Disease Detection in Crops using Deep Learning

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Abstract. In recent years, plant diseases have caused significant damage to crop production, leading to huge economic losses. Therefore, the early detection of plant diseases is essential to minimize the damage and increase crop yield. In this paper, we present a comparative study of two popular deep learning models, VGG16 and ResNet50, for the detection of plant diseases. we compared the performance of these two models in detecting diseases in four crops, namely tomato, cotton, rice, and sugarcane. Our experimental results show that VGG16 achieved higher accuracy than ResNet50 for all four crops, with an average accuracy of 91.2% compared to 88.3% for ResNet50, demonstrating its effectiveness in plant disease detection.

Keywords: Disease Detection, Deep Learning Models, Resnet50, VGG16.

1 Introduction

Agriculture is a critical sector that plays a vital role in ensuring food security and driving economic development. Unfortunately, crop growth can be hindered by various factors, such as pests, diseases, and unfavorable weather conditions. Among these factors, plant diseases pose a significant threat to crop yield and quality. It is therefore essential to detect and diagnose plant diseases promptly and accurately to minimize crop losses and maximize yields. The traditional methods of detecting plant diseases are laborious and time-consuming, and they require skilled personnel. Fortunately, the advent of deep learning technology has brought about a significant change in the field of plant disease detection. Deep learning models have demonstrated impressive results in the detection of plant diseases, thereby helping to save crops and increase yields. In this study, we compare the performance of two deep learning models, namely VGG16 and ResNet50, in detecting and classifying diseases in four crops: tomato, cotton, rice, and sugarcane. We employed publicly available datasets for each crop, preprocessed the images, and trained the models using transfer learning techniques. Both VGG16 and ResNet50 are deep convolutional neural network (CNN) architectures that have achieved remarkable performance in various tasks. These models use numerous convolutional layers to extract features from input images, which are then followed by fully connected layers to classify the images. By harnessing the capabilities of these models, we aim to develop a highly accurate and efficient system for detecting plant diseases.

2 Review of Literature

[1] The author presented PlantVillage (54,306 images) and Tomato-Plant-Disease (18,440 images). The authors finetune three pre-trained CNN models: ResNet50, DenseNet121, and InceptionV3 for plant disease detection. The fine-tuned models achieve high accuracy in detecting plant diseases on both datasets. The proposed system can be used for early disease detection in plants, leading to better crop management and increased yields.
[2] The research discussed a technique for using photos of tomato leaves to detect and categorise diseases using the AlexNet convolutional neural network. The pre-trained model was adjusted by the authors, who improved accuracy over earlier techniques. The recommended approach is put out as a potential remedy for real-world applications in managing and diagnosing plant diseases.
[3] Using a dataset of 2,400 photos of crops with bacterial blight, yellow spot, and septoria leaf blotch, the paper suggested a deep learning-based method for identifying leaf diseases in agricultural plants. The method extracts features using a convolutional neural network (CNN), then classifies data using a support vector machine (SVM). The suggested technique successfully detects the three diseases with high accuracy, highlighting its potential for usage in agricultural applications. The study emphasises the value of applying deep learning techniques for early disease identification and prevention in crops, which can have a big influence on crop production and food security.
[4] The research suggests a novel CNN architecture for identifying plant diseases as far as the models employed are concerned. Three convolutional layers, two maxpooling layers, and two fully linked layers make up the proposed model. The authors also show that their suggested model surpasses both the VGG16 and ResNet50 CNN models in terms of accuracy and F1-score when they compare the performance of their model with those two already-existing CNN models.
[5] The convolutional neural networks (CNNs) in detecting plant leaf diseases is described. It emphasizes the importance of early detection in preventing losses in agriculture. The review covers different CNN architectures, datasets, and performance metrics used in plant disease detection, including PlantVillage, FungiNet, Tomato Disease, Grapevine Diseases, and Cassava Leaf Disease Datasets. The authors provide insights into the limitations and future directions of using CNNs in this field. Overall, the paper offers a comprehensive overview of the use of CNNs in detecting plant leaf diseases.

