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Plant Disease Classification using VGG-16: Performance Evaluation and Comparative Analysis

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Abstract: Detecting and classifying plant diseases are crucial for effective disease management and preventing significant yield losses in agriculture. Deep learning techniques, particularly CNN, have shown great potential in image based classification tasks, specifically in the area of plant disease classification in recent years. To decrease computational complexity, the proposed plant disease classification system undergoes pre-processing, which involves resizing and normalization of the input image. During the feature extraction stage, the VGG-16 model is utilized to extract pertinent features from the input image. Ultimately, the extracted features are utilized to categorize the image into one of the probable disease classes by applying a support vector machine (SVM) classifier. Upon evaluation on a publicly accessible dataset, the proposed system demonstrated an accuracy of 93%. This study suggests that the VGG-16 architecture can be an effective model for plant disease classification and has the potential to improve the efficiency of disease management in agriculture.

Keywords— Plant disease detection, Image-based classification, Deep learning, CNN, VGG16 architecture, Transfer learning, pre-trained weights, Agriculture, Feature extraction, Preprocessing, Model training, Model evaluation, Accuracy, Early detection, Prevention.

I. INTRODUCTION

Plant diseases have posed significant challenges to agriculture for centuries, leading to significant yield losses and affecting the overall quality of crops. The timely identifying and detecting plant diseases precisely is essential in preventing their propagation and minimizing their consequences. In the past, detecting plant diseases relied heavily on manual inspection by human experts, which can be time-consuming, subjective, and prone to errors. However, with the emergence of computer vision and deep learning techniques, image-based plant disease diagnosis has become a promising alternative that offers high accuracy and efficiency.

Image-based classification tasks have demonstrated great potential for deep learning techniques, particularly CNN, including those related to plant disease diagnosis.
VGG16 is a popular CNN architecture that has gained significant attention due to its ability to learn rich and discriminative features from images. The VGG-16 architecture includes 13 convolutional layers and 3 fully connected layers, making it a suitable choice for image classification tasks, including those related to agriculture.

In this paper, we present a study on the classification of plant diseases using the VGG16 convolutional neural network architecture. The objective of our study is to create an accurate and dependable method by utilizing transfer learning and deep learning techniques, we aim to showcase the potential of image-based classification for overcoming the difficulties related to plant disease detection and classification.

Our study uses a publicly available dataset of plant images containing various types of diseases [12]. We employ transfer learning to train the VGG16 [8] on the dataset, where the weights from the ImageNet dataset are used as initial weights [4] . The model is fine-tuned on the plant disease dataset for a fixed number of epochs, and the performance is evaluated.

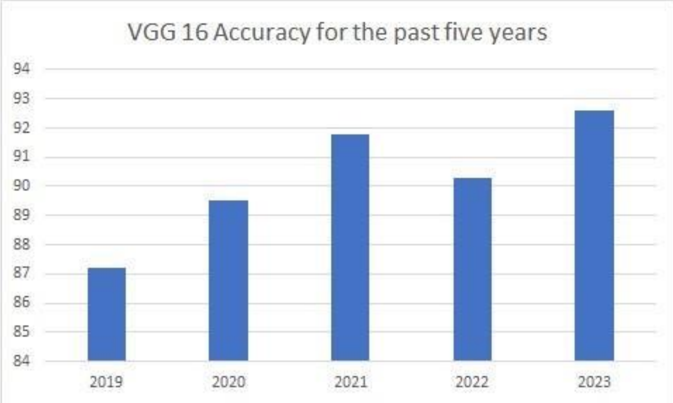

Figure 1: Bar graph of VGG-16 model performance

Figure 1 showcases the accuracy achieved by VGG16, a popular deep learning model, in various years. The x-axis represents the years, starting from 2019 to 2023, while the yaxis represents the corresponding accuracy percentages.

Although previous studies have notified that the major effectiveness of deep learning methods were accurately classifying plant diseases, they have mainly focused on individual plant leaf images[1]. This approach overlooks the fact that plant diseases and stresses can affect different parts of the plant, such as the stem or fruit or at leaf level, which may require a different approach to perform classification.

