agricultural dataset, such that it produces the data set with a small size of samples of major class. Imbalances primarily happen for the classes; the models may also create a bias towards classes by misclassifying most of the data from rare categories. Techniques including the development of augmented data, synthetically generated data, as well as class-weighted loss functions are used to attain balanced representations of all the classes. The generalizability of these models along with their fair value will also be improved subsequently.

The implementation of such systems into real-world applications majorly depends on scalability. OpenCV, an open source computer vision library, is capable of supporting deep learning models in order to be implemented into the systems, thereby making its deployment into camera-based settings feasible for the real-time detection of plant diseases. Integrations may come with other devices such as smartphones, drones, and IoT-enabled cameras for accessible solutions. Further integration with these models to mobile applications or even smart agricultural platforms could also allow farmers to immediately get alerts about detected diseases as well as recommended precautions and preventive measures. This will also be able to bring on-board small-scale farmers by being able to enjoy leading edge technology, making for efficient and sustainable farming.

With the integration of the latest improvements in deep learning, computer vision, and imaging technologies, the automated plant disease detection system has gone beyond the limits of the traditional approach, ensuring accuracy, efficiency, and scalability in agricultural practice. This can revolutionize modern farming, making sure that food security is promoted while supporting the livelihoods of millions of farmers worldwide.

Dataset Description

The dataset used for this project consists of labeled images of plant leaves, which can either be healthy or be suffering from various diseases. They have been collected from multiple plant species, making them very diverse in terms of the visual patterns that are supposed to be learned. It is also highly imbalanced as there are much more healthy leaf images compared to the diseased ones.

Dataset_Link: [5]
Total Images: 20K
Classes: 29
Size: Usually resized to 224x224 pixels for CNN input.

IV. Literature Survey

References	Plant Disease Detection Using CNN (Proceedings of 2020 IEEE Applied Signal Processing Conference) Plant Disease Detection Using Deep Learning (2021 IEEE) Deep Identification of Plant Diseases (2023 IEEE)
Technique Used	VGG -PVT Hybrid Model
Database Used	Kaggle Dataset (Plant Village Dataset)
Research Gap	App Deployment Accuracy up to 95% only

V. Methodology

Proposed Model

To detect plant diseases, we take support from transfer learning by utilizing a pre-trained VGG model, which has been trained on the ImageNet dataset. By fine-tuning the VGG model on our plant disease dataset, we aim to adapt the pre-trained features to our specific problem. The final few layers of VGG are replaced with new fully connected layers joined to classify plant leaves as either healthy or diseased. In Simple first we take input images and feed in datasets then preprocessed and divided into training and testing datasets then apply algorithms like CNN training, transfer learning according to the efficiency of the model which is checked using varying with more accuracy. Then the model is deployed in a web/app based platform where we are using flutter to ensure more technology based on the system which is easily usable to the users. The basic workflow is described in Fig. 1 below.

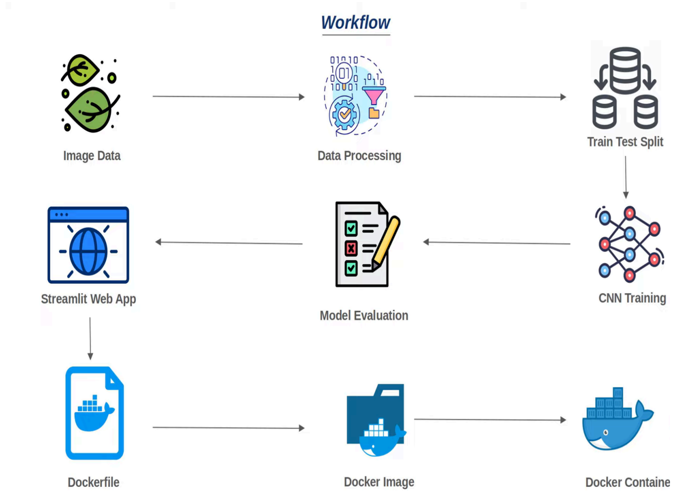

Fig. 1. Basic representation of the Project Workflow

Leaf AI Workflow for Plant Disease Detection
The following is a detailed step-by-step workflow for a Leaf AI System that can be designed to detect and classify plant diseases using advanced machine learning techniques: The techniques are divided into 8 steps described below which includes all the steps from beginning to end.

