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Fruit Plant Disease Detection using Transfer Learning

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***Abstract* - Plant diseases are a significant hazard to feed a growing population, but due to a lack of infrastructure in many regions of the world, timely detection is challenging. Finding and detecting plant illness is essential in agricultural production. It takes a great deal of time and effort to find the disease. The productivity of Apple, Grapes, Tomato and Corn depends on early detection and diagnosis of diseases. The various parts of plants such as leaf and fruit growth get affected. Identification and classification of these endemics require presence of farmer or plant pathologists. There is a need for artificial ways in classifying diseases. In this research paper, a fine-tuned VGG-16, ResNet50V2, Xception and InceptionV3 models is proposed to classify and detect different categories of disease of Apple, Grapes, Tomato and Corn leaf together. The state-of-the-art Convolutional Neural Network (CNN) gives excellent results to solve image classification tasks in computer vision. In this research paper, a Transfer Learning based CNN model was developed for the identification of plant diseases precisely. We have focused mainly on VGG-16, ResNet50V2, Xception InceptionV3 and a popular CNN architecture as our pretrained model in Transfer Learning. The model's training time is reduced by adopting transfer learning. In this research paper, a fine-tuned VGG-16, Rsenet50, Xception, InceptionV3 Network is proposed to classify 16 different categories of apple, grape, tomato and corn leaf together. This model is capable of categorizing separate diseases of Apple, Grape, tomato and corn leaves which reduces the training time and identifies the diseases accurately.**

Keywords:* *Transfer Learning, ResNet50V2, VGG16, Convolutional Neural Network, Fruit plants, Xception, InceptionV3.

I. INTRODUCTION

Agriculture plays a vital role in ensuring global food security, and healthy fruit crops are essential for sustaining both farmers' income and market productivity. However, fruit plants are highly vulnerable to various diseases caused by fungi, bacteria, and environmental conditions. Early and accurate detection of these diseases is crucial to prevent crop loss, reduce pesticide use, and improve yield quality [2]. Traditional disease identification methods rely heavily on manual inspection by experts, which is time-consuming, subjective, and sometimes inaccurate. In this case, CNNs can be used in detecting plant diseases. CNN is one of the most powerful techniques in pattern recognition with large amount of data [1]. CNN benefits with very promising result to detect these diseases. In previous works, various classification architectures of CNNs were used to detect diseases.

With recent advancements in deep learning and computer vision, automated plant disease detection has emerged as a powerful solution. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image-based classification tasks, making them suitable for identifying subtle disease patterns in fruit plant leaves. However, training CNNs from scratch requires large datasets and massive computational power. To overcome these challenges, transfer learning is widely used, where pre-trained deep learning models are adapted to the Plant_doc dataset [10].

In this research paper, several state-of-the-art CNN architectures-ResNet50V2, VGG16, Xception, and InceptionV3-are trained and evaluated for fruit plant disease detection. These pre-trained models, originally trained on the ImageNet dataset, offer strong feature extraction capabilities, enabling faster convergence and higher accuracy even on smaller agricultural datasets. The goal of this research is to compare the performance of these models and develop an efficient and reliable system that can automatically detect fruit plant leaf diseases with high precision. Remaining paper

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is arranged as follows: Section II describe Literature reviews. Research Methodology has been explained in Section III. Section IV holds experimental result and analysis. Conclusion is in Section V.