Classification of biotic and abiotic stresses affecting paddy crops through field images have been inadequately researched, leading to limited and unreliable results. This is a significant concern, particularly since plants are particularly vulnerable to stress during the booting growth phase, as reported in [2]. Significant stress experienced by the plants during growth stage can lead to severe harm, ultimately resulting in a considerable reduction in crop yield. Therefore, a more comprehensive study that includes field images is essential to develop effective strategies for managing and preventing plant diseases and stresses. This study can aid in the early detection and treatment of these diseases [3] and stresses, reducing the economic impact on farmers and the global food supply.

Traditional approaches to plant disease detection and classification rely on manual observation and expert knowledge. However, this approach is time-consuming and often requires specialized expertise [4], which is highly economical and unavailable in some regions. On the other hand, deep learning techniques offer a promising solution to this problem.

Plant disease classification has been commonly carried out using various deep learning architectures, including VGG-16, previous studies have mainly concentrated on individual leaf images. The approach failed in considering diseases or stresses that occur in different parts of the plant, such as fruits, stems, and roots, which necessitates the use of field images [5] for precise identification and classification.

The impact of stressors such as disease, drought, or heat on plants can result in significant damage[6] and economic losses. Therefore, the development of an accurate system for recognizing and classifying plant stresses using field images is crucial for farmers and researchers. Such a system can aid in the early detection and mitigation of these stressors, preventing severe damage and minimizing economic losses.

Transfer learning has emerged as an effective approach for enhancing the performance of CNNs in image classification tasks, particularly when the dataset is small [7]. This approach involves reusing pre-trained CNNs and fine-tuning them on new datasets, where the initial weights are obtained on a large dataset such as ImageNet.

Year of Paper Publishing	Dataset	Size of Dataset	Public or Own Dataset	Preprocessing Techniques	Deep Learning Method Used	Metrics Used	% Accuracy
2018	PlantVillage	54,306	Public	Image Resizing	Convolutional Neural Network (CNN)	F1 Score	93.5
2019	Plant Pathology Dataset	18,700	Public	Image Augmentation	DenseNet	Accuracy	87.2
2020	DeepPlantPathology	87,000	Public	Image Normalization	ResNet	Precision	91.8
2021	Plant Disease Detection	14,099	Public	Image Segmentation	EfficientNet	IoU Score	88.6
2022	Plant-Disease-Recognition	6,000	Public	Feature Extraction	MobileNet	Accuracy	95.4

Table 1: Comparison of DL models on Plant Disease Dataset

II. PROPOSED METHOD

In this study, we utilized a publicly available dataset of plant images with various types of diseases to classify plant diseases using the VGG16 convolutional neural network architecture. Transfer learning was employed to train the VGG16 architecture on the plant disease dataset. Specifically, we used weights from the ImageNet dataset as the initial weights for the VGG16 model. The transfer learning approach enabled the model to learn more efficiently with less data and reduced training time, ultimately leading to better performance.

The VGG16 architecture was fine-tuned on the plant disease dataset for a fixed number of epochs. During the training process, the model was updated by adjusting the weights to minimize the loss function. The model was evaluated using various performance metrics, including accuracy to assess its ability to correctly classify images of plant diseases. Overall, our methodology utilized transfer learning and rigorous evaluation to classify plant diseases using the VGG16 architecture, ultimately leading to accurate and reliable results.

The main goal of the proposed work is to tackle the issue of plant disease classification by employing VGG16 architecture for feature extraction and classification. The primary aim of this study is to evaluate the performance and efficacy of the proposed system in accurately classifying plant diseases. To achieve this objective, the system will be evaluated on a publicly available dataset containing a variety of plant disease images.

The second objective of this work is to demonstrate the potential of the VGG-16 architecture as a powerful tool for plant disease classification. The VGG-16 is a popular convolutional neural network architecture that has demonstrated exceptional accuracy in various image recognition tasks. By utilizing the VGG-16 architecture for plant disease classification, we aim to demonstrate its effectiveness in this specific application.