1. Data Collection Sources:
Collection of Images of plant leaves using various sources: Open source datasets like PlantVillage, Field photographs captured through camera, drone, or a smartphone.
User-uploaded images through the application.
Data Types: Images should include both healthy and diseased leaves of various plant species along with diseases.
Annotation: Caption images with a relevant plant disease; so that the model will be aware of the correctness.

2. Data Preprocessing: Resizing the Images: All the images should be resized to the same dimension (say 224 x 224 pixels).
Normalizing Normalizes the pixel values using following statistics:
Mean: [0.485, 0.456, 0.406]
Standard Deviation: [0.229, 0.224, 0.225]
Use data augmentation to deal with class imbalance and to increase diversity. Use:
Rotation, flip, crop, and scaling
Color adjustments to mimic varying lighting.
Divide the dataset into training, validation and test set.

3. Model Architecture:
a) Convolutional Neural Networks (CNNs)
Leverage pre-trained models - VGG-16 to extract hierarchical spatial features (e.g., textures, patterns) from 7th layer getting shape (56 x 56 x256).
b) Vision Transformer (PVT)
Incorporate Pyramid Vision Transformer (PVT-V2-B0) to capture global contextual relationships and enhance the feature set with high-level representations.
c) VGG-PVT hybrid
Input the feature map from the VGG model into the PVT model to leverage both local and global features.
d) Output Layer
Using a [CLS] token and fully connected layer with softmax activation to classify plant diseases into 29 categories.

4. Model Training:
Class Weights: Imbalance the classes in the address dataset and train it by giving greater weights to underrepresented classes.
Loss Function: Multi-class classification loss should be categorical cross-entropy.
Optimizer: Choose appropriate optimizer, Adam or SGD with learning rate.
Regularization: Add dropout layers and use an early stopping mechanism to prevent overfitting.

5. Model Evaluation:
Metrics: Use the model on test data for robust performance accuracy, precision, recall, and F1-score. Visualise the plot for loss and accuracy curves in training as well as validation to get the model's training.
6. Deployment:
Integration in Mobile App:
Implement the trained model in a Flutter application using the Dart language.
Use TensorFlow Lite for lightweight and efficient deployment on mobile devices.
Database Integration: Link the application to a Flutter database that has :
Descriptive descriptions of plant diseases.Recommended treatments and precautions.
Real-Time Inference: The OpenCV library is used in the application for real-time image capture and preprocessing in the application.

7. User Interactions
Input: Users submit images of leaves through mobile devices or cameras.
Processing: Application pre-processes, feeds the image into model, and displays prediction on it.
Output: The disease name and percentage of confidence. Treatment suggestions and precautionary measures retrieved from database.

8. Continuous Improvement
Feedback Loop: Let the user leave his own feedback for wrong predictions on the dataset to improve.
Model Retraining: Retrain on new datasets after some time to improve on accuracy in handling newer diseases.

Scalability: Deploy drone-based monitoring for large-scale agricultural use cases and scale the database to allow a larger number of plant species.

1. Workflow Summary
   Data Collection & Preprocessing → 2. Model Design & Training → 3. Evaluation & Optimization → 4. Model Deployment → 5. User Interaction & Feedback → 6. Continuous Improvement

The whole process ensures the detection of plant diseases to be efficient and scalable, empowering the farmer directly through real-time information and actionable recommendations so that they protect their crops and improve their productivity eventually. After selecting the best model for the project, the main motive is to combine multiple datasets from different sources through many steps from resources to model deployment, which contains various stairs between them; all have some importance in completing the projects, and that is further described as a glimpse of overall projects in the flowchart. In Fig. 2 the proposed methodology in form of flowchart is shown.