3 Proposed Architecture and Methodology

3.1 Datasets

We used the following datasets for each crop:

1. Tomato: Tomato Leaf Disease Detection
2. Cotton: Cotton Leaf Disease Dataset
3. Rice: Rice Diseases Image Dataset
4. Sugarcane: Sugarcane Leaf Disease Classification

We used 80% of the dataset for training and 20% for validation. We used transfer learning to train the VGG16 and ResNet50 models on the preprocessed images. We used the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. We trained each model for 50 epochs and evaluated the performance on the validation set after each epoch.

3.2 Datasets

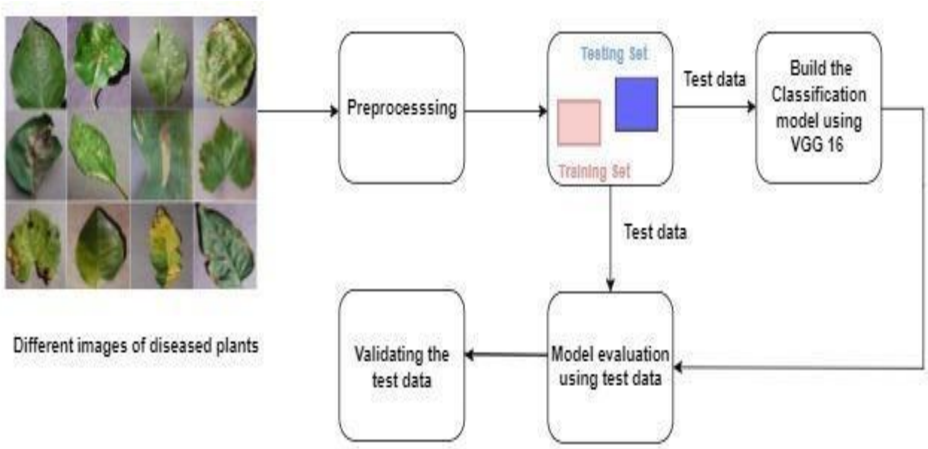


Fig. 1. Architecture of the proposed work

The proposed system's architecture, as illustrated in Fig.1, aims to classify crop disease images captured under different conditions such as diverse soil types and growth stages. Preprocessing, the first stage of the system, entails getting the images ready for analysis. The dataset is then split into two subsets: training and testing data. The training subset is used to train the VGG16 classification model, which takes in several parameters and iteratively updates its internal weights to enhance its accuracy. On the other hand, the testing subset is used to assess the model's performance. Once the training process is complete, the model is saved and assessed using the test data. If the model's precision is adequate, it can be used to categorise crop disease photos in practical situations.

3.3 Data Preprocessing

Data preprocessing is a vital step in ensuring the accuracy of machine learning models. To improve model performance in this research, many data preparation operators were used.

- One of the operators utilised was randomResizedCrop(), which randomly selects an image's size before cropping and resizing it.
- With a default probability of 0.5, another operator called horizantalFlip() randomly flips the input images.
- Images are cropped from the centre using the centerCrop() operator. If an image is smaller than the output size that is intended, it is first padded with zeros.
- The normalise() operation normalises input images using their specified mean and standard deviation.
- To resize photos to a given size, use the resize() operator.

3.4 Description of Algorithm

1. Input the image into the VGG16 model
2. For i:=1 to epochs:
   2.1 Convolutional filters of different sizes (e.g., 3x3, 5x5, etc.) are applied to extract features from the image.
   2.2 Activation functions (such as ReLU) are used to introduce non-linearity into the output of each filter.
   2.3 Max pooling is applied to reduce the dimensionality of the output from each filter.
   2.4 If the predicted label does not match the actual label:
      2.4.1 Apply the Cross-Entropy loss function:
      Cross-Entropy Loss = $-\Sigma(y * \log(p) + (1 - y) * \log(1 - p))$

      where y is the true label (either 0 or 1) and p is the predicted probability of the positive class (i.e., the class associated with the disease).
   2.5 If classification:
      Apply the Cross-Entropy loss function is applied.
   2.6 Else:
      Mean Squared Error loss function is applied.
3. Output the probabilities of the class labeThe class label with the highest probability is the predicted label.