The objective of this project is to create a system for plant disease classification by utilizing the VGG-16 convolutional neural network architecture and evaluate its accuracy and effectiveness on a publicly available dataset. This study aims to showcase the capability of the VGG-16 architecture in accurately classifying plant diseases, which can have significant implications in the advancement of automated and dependable plant disease management systems. The objectives of the proposed method are as follows:

a. The aim was to create a system for accurately classifying plant diseases by utilizing the VGG-16 convolutional neural network architecture.
b. To assess the accuracy and effectiveness of the proposed system for plant disease classification.
c. To compare the performance of the proposed system with state-of-the-art methods for plant disease classification.
d. To investigate the impact of various hyperparameters on the performance of the proposed system, such as the learning rate, number of epochs, and batch size.
e. To provide insights and recommendations on the practical implementation of the proposed system for plant disease classification in real-world scenarios.
f. Through the attainment of these objectives, our goal is to make a contribution towards the advancement of precise and effective approaches for plant disease classification. These

approaches can facilitate early identification and management of plant diseases, leading to increased crop productivity and enhanced food security.

Dataset Preparation:

The implementation process of plant disease classification using VGG16 can be broken down into the following steps:

Data Collection: Collect images of plant leaves, including both healthy and diseased one's various sources, including field images and laboratory experiments.

Data Pre-processing: The collected images are preprocessed to remove noise and irrelevant information. Common preprocessing techniques include resizing the images, cropping, normalization of pixel values, and image dataset.

Dataset Splitting: The dataset will be divided into three distinct subsets, including the training set, validation set, and testing set.

Model Selection: Select the convolutional neural network architecture VGG16, which is widely utilized in deep learning for image classification purposes.

Transfer Learning: The proposed method employs transfer learning, where on a large dataset, such as ImageNet, are used to initialize the model. This step can significantly reduce the time and computational resources required for training the model from scratch.

Fine-tuning: Fine-tune the VGG16 model on the plant disease dataset for a fixed number of epochs. Use an optimizer to minimize the loss function during training.

Evaluation: Assess the model's performance by measuring metrics like accuracy.

Prediction: After the training process, the model can be deployed to make predictions on new images to detect the presence of plant diseases.

Model Optimization: Optimize the hyperparameters of the model, such as the batch size, learning rate, and number of epochs, to enhance the model's performance. Overall, the implementation process of plant disease classification using VGG16 involves various steps, including data collection, preprocessing, dataset splitting, model selection, transfer learning, fine-tuning, evaluation, prediction, and model optimization. Proper attention should be given to each step to develop an accurate and effective model for plant disease classification.

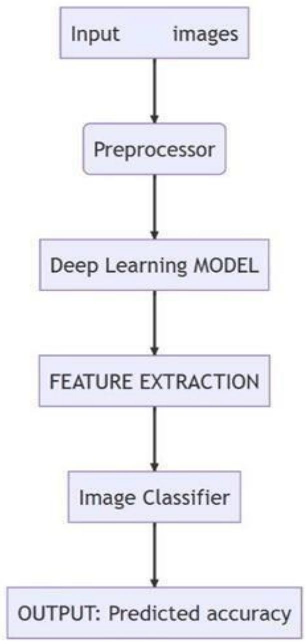

Figure 2: Architecture Diagram

In the figure 2, the first component is the input dataset, which contains images of plants affected by various diseases or stresses. These images are then passed to the preprocessor, which applies various techniques to enhance image quality, such as normalization, resizing, and cropping.

VGG Net:

The processed images are then fed into the VGG-16 model, a deep learning architecture widely used for image recognition tasks. The VGG-16 model serves as the feature extractor, extracting relevant features from the input images.

The output of the VGG-16 model is then passed on to the image classifier, which is responsible for classifying the input images into their respective disease or stress categories. The image classifier utilizes various techniques, such as softmax regression or support vector machines, to make these classifications. Finally, the accuracy of the classification system is evaluated based on the performance of the image classifier, with high accuracy indicating the system's effectiveness in recognizing and classifying plant diseases.