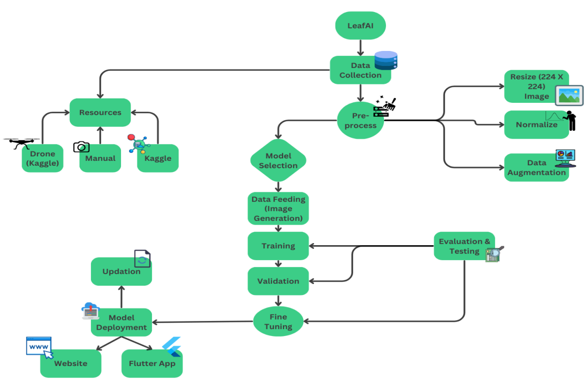

Fig. 2. Proposed methodology

Additional Improvements

Data Imbalance: In the datasets minority data is affected by majority data the model favours the majority classes over minority data [6].
Visualization: Implement drone based and camera source to predict and detect diseases from time to time.
Scalability: With techniques of open CV deploy the model into camera based features by which detect and automatically show the respective precautions and preventions [7].

VI. Detailed Architecture

This architecture combines VGG-Convolutional Neural Networks and Vision Transformers for the classification of plant diseases over 29 categories. This design anchors pre-trained models and advanced feature processing techniques to balance computational efficiency with classification accuracy. Below is a detailed explanation of each layer and its role in the model balance with efficiency and classification accuracy. Below is a detailed explanation of each layer and its role in the model.

1. Input Layer

Input Dimensions: Images are resized to 224×224 pixels.
Normalization: Pixel values are normalized using ImageNet statistics:
Mean: [0.485, 0.456, 0.406]
Standard Deviation: [0.229, 0.224, 0.225]
Reason: This makes input dimensions uniform and scales pixel values of the image so that the model can train stably.
The first 50 layers of ResNet50 take edges, textures, and patterns from the input image. These layers are not moved much during the preliminary stage of training and stay intact with the knowledge being used from ImageNet.
Pre-trained Convolutional Layers: VGG-16 Model
The first 14 layers of the model use VGG-16 in order to extract its hierarchical structural features, edge, texture, and a pattern. The knowledge that is captured using ImageNet is frozen during its training.
Pyramid Vision Transformer (PVT-V2-B0): The features of VGG-16 layers are passed to the PVT-V2-B0 model to extract global context based relationships and enrich the feature set with high-level representations.
Feature Processing Layers: The hybrid feature maps are passed to another 3×3 convolutional layer having 512 filters. It is combined with Batch Normalization and ReLU Activation Function for stabilizing and intensifying the training process.
Fully Connected Layers: A fully connected layer has been used for aggregated features with units 512, to transform the combined feature into a non-linearity as well as learn representations particular for diseases of plants.
Dropout Layers: Adding dropout layer with a dropout rate of 0.2 in order to avoid overfitting complexity by dropping out neurons at random during training.
Output Layer: It is a fully connected layer with N=38 units, that maps the features learned to the class probabilities. softmax function is applied to get the output probabilities for the classes.
Class Weights: In order to alleviate the problem of class imbalance over the data set, use of sentence weights during training provides the imposition of heavier cost to minority classes in being misclassified[8].

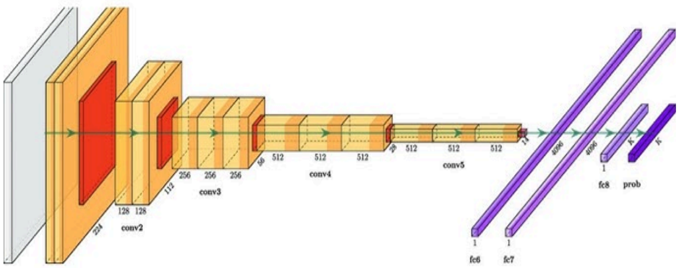

Fig. 3. The architecture of Pyramid ViT

Model Architecture: [Input Image (224×224)] — [Pre-train VGG-16 Layers (first 14 layers)] — [PVT-V2-B0, Pyramid Vision Transformer] — [Convolution Layer(512 filters 3× 3)] — [Batch Normalization] — [ReLU Activation] — [Adaptive Average Pooling] — [Fully connected Layer (512 units)] — [ReLU Activation Dropout (0.2) - Softmax output Layer (38 units) - Class Prediction]