4 Discussion

4.1 Dataset

1. **Rice Crop :** The Kaggle website provided the dataset for the rice crop. 5750 pictures and 5 labels are included in the collection. Different lighting situations and soil types are used when taking the pictures. Bacterial Blight, Tungro, LeafSpot, Healthy, and LeafBlast are the names of the diseases. Fig. 2 displays sample photos for each class, scaled to a certain size.

Fig. 2. Sample Images of Rice Crop Diseases

2. Tomato Crop : The Kaggle website provided the dataset for the tomato crop. There are 10,000 photos and 10 labels in the collection. Images are captured under a variety of circumstances, including varied soil types and natural lighting. Bacterial Spot, Early Blight, Late Blight, Leaf Mould, Septoria, Leaf Spot, Mosaic virus, Healthy, and Spidermites are the names of the illnesses. Each class's representative photographs are shown in **Fig. 3.**

3. **Sugarcane Crop :** The dataset for sugarcane crops is acquired from Kaggle. There are 608 photos and 3 labels in the collection. Images are captured under a variety of circumstances, including varied soil types and natural lighting. The illnesses are known by the names Bacterial Blight, RedRot, and Healthy. Figure 4 displays sample photos for each class.

Fig. 4. Sample Images of Sugarcane Diseases

4. **Cotton :** The dataset for the cotton crop was obtained from Kaggle. There are 3068 photos and 4 labels in the collection. Images are captured under a variety of circumstances, including varied soil types and natural lighting. The diseases are known by the names Bacterial Blight, Healthy, Crowngall, and Grey Mildew. Fig. 5 displays examples of photos for each class.

Fig. 5. Sample Images of Cotton Diseases

4.2 Discussion on Results

The environment used to construct and validate the model is Kaggle. Kaggle is a platform that offers various tools and resources for data scientists and machine learning engineers to build models. Kaggle hosts a vast repository of datasets that data scientists can use to build models. These datasets cover a wide range of topics, from healthcare to finance to sports, and provide opportunities for data scientists to explore different types of data and build models to analyze and understand it. Kaggle provides an interactive coding environment called Kaggle Notebooks, which allows data scientists to write and run code in a web browser. These notebooks provide a collaborative workspace where data scientists can share code and ideas, and they include built-in tools for data visualization and exploration.

Fig. 6,7,8,9 shows how the diseases of rice crop, tomato, sugarcane, cotton are predicted respectively.