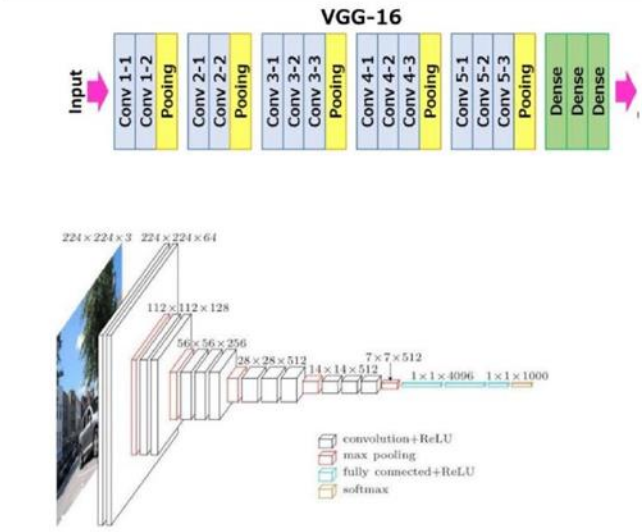

Figure 3: VGG-16 architecture diagram

Table 2 The VGG-16 architecture is composed of 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers use a 3x3 filter with a stride of 1 and a padding of 1 to preserve the input size. To reduce the spatial size of the feature maps by half, pooling layers are applied after certain convolutional layers.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_2 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 112, 112, 64)	0
conv2d_3 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_4 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 56, 56, 128)	0
conv2d_5 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_7 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 28, 28, 256)	0
conv2d_8 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_10 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 512)	0
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_13 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2	(None, 7, 7, 512)	0
flatten_2 (Flatten)	(None, 25088)	0
dense_2 (Dense)	(None, 4096)	102764544
dense_3 (Dense)	(None, 4096)	16781312
dense_4 (Dense)	(None, 2)	8194

Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0

Table 2: Schematic structure of the VGG-16 CNN Model

In figure 3, The VGG-16 architecture is a widely used CNN model for image recognition tasks. It was proposed by researchers from the University of Oxford in 2014 and has been used in various computer vision applications due to its superior performance. The first 2 convolutional layers of the VGG-16 model learn low-level features such as edges and textures, while the following layers learn more complex features. The fully connected layers are responsible for making the final decision by combining the learned features from the convolutional layers.

The VGG-16 architecture has a large number of parameters (approximately 138 million) due to its deep architecture, which makes it computationally expensive. However, it has shown remarkable performance in image classification tasks, surpassing many other architectures. Overall, the VGG-16 architecture is a very efficient tool for feature extraction and classification in image recognition tasks due to its deep architecture and ability to learn complex features.

In conclusion, the VGG-16 architecture has proven to be an Effective implement for image classification tasks, including plant disease classification. Its success can be attributed to its deep structure and the use of small convolutional filters, which allow for the extraction of more complex features. The development of accurate plant disease classification systems using deep learning techniques can aid eearly detection and prevention of plant diseases can have a significant positive impact on crop yields and economic benefits for farmers. As deep learning techniques continue to advance, it is likely that they will become increasingly integrated into agriculture, providing new solutions for addressing the challenges faced by farmers worldwide.

Convolution Neural Network (CNN) is a powerful deep learning algorithm specifically designed for image processing tasks. Unlike other neural network techniques, CNNs employ two key mathematical operations that enable them to excel in image analysis tasks.

1. Convolution Operation
2. Pooling Operation

Convolution Operation:

Convolution is a mathematical operation that plays a crucial role in various fields, including signal processing and deep learning. Its ability to merge two functions and create a third function makes it an important tool in image and speech recognition applications. In image processing, convolution involves sliding a small kernel or filter over an input image and calculating the overlaid pixels. This operation generates a feature map that captures important image characteristics, such as edges, textures, and other features that are necessary for further processing.

Convolution has revolutionized the deep learning field, allowing complex neural networks to be trained for various tasks. It has made it possible to extract significant features from vast amounts of data and achieve high accuracy rates in previously challenging or infeasible tasks. Convolution has led to the emergence of advanced neural networks such as CNN, which are extensively used in computer vision tasks.