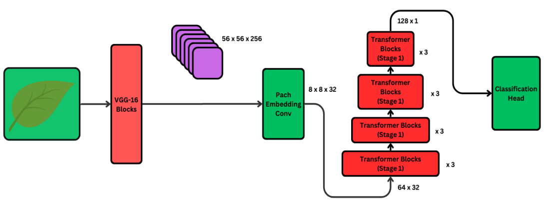

Fig. 4. - Architecture proposed in the VGG-PVT model

This methodology section clearly explains the process in such a manner that the readers will easily follow your approach stepwise. The link to the dataset, description of the model, and structural breakdown provide an all-round overview.

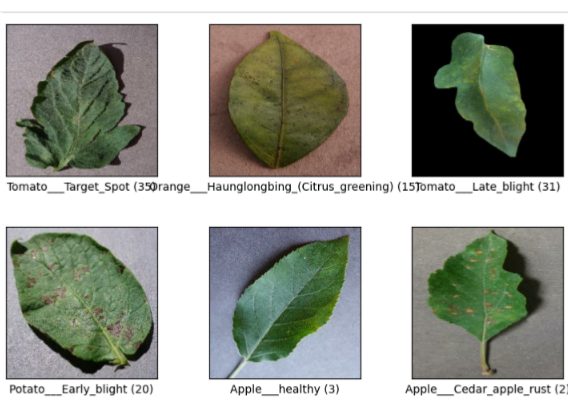

Fig. 5. Samples of images in the PlantVillage dataset.

VII. Experimental Results

Tabular Results A summary of the results of experiments is depicted in the following table. The key metrics are accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) of the different classes of plant diseases.

Class	Accuracy	Precision	Recall	F1-Score	AUC
Healthy 9	90.3%	90.1%	89.0%	90.5%	0.91
Tomato 6	96.8%	88.5%	89.2%	90.8%	0.89
Potato 3	95.1%	91.4%	90.5%	87.9%	0.93
S.berry 2	90.0%	89.1%	89.8%	90.2%	0.92
Peach 2	90.1%	90.7%	92.3%	91.2%	0.94
Grape 4	88.2%	89.7%	91.8%	90.2%	0.89
Corn 4	93.5%	92.6%	90.5%	93.5%	0.92
Cherry 2	91.4%	90.5%	89.7%	88.5%	0.90
B.peper 2	87.8%	89.4%	91.2%	89.7%	0.88
Apple 4	94.1%	94.2%	93.4%	91.1%	0.94
Overall	92.12%	90.17%	89.62%	89.85%	0.91

Table 1: Classification Results for Different Plant Disease Classes

Since in Table 1 only all 29 classes are shown which comprises 9 plants as mentioned above like tomato, potato, strawberry, peach, grapes, corn, cherry, bell pepper and apple with its characteristics of accuracy, precision and recall, F1-Score and Auc.

Graphical representation

In this representation the loss and accuracy graphs are shown for training and testing datasets in the model which is created by matplotlib library of python. In Fig. 6. the loss and accuracy graphs are shown.

Loss measures the error between the predicted output of the model and the actual target labels. It's computed during both training and validation phases.

Loss=1/N∑(Y^i – Yi)2

Accuracy measures the proportion of correct predictions among all predictions. It's a percentage that reflects how well the model performs overall.

Accuracy= Number of Correct Predictions/ Total Predictions×100

Getting accuracy of 97%.