Fig. 6. Input Images and Predicted Labels of Rice crop

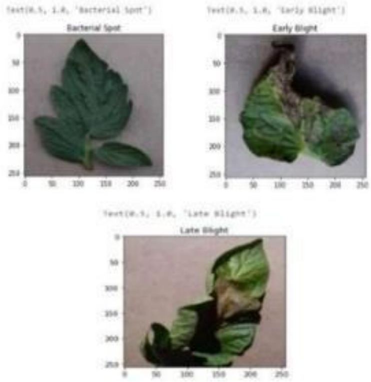


Fig. 7. Input Images and Predicted Labels of Tomato crop

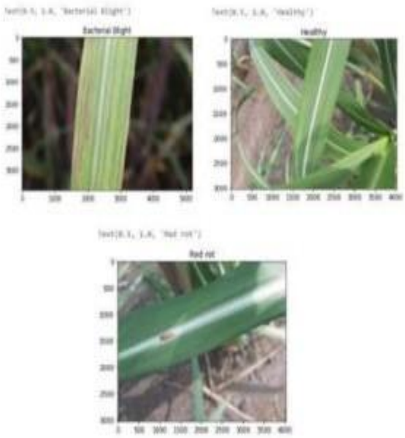


Fig. 8. Input Images and Predicted Labels of Sugarcane crop

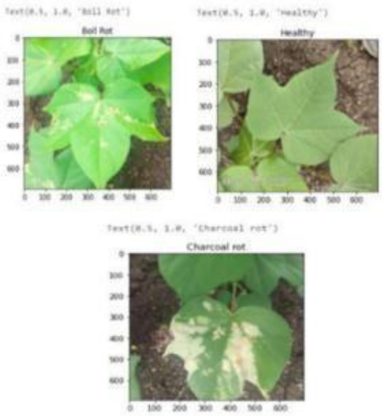
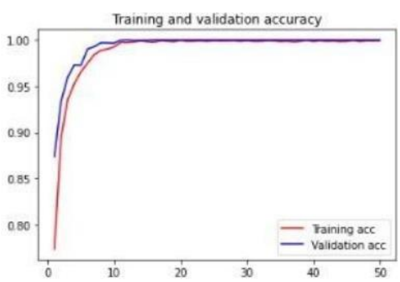


Fig. 9. Input Images and Predicted Labels of Cotton crop

The below graphs shows the accuracy and loss graphs for four crops.

1. Rice Crop :



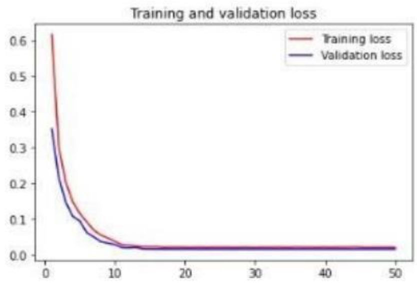
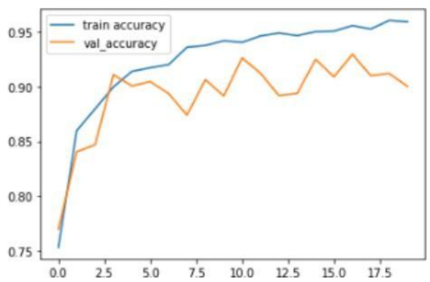


Fig. 10. Training and validation accuracy of rice crop using VGG16 model

Fig.11. Training and validation loss of rice crop using VGG16 model

The graph displayed in **Fig. 10** illustrates the accuracy for a total of 50 epochs. The validation accuracy was 0.875 and the training accuracy was 0.728 at epoch-0, while at epoch-50, the validation accuracy reached almost 0.998 and the training accuracy was 0.989. Similarly, the loss graph shown in **Fig. 11** also depicts 50 epochs. At epoch-0, the validation loss was 0.371 and the training loss was 0.628, whereas at epoch-50, the validation loss was almost 0.023 and the training loss was 0.024.

2. Tomato Crop :



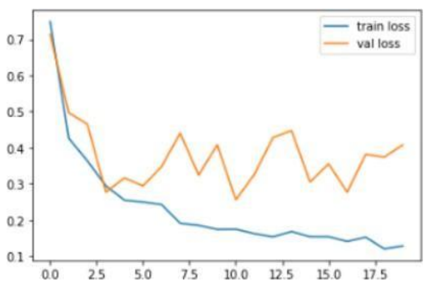
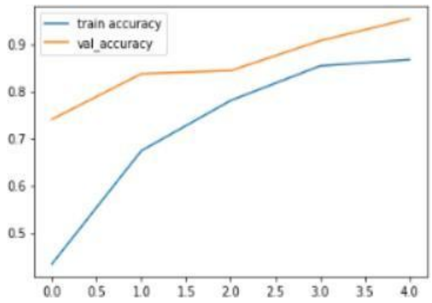


Fig. 12. Training and validation accuracy of Tomato crop using VGG16 model

Fig.13. Training and validation loss of Tomato crop using VGG16 model

The graph presented in **Fig. 12** represents the accuracy for a total of 20 epochs. At epoch-0, the validation accuracy was 0.772 and the training accuracy was 0.751. By epoch-20, the validation accuracy increased to almost 0.898 and the training accuracy reached 0.986. The loss graph depicted in **Fig. 13** also spans 20 epochs. At epoch-0, the validation loss value is missing and the training loss was 0.628. At epoch-50, the validation loss was almost 0.411 and the training loss was 0.125.