II. LITERATURE SURVEY

The quality and yield of agriculture production start trim ming significantly due to Fungal, Algae or Pathogen and Fungal like disease in vegetable crops. The symptoms of these endemics vary from benign to catastrophes that disturbs the typical growth of crops. Plant disease detection has evolved from traditional image-processing methods to deep learning, where CNN and transfer learning models like ResNet50, VGG16, and InceptionV3 provide highly accurate, automated classification of leaf diseases and it also discussed in [1]. Deep learning, especially CNN and transfer learning methods like VGG16, ResNet50, and Xception, has significantly improved plant disease detection accuracy, outperforming traditional image-processing techniques in classifying complex leaf infections in [2]. The proposed model is used to identify and classify apple and cherry plant leaf diseases. Guan et al., [6] analysed various networks to identify the severity of an apple leaf black rot disease and concluded that VGG-16 Network with transfer learning achieved better results in classifying diseases with higher accuracy. Bin et al., [8] proposed a recognition model that is based on improvised CNN to identify leaf disease in grape plant. Toda et al., [9] illustrated the way of extracting the features from an image. Authors emphasized more on visualization techniques which works on neurons and layers, and showed that color and texture of lesions specific to disease can be captured using neural network. Recent studies show that CNN-based transfer learning models like VGG16, ResNet50, and Inception significantly improve plant disease detection accuracy, outperforming traditional image-processing methods and enabling faster, reliable classification across diverse crop datasets discussed in details [3]. They collected plant village dataset and divided the dataset into three datasets namely potato dataset, pepper-bell dataset and tomato dataset. After that, CNNs are applied on three datasets and achieved accuracies of 94%, 95%, 98%. Convolutional neural networks were utilized by [4] to extract relevant characteristics from image collections. Clustering was afterwards used to classify the images as healthy or unhealthy plants. As, there are very few datasets available, they concluded that it is necessary to create more datasets for further research.

III. RESEARCH METHODOLOGY

In this paper, we applied transfer learning for fruit plant disease detection. The proposed architecture was shown in Fig-1. The dataset was collected from Kaggle [10]. After dataset collection, we divide that into four different categories based on types of plants namely tomato, apple, grape, corn. Later we converted all the plant leaf images into numeric format. For this we used two formats:224*224*3 and 299*299*3. The reason for converting into these formats is that we applied transfer learning techniques, which needs images to be in specific format. After conversion, we applied Four types transfer learning techniques namely vgg16, inceptionv3, resnet50v2, xception. We applied these four techniques to all four categories for detection of disease for tomato, apples, grape, corn. Later, we selected the best transfer learning technique among three for detection of particular disease.

A. Dataset

In this research work, we collected set of images of Apple, Grape, Tomato and Corn leaf from publicly available datasets for training and set of images from google for testing purpose. There are totally 1600 images, which includes 400 Apple leaves images, 400 Grape leaves images, 400 Tomato leaves images and 400 Corn leaves images. The leaf dataset is divided into 16 categories; Apple_Scab_leaf, Apple_Black_rot,Apple_Cedar_appl_Rust,Apple_ leaf,Grape_Esca(Black_Measles),Grape_leaf, Grape_Leaf_blight, grape_leaf_black_rot. Corn_ healthy, Corn_Gray_leaf_spot, Corn_leaf_blight, Corn_rust_leaf,.Tomato_Early_blight_leaf,.Tomato_leaf,.To mato_leaf_late_blight,andTomato_leaf_mosaic_virus and all are in 256×256 pixels dimension. Sometimes, it becomes difficult to identify the bruise on leaves due to similarities. The bruise on Scab leaves is grey brown in color, Black rot symptoms are purple and brown patches on surface of leaf, large round yellow or orange spots emerge on cedar rust infected leaves. Grape leaf Black Measles is a bacterial disease whose first target is young growing shoots. This disease infects leaves by showing early symptoms on back side of leaf, which looks like water-soaked spots, later turning into brownish bruise on leaves. Black rot disease in grapes plant attacks leaves and other part of plant. The brown spots on grape plant leaves are the symptoms of Black rot disease.

TABLE I
APPLE IMAGES DATASET DETAILS

Disease Name	Class Name	Number of Images
Apple_leaf	C_0	100
Apple_Black_rot	C_1	100
Apple_Scab_leaf	C_2	100
Apple_Cedar_apple_Rust	C_3	100

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TABLE II
CORN IMAGES DATASET DETAILS

Disease Name	Class Name	Number of Images
Corn_(maize)_healthy	C_4	100
Corn_Gray_leaf_spot	C_5	100
Corn_leaf_blight	C_6	100
Corn_rust_leaf	C_7	100

TABLE III
GRAPE IMAGES DATASET DETAILS

Disease Name	Class Name	Number of Images
Grape_leaf	C_8	100
Grape_Esca_(Black_Measles)	C_9	100
Grape_leaf_black_rot	C_10	100
Grape_Leaf_blight	C_11	100