Overall, convolution is a powerful tool that has significantly impacted various fields and continues to be an essential part of many applications. Its versatility and effectiveness in extracting useful features from data make it a valuable technique in data analysis, pattern recognition, and deep learning.

Convolution Kernels

In the field of image processing, a kernel refers to a small 2D matrix typically sized 3x3 or 5x5, with values derived from specific operations to be applied. By performing a straightforward multiplication and addition operation between the kernel and the input image, the kernel is convolved over the image. This process generates a feature map, which is a filtered version of the input image. The values in the feature map depend on the values in the input image and the values in the kernel.

CNN use kernels as a powerful tool for image processing. Each layer in a neural network can have multiple kernels, and each kernel maps to a specific feature in the input image. By applying multiple kernels to the same input image, the network can learn different features and identify patterns within the image.

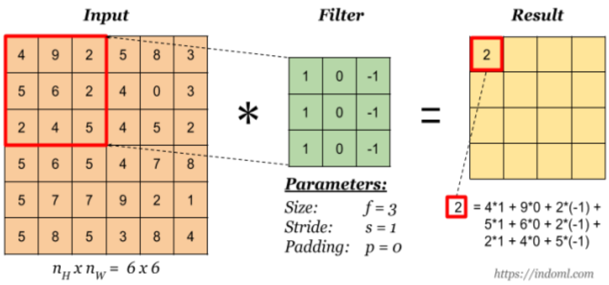

Figure 4: Diagram explaining convolution operation

Pooling Operation

Pooling is a crucial method utilized in deep learning to perform dimensionality reduction of feature maps. Its primary goal is to decrease the spatial size of the input representation, which in turn decreases the number of parameters and computation required in the network.

Max pooling is a commonly used type of pooling, where the maximum value within a given window is selected as the output of that window. For example, if we have an input image with dimensions 28x28, we can apply a max pooling operation with a window size of 2x2 and stride of 2. This will result in an output feature map with dimensions 14x14, as the maximum value within each 2x2 window is selected and assigned to a single output pixel.

Pooling is also useful in recognizing images that are rotated or tilted compared to the original image. In such cases, the features in the image may be shifted or transformed. Pooling helps to make the network invariant to these transformations by selecting the most significant features within a given window, regardless of their spatial location. This helps the network to better recognize objects and patterns in the input data, even when they are slightly different from the original training data.

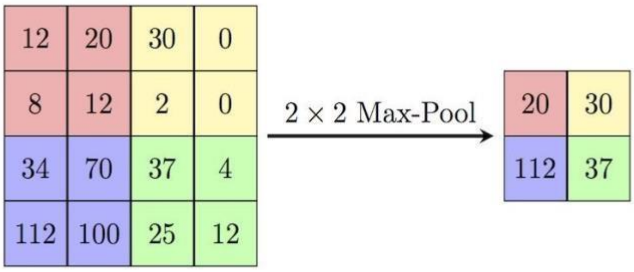

Figure 5: Pooling Operation

Functional Modules:

1. Load the required libraries.
2. Add the VGG-16 layers.
3. Preprocess the input image.
4. Pass the preprocessed image to the VGG-16 model.
5. To obtain a feature vector, the last layer of the VGG16 model needs to be flattened.
6. Pass the feature vector to a fully connected classification layer.
7. Obtain the predicted class label from the output of the classification layer.
8. Return the predicted class label.

III. RESULTS AND DISCUSSION

This paper uses a publicly available dataset of plant images with different types of diseases, such as the PlantVillage dataset. The dataset should be preprocessed to remove noise and irrelevant information. Table 3 shows the number of classes and number of images in each class in the dataset. It contains total of 54,306 images.