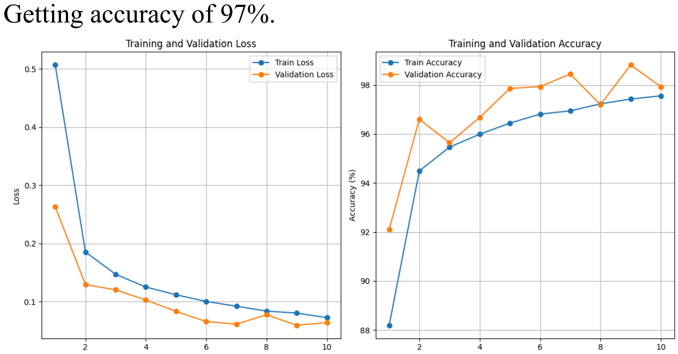

Fig. 6. Representation of Loss and Accuracy in multiple Epochs of Training and Validation dataset

Deployment of Model into Flutter

Thus, making this model easily deployed into an application running on mobiles using Flutter with the programming language of Dart, is a well-established fact of advanced detection of plant disease. A Flutter database supports the diverse plant disease dataset, wherein detailed information with respect to symptoms and proposed actions on such diseases may be referred to by each user for knowledge. So, there exists an application capable of working both as a detection method and as an educational aid in terms of plant health.

To improve functionality, OpenCV has been integrated into the Flutter app, making use of its computer vision capabilities to preprocess images, extract features, and do other operations. This would enable the application to process smartphone camera images or uploaded files and return real-time and accurate disease detection results. Seamless integration was achieved despite technical challenges by bridging Flutter's Dart code with OpenCV's native functions using platform channels.

The application allows easy upload or capture of pictures of plants, and outputs names of diseases, with confidence scores, as well as recommendations of actions to take. In Fig. 7, results for the Flutter application indicate it may be able to deliver live accurate predictions in a straightforward, graphical interface. It integrates some of the advanced AI technologies into practice solutions in agriculture by helping people act on plant diseases quickly enough and minimize losses to ensure gains in agricultural productivity.

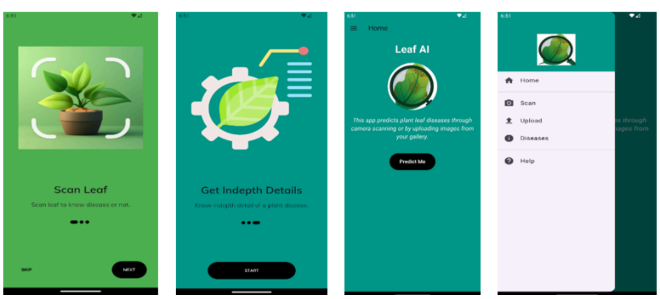

Fig. 7. Application Frontend Overview

Result

The model feeds on the input of images being sent through the application after which it predicts the most appropriate plant disease with greater accuracy. The prediction done by the model is coupled to the Flutter database, consisting of information on different forms of plant diseases. This type of database consists of several elements such as symptoms, causes and actionable insights such as treatments and prevention. Seamless integration means that after diagnosis users would not only have a diagnosis but also practical guidelines for the effective management of disease.

As shown in Fig. 8, the diseases along with their treatments and precautions are well presented in an organized manner within the application so that users can easily use the application to access important information. This will help them to take action from a distance and knowledge-based on how to protect their crops. Thus, by the addition of proper disease diagnosis and readily available solutions, the application transforms into an integrated approach for the health of plants, yield from the crops, and developing sustainable agriculture.