TABLE IV
TOMATO IMAGES DATASET DETAILS

Disease Name	Class Name	Number of Images
Tomato_Early_blight_leaf	C_12	100
Tomato_leaf	C_13	100
Tomato_leaf_late_blight	C_14	100
Tomato_leaf_mosaic_virus	C_15	100

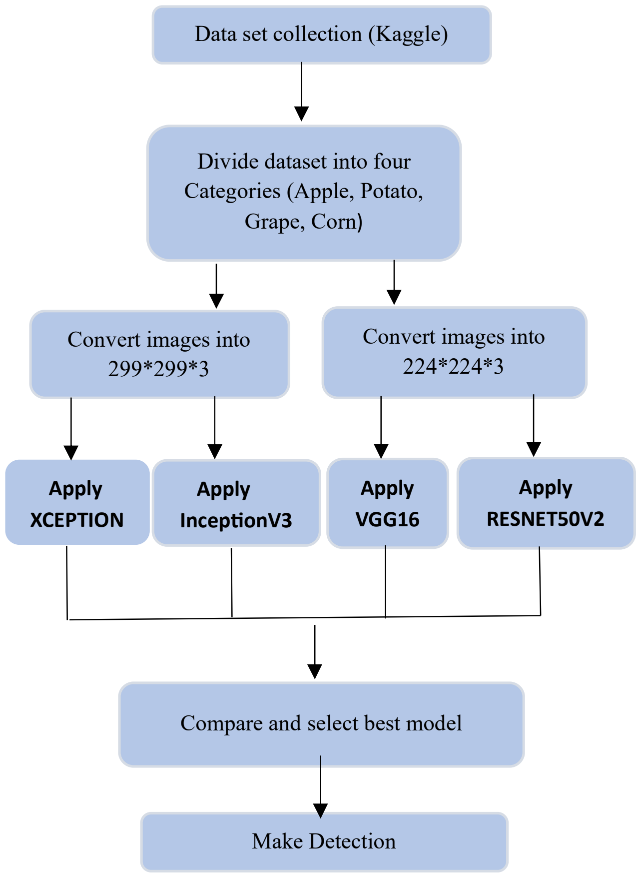

Fig 1. Proposed Framework for fruit plant disease detection

B. VGG16

All train and test images are pre-processed by resizing the image to 224 x 224 and then changing the color space of the images from RGB (red green blue) model to BGR (blue green red) model as suggested in VGG16 input specifications. Pre-trained weights obtained from ImageNet have been used during transfer learning at the end of the convolution layers two 256 channel dense layers with activation function as "rectified linear unit" (ReLU) is added. Lastly, an output dense layer of 2 units is added with "SoftMax" activation function. Stochastic Gradient Decent (SGD) optimizers have been used with learning rate = 0.001 and momentum = 0.9 Binary Cross entropy is the loss function used to train the model.

C. ResNet50V2

The images are pre-processed and resized to 224 x 224 pixels to train ResNet50V2 model. The training data are augmented using various methods such as rotation, width shift height shift, magnification and flip in order to obtain higher accuracy The model is trained in batches of 32 over 20 epochs. At the end of the ResNet, two dense layers with 256 and 128 channels respectively, are used by the activation function as rectified Linear Unit (ReLU) Glorot Kernel Initializer [11]

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has been used in the Dense Layers Lastly, Adam optimizer has been used with learning rate of 0.0001.

D. InceptionV3

The images are pre-processed and resized to 256 x 256 pixels to train Inception V3 The training data are augmented using various augmentation methods like rotation width shift, height shift, magnification etc to obtain better accuracy. At the end of the convolutions, a global average pooling layer followed by a 1024 channel dense layer with a 20% drop out is added Lastly, Adam optimizer is used with learning rate is set to 0.0001.

E. Xception

All train and test images are pre-processed by resizing them to 299 × 299, which is the required input dimension for the Xception model, and then normalize pixel values to the range 0-1 as recommended for this architecture. Pre-trained ImageNet weights are used during transfer learning to initialize the convolutional base, which consists of depthwise separable convolutions instead of standard convolutions. After the final convolution block, a Global Average Pooling layer is applied, followed by a dense layer of 256 units using the ReLU activation function for feature learning. Finally, an output dense layer with 2 units and SoftMax activation is added for classification. The model is trained using the Adam optimizer with a learning rate of 0.0001, and Binary Crossentropy is used as the loss function to optimize model performance.