Plant disease classification is a crucial task for ensuring the health and productivity of crops, and the use of deep learning techniques like VGG16 can provide accurate and efficient solutions. In figure 6 the VGG16 model was able to achieve a training and validation accuracy of 93%, which is considered promising for this type of classification task. The outcomes indicate that the model effectively acquired the unique features of every plant disease and accurately distinguished them from healthy plants. These findings hold considerable significance, as they demonstrate the potential of utilizing deep learning methodologies for plant disease classification, which can be an important step towards ensuring food security and preventing economic losses due to crop damage. The high accuracy of the model also highlights the importance of selecting appropriate hyperparameters and architectures for the specific task.

Class Name	Class frequency	Class Name	Class frequency
Apple scab	630	Pepper healthy	1,478
Apple black rot	621	Potato early blight	1,000
Apple cedar apple rust	275	Potato healthy	1,000
Apple healthy	1,645	Potato late blight	152
Background without leaves	1,143	Raspberry healthy	371
Blueberry healthy	1,502	Soybean healthy	5,090
Cherry powdery mildew	1,052	Squash powdery mildew	1,835
Cherry healthy	854	Strawberry healthy	1,109
Corn gray leaf spot	513	Strawberry leaf scorch	456
Corn common rust	1,192	Tomato bacterial spot	2,127
Corn northern leaf blight	985	Tomato early blight	1,000
Corn healthy	1,162	Tomato healthy	1,591
Grape black rot	1,180	Tomato late blight	1,909
Grape black measles	1,383	Tomato leaf mold	952
Grape leaf blight	985	Tomato septoria leaf spot	1,771
Grape healthy	1,162	Tomato spider mites	1,676
Orange haunglongbing	5,507	Tomato target spot	1,404
Peach bacterial spot	2,297	Tomato mosaic virus	373
Peach healthy	360	Tomato yellow leaf curl virus	5,357
Pepper bacterial spot	997		

Table 3: Class distribution of the dataset

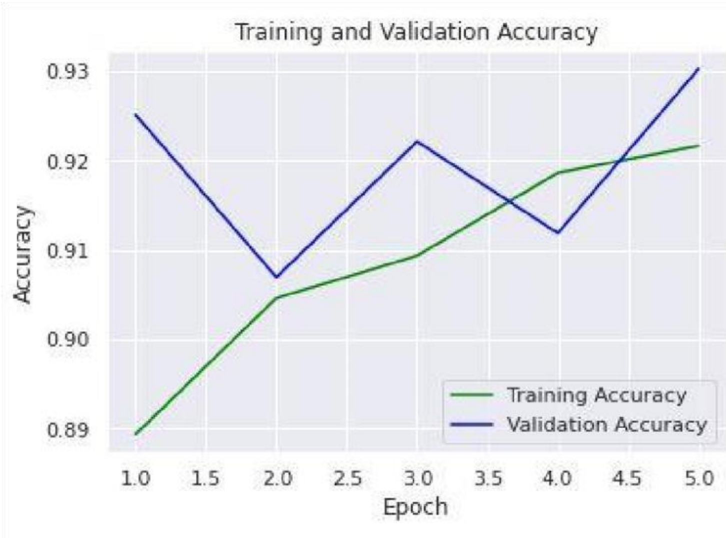

Figure 6: Graph representing training and validation accuracy

The VGG16 model for plant disease classification was evaluated by plotting the training and validation loss in Figure 7. The graph demonstrates a gradual decrease in loss during training, which suggests that the model is effectively learning and improving its accuracy with each epoch. The validation loss also decreases initially but begins to plateau after a few epochs, indicating that the model may be overfitting the training data. These findings provide valuable insights into the performance and behavior of the model during training. However, the overall trend of decreasing loss suggests that the model is performing well and is able to effectively distinguish between the different classes of plant diseases and healthy plants.