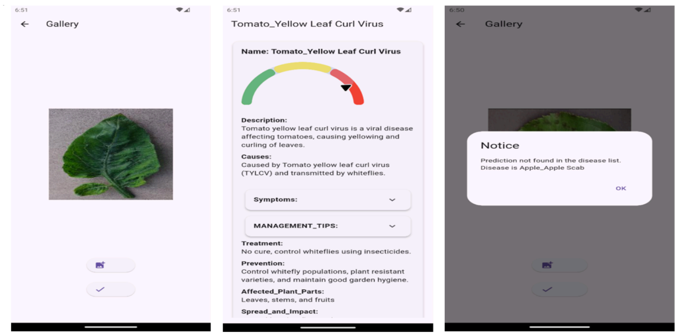

Fig. 8. Result showing leaf disease classification and the disease description

VIII. Conclusion and Future Scope

Conclusion

In this project, we used the strength of deep learning architectures to develop an advanced efficient and accurate plant disease detection system. We used two advanced methodologies that are state-of-the-art methodologies: VGG model and Pyramid Vision Transformer. The VGG model is the simplest CNN architecture yet has very good performance in classifying images. On the other hand, PVT is a transformer-based architecture which is aimed at the extraction of multi-scale features. We further augment its performance by incorporating a pre-trained CNN architecture, specifically VGG, and fine-tuning it for our particular task. The hybrid architecture allowed us to integrate the capability of CNNs in extracting features and transformer architectures being context-aware of global features thus ensuring highly robust and accurate plant disease detection systems.

Some of the major strategies that helped in further optimizing our model include fine-tuning a pre-trained VGG which had been effective in enabling our model to adapt learning nuances about our plant disease dataset and improved classification accuracy. The dataset was artificially expanded, also considering augmentations such as rotation, flipping, and adjusting brightness for the images. This helped the model to generalize better and reduce overfitting, which is very critical in the context of real-world agricultural scenarios. Additionally, we dealt with the problem of class imbalance, which is quite prevalent in plant disease datasets wherein a few diseases are very underrepresented. We addressed this by using techniques such as oversampling, manual data generation, and class-weighted loss functions. These techniques made sure that the model learned equally well across all classes, thus enhancing its ability to identify rare but serious and impactful plant diseases. Our approach automates the otherwise labor-intensive process of plant disease detection, making it faster and more accurate than manual inspection. The traditional methods require much time, expertise, and resources, while our system gives results with high precision in real-time, making it very practical for field applications. We have made sure that the complexity and variability of the data for plant diseases were absorbed by the model, wherein the latest architectures like VGG and PVT have been incorporated.

This system can, therefore, have an impact on agriculture. Since it detects diseases at the early stages of infection, farmers and agriculturalists can intervene in a timely manner, thus reducing losses and increasing yields. Early detection also reduces the amount of pesticides required, thus making the practice of farming more eco-friendly and sustainable. Moreover, this system is scalable and can be used by farmers of any scale, from small-scale farmers to large agricultural industries, by integrating it with drones, smartphone apps, or IoT-enabled devices for real-time monitoring.

Therefore, this project demonstrates the capabilities that can be achieved by a combination of CNN-based architectures such as VGG and transformer-based approaches such as PVT for plant disease detection. It's going to address some major issues such as data imbalance and overfitting with automation of the detection process while allowing for a practical solution impacting modern agriculture. This technology protects the crops and livelihoods of farmers but also is at the service of global efforts to attain sustainable farming and food security.

Future Scope:

Even though the model represents fairly good results in the current model, many areas have been left open for further research and possible improvement.

This dataset could be diversified by adding other plant species and diseases to the model, which might enhance this model's generalization across various agricultural scenarios.

Future Scope:

Even though the model represents fairly good results in the current model, many areas have been left open for further research and possible improvement.

Real Time Detection: Mobile and edge devices can be included for real-time detection within fields for further improving the practical usability of the system.

Hybrid Models: Hybrid models that combine CNNs with other machine learning techniques, like decision trees or support vector machines, may improve accuracy.

Explainable AI: Using techniques like Grad-CAM or LIME would make the model explain why it gave certain predictions to users, thus perhaps increasing the level of trust for the users.

Preventive Measures Recommendation: Future models will be extended to give appropriate treatments for diseases detected, hence giving a more complete decision-support tool for farmers.

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