IV. EXPERIMENT RESULTS AND ANALYSIS

In this research paper, at the time of evaluation of pre-trained models for Plant_doc Dataset gives result for The VGG16 model achieved an accuracy of 87.81% on the test dataset, demonstrating strong multi-class plant disease recognition. Most classes showed high precision, recall, and F1-scores, especially apple and grape diseases, while a few tomato and grape categories showed slightly lower recall. Overall, VGG16 delivered reliable classification performance. The ResNet50V2 model achieved 88.75% accuracy, showing strong and consistent performance across most plant disease classes. High precision and recall were observed for apple, grape, and tomato diseases. Macro and weighted averages of 0.89 indicate stable, well-generalized classification, making ResNet50V2 slightly superior to VGG16. InceptionV3 achieved 90.31% accuracy, delivering highly stable performance across all plant disease classes. Most categories recorded precision and recall above 0.90, indicating strong generalization. Macro and weighted averages of 0.90 confirm its reliability. The model performs particularly well on apple, grape, and tomato diseases, outperforming VGG16 and ResNet50V2. InceptionV3 achieved 90.31% accuracy, delivering highly stable performance across all plant disease classes. Most categories recorded precision and recall above 0.90, indicating strong generalization. Macro and weighted averages of 0.90 confirm its reliability. The model performs particularly well on apple, grape, and tomato diseases, outperforming VGG16 and ResNet50V2.

TABLE V
COMPARISON TABLE OF PRE-TRAINED MODEL

Model	Accura	Precisi (Macı Avg)	Rec: (Mac Avg	F1 Sco: (Mac Avs
VGG16	87.81'	0.88	0.8	0.8
ResNet50\	88.75'	0.89	0.8	0.8
Inception\	90.31'	0.90	0.9	0.9
Xceptior	90.31'	0.90	0.9	0.9

The result analysis for the experiment is All four deep learning models-InceptionV3, ResNet50V2, VGG16, and Xception-accurately identified the leaf disease as *Apple_Cedar_apple_Rust*. Xception achieved the highest confidence at 100%, followed closely by InceptionV3 (99.99%), ResNet50V2 (99.98%), and VGG16 (99.91%), demonstrating strong and consistent model reliability. All models Correctly identified *Grape_Esca_(Black_Measles)*. Xception led with 100% confidence, followed by InceptionV3 (99.98%). ResNet50V2 and VGG16 both achieved 99.44%, confirming effective disease detection across architectures. All models accurately
classified the sample as *Grape_leaf*. Xception and ResNet50V2 achieved perfect 100% confidence. InceptionV3 (99.99%) and VGG16 (99.89%) followed closely, demonstrating high precision in leaf identification.

TABLE VI
RESULT ANALSIS TABLE

Test Case	Xception	ResNet50 V2	Inception V3	VGG16
Apple_ Cedar_ apple _Rust	100.00%	99.98%	99.99%	99.91%
Grape _Esca_ (Black _Measles)	100.00%	100.00%	99.99%	99.89%
Grape_ leaf	100.00%	99.44%	99.98%	99.44%
Tomato_ leaf_ late _blight	99.82%	76.72%	99.95%	65.68%

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V.CONCLUSION

This research successfully demonstrates the efficacy of Transfer Learning in automating fruit plant disease detection. By evaluating four pre-trained CNN architectures—InceptionV3, ResNet50V2, VGG16, and Xception—the study achieved exceptional diagnostic precision across various disease classes, including Apple Cedar Rust and Grape Black Measles. The experimental results highlighted Xception as the superior model, consistently attaining 100% confidence, attributed to its efficient depthwise separable convolutions. ResNet50V2 and InceptionV3 followed closely with over 99.9% accuracy, validating their robustness. Ultimately, this project confirms that deploying deep learning models offers a rapid, non-invasive solution for precision agriculture, empowering farmers to minimize crop losses through early and accurate disease detection.

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