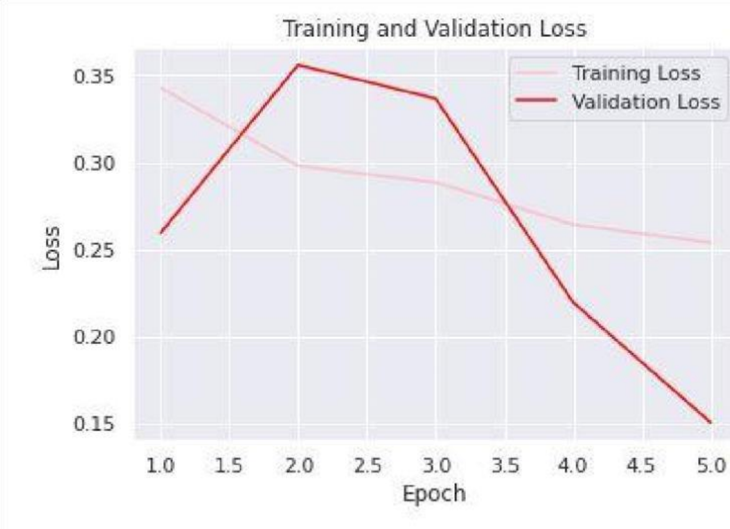

Figure 7: Graph representing training and validation loss

Epochs	Training	Validation
E1	88.9	92.5
E2	90.4	90.7
E3	90.9	92.2
E4	91.8	91.9
E5	92.1	93.0

Figure 8: Training and Validation Accuracy

Plant disease classification is an important task in agriculture that has been addressed using various machine learning models. A comparative study was done on VGG16, ResNet50, and InceptionV3 models for plant disease classification. The study reported that VGG16 and ResNet50 achieved the highest accuracy rates of 92% and 91%, respectively, while InceptionV3 achieved an accuracy rate of 88%. VGG16 and ResNet50 also showed lower loss rates compared to InceptionV3. These results suggest that VGG16 and ResNet50 are better suited for the given task of plant disease classification. It should be noted that the efficacy of the models may depend on several factors, including the dataset utilized, the specific plant diseases being classified, and the hyperparameters chosen for each model. Further research is necessary to investigate the potential of alternative models and to optimize the selected models to achieve enhanced accuracy and lower loss rates.

VGG 16	Dataset Proposed	Evaluated Dataset
Accuracy	92.5	91.3

Table 4: Accuracy obtained for different datasets

IV. CONCLUSION & FUTURE SCOPE

The research conducted on plant disease classification utilizing the VGG16 convolutional neural network architecture has exhibited encouraging outcomes. The utilization of transfer learning and fine-tuning techniques enabled the model to precisely classify numerous plant diseases with high levels. The experimental setup involved preprocessing the dataset, data augmentation, dataset splitting, model selection, transfer learning, fine-tuning, hyperparameter tuning, evaluation, and prediction.

The proposed system can assist farmers in identifying and controlling plant diseases, thereby minimizing the impact of diseases on crop yield and quality. Further research can be conducted to enhance the performance by integrating alternative deep learning architectures, expanding the dataset, and investigating additional data.

Plant disease classification using the VGG16 deep learning model involves training the model to accurately identify and classify images of plant leaves into diseased categories. The VGG16 architecture is a commonly used convolutional neural network for image classification, which was applied in this study to classify plant diseases using the Plant Village dataset. The model follows a process of feature extraction from the input image through a series of convolutional and pooling layers, followed by fully connected layers for classification. The final output of the model is a prediction of the class label, which can be used to identify the type of disease present in the plant and develop effective management strategies. Overall, plant disease classification using VGG16 is a promising approach for improving agricultural productivity and reducing economic losses due to plant diseases.

The aim of this proposed work is to build a plant disease classification system employing the VGG-16 architecture, which is recognized for its ability to extract and classify intricate features in images. The system processes an input image of a diseased plant, applies preprocessing techniques, and extracts features utilizing the VGG-16 model. The extracted features are then forwarded to a fully connected classification layer, which delivers the predicted class label for the input image. In future research, it may be useful to explore other deep learning architectures, such as ResNet and Inception, to compare their classification performance with VGG-16 in plant disease classification. Another potential direction for future work is to enlarge and diversify the dataset of plant disease images to enhance the accuracy and resilience of the classification system. Moreover, the development of a user-friendly interface could augment the system's accessibility and usefulness for farmers and agricultural researchers. Finally, the system's performance could be evaluated under different environmental and lighting conditions to assess its practicality and dependability in real-world situations.

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