3. Sugarcane Crop :



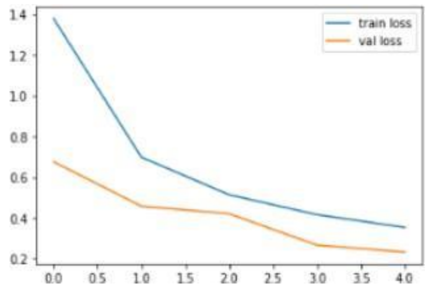
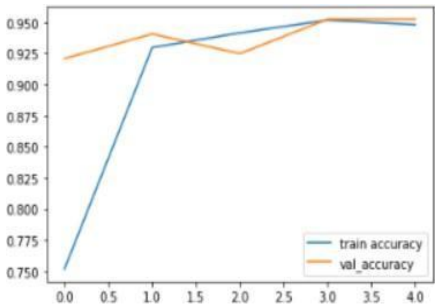


Fig. 14. Training and validation accuracy of Sugarcane crop using VGG16 model

Fig.15. Training and validation loss of Sugarcane crop using VGG16 model

The accuracy graph presented in **Fig.14** spans across 40 epochs. At epoch-0, the validation accuracy was 0.748 and the training accuracy was only 0.126. However, by epoch-40, the validation accuracy increased significantly and was almost 0.987, while the training accuracy improved to 0.839. On the other hand, the loss graph shown in **Fig.15** also covers 4 epochs. At epoch-0, the validation loss was 0.643 and the training loss was 1.389. At epoch-40, the validation loss decreased to almost 0.225, and the training loss reduced to 0.396.

4. Cotton Crop :



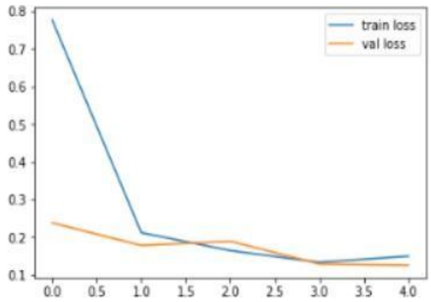


Fig. 16. Training and validation accuracy of Cotton crop using VGG16 model

Fig.17. Training and validation loss of Cotton crop using VGG16 model

The accuracy graph displayed in **Fig. 16** is based on 40 epochs. At epoch-0, the validation accuracy was 0.924 and the training accuracy was 0.724. By epoch-40, the validation accuracy improved to nearly 0.948, while the training accuracy reached 0.946. Additionally, the loss graph shown in **Fig.17** also covers 4 epochs. At epoch-0, the validation loss was 0.248, and the training loss was 0.798. By epoch-40 the validation loss reduced to almost 0.139, while the training loss was 0.175.

The performance of VGG16 and ResNet50 on the four crops is summarized in the following table.

TABLE I

Crop	Model	Training Accuracy	Validation Accuracy
Tomato	VGG16	0.96	0.86
	Resnet50	0.93	0.80
Cotton	VGG16	0.97	0.87
	Resnet50	0.94	0.85
Rice	VGG16	0.98	0.86
	Resnet50	0.96	0.82
Sugarcane	VGG16	0.93	0.88
	Resnet50	0.96	0.83

5 Conclusion

Plant disease detection is a critical component of agricultural production, as it enables the timely and accurate identification of diseased crops and allows for targeted treatment and prevention measures. The developed model focuses on plant disease detection using VGG16 with high accuracy and efficiency. The use of VGG16, a pre-trained deep learning model, can significantly improve the accuracy of plant disease detection. It also places emphasis on computational efficiency, which is important for real-time detection in agricultural settings. The ability to retrain the model with new data allows for ongoing improvements in its performance and the identification of new disease patterns. It has the potential to revolutionize plant disease detection in agriculture, reducing the reliance on manual inspection and enabling targeted treatment of diseased crops. However, further research is needed to evaluate the model's performance in real-world field conditions. Researchers could also investigate the integration of multi-spectral or hyperspectral imaging techniques to enhance crop disease detection accuracy by capturing detailed information about crops' structure, chemical composition, and physiological state. Overall, continued research in this field could significantly improve the efficiency and sustainability of agriculture.

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