Scalable Plant Disease Detection utilizing VGG based Deep Models

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Abstract. Plant disease detection is essential for enhancing sustainability in agriculture domain, as it enables early detection of any possible crop loss. It allows to have reduced production loss and chemical dependency. This paper proposes deep architectures utilizing VGG16 and VGG19 for automated plant disease detection. For experimentation, the PlantVillage dataset is used. The emphasis is on enhanced crop production along with low-resource environments. Growing population and lowering fertility of land demands sustainable crop production. The work demonstrates that VGG19 outperforms VGG16 in classification accuracy while maintaining reasonable computational requirements. The proposed approach offers a scalable and environmentally conscious solution named "Deep Green" for real-time plant disease diagnosis, supporting the broader goals of precision farming and food security. Deep is inspired by the deep neural network architecture and Green has emerged from green revolution. This study contributes a deep architecture for reducing crop loss by predicting the disease in advance and allowing the possible solutions providing insight into the anticipated problems.

Keywords: Plant Disease; VGG16; VGG19; Sustainable Agriculture; PlantVillage Dataset.

1 Introduction

Continuously increasing demand for food over the globe, along with occurring climatic changes and emerging plant pathogens, raises concern about food production and food security. Early detection of possible disease in crops is somewhat essential to ensure sustainable crop production and suffice the global food demands. AI, especially deep networks, provide a powerful tool for plant disease detection by processing leaf images [1].

Along with technological development and supporting food security, AI based plant disease detection contributes to multiple SDGs [2]. It enables timely and precise diagnosis of crop diseases; and directly supports SDG 2 by reducing yield loss and enhancing food security. Furthermore, early prediction of possible diseases in crops helps to balance the chemical usage and hence lowers the environmental burden of agriculture,

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supporting SDG 13 through more sustainable farming practices [3]. Integrating deep learning for agriculture reflects the digital transformation through fostering innovation and smart infrastructure which is in line with SDG 9 [17]. Last but not the least, through prevention of the spread of crop diseases and preserving plant biodiversity, AI-based solutions also contribute to SDG 15. The idea is to leverage the 'deep' networks for keeping our crops in healthy state signified as being 'green'.

1.1 Motivation behind the Study

A global estimate highlights the loss of almost 40% of crop production due to diseases in plants annually, which involves 45-90% of wheat and tomatoes like crops [4]. This situation calls for food security that can be ensured by early disease detection and crop protection. The motivation behind the study is availability of limited resources along with increasing need for food which necessitates the sustainable agriculture aligned with global development goals to ensure food availability to feed the world.

1.2 Contributions from the Study

This study contributes a scalable deep model for plant disease detection using VGG16 and VGG19 models built over PlantVillage dataset. It focuses on the alignment of crop protection using deep models for plant disease detection with five UN Sustainable Development Goals (SDGs). It contributes a sustainable model for sustainable agriculture in future.

1.3 Organization of the Study

The paper is organized as follows: Section 2 reviews the literature about the applications of deep networks in plant disease detection. Section 3 describes the methodology and the architecture used for the study. Section 4 discusses the findings in the context of scalability and sustainability, with reference to relevant SDGs. Finally, Section 5 gives the future scope of the work along with concluding remarks.

2 Literature Works

This section glances at the SOTA of the application of deep networks for plant disease detection. From the literature, it is observed that traditional methods for plant disease detection majorly rely upon manual techniques and methods which are slow and tedious [5]. Deep Learning (DL) techniques are profoundly being applied for automation of plant disease detection. Deep networks have gained significant traction due to their ability to automatically learn discriminative features from raw image data [6]. Unlike traditional machine learning (ML) methods that require handcrafted features, DL models capture complex patterns and visual cues, enabling more accurate and scalable disease classification.

Biswas et al. 2024 [7] introduces an EE CNN for plant disease detection, evaluated on PlantVillage, cassava, and rice datasets. It achieved accuracies of 95.17%, 99.8%, and 63% respectively, outperforming VGG19 and Inception V3 on PlantVillage and rice, and performing comparably on cassava. The model is also significantly faster-about 5× faster than Inception V3 and 2× faster than VGG19.

Pandian et al. 2022 [8] proposes a 14-DCNN for plant disease detection, and a newly created dataset of 147,500 images covering 58 plant classes contributed. Data augmentation with DCGAN is done. Random search deployed for parameter fine-tuning. The model shows 99.97% accuracy better than SOTA transfer learning methods.

Qiu et al. 2024 [9] demonstrated the effectiveness of AlexNet on 54,306 leaf images, achieving 99.27% accuracy across 14 crop species and 26 diseases.

Santoso et al. 2024 [10] compares a conventional CNN and DenseNet121 for tomato leaf disease detection using a combined dataset of 18,815 images spanning 13 disease classes. Data preprocessing included normalization, augmentation, and class balancing. DenseNet121 outperformed CNN, achieving 98.27% training accuracy, 87.47% validation accuracy, and average F1 scores of 87%. In contrast, CNN achieved 90.41% training accuracy and 83.33% validation accuracy. Owing to its superior performance, DenseNet121 was selected for deployment in the Tanamin.id mobile application.

Krishna et al. 2025 [11] propose multi-dataset strategy for deep networks based plant disease detection. They combined PlantDoc dataset with new images and contributed a modified dataset. Using EfficientNet-B3, the study improves model robustness and achieved up to 80.19% accuracy.

From the related literature, it is observed that Deep learning models, especially CNN-based architectures, have consistently outperformed traditional and handcrafted-feature methods in plant disease detection, achieving high accuracy across diverse datasets and crops [12][13]. Recent studies explore energy-efficient CNNs, deep custom architectures, transfer learning models like DenseNet121, and multi-dataset strategies to boost performance, speed, and robustness [14][15][16].

3 Methodology

The PlantVillage dataset, consisting of 61,486 images, was created to aid in detecting 39 different plant diseases. To increase diversity and improve model generalization, six augmentation techniques were applied (as shown in Fig. 1): scaling (resizing images to introduce size and perspective variation), rotation (rotating images by a fixed angle), noise injection (adding Gaussian noise to mimic environmental variability), gamma correction (adjusting brightness using a non-linear gamma function), PCA color augmentation (modifying color distribution while preserving structure), and image flipping (mirroring images horizontally or vertically). These methods simulate varied real-world conditions, enhancing the robustness of disease detection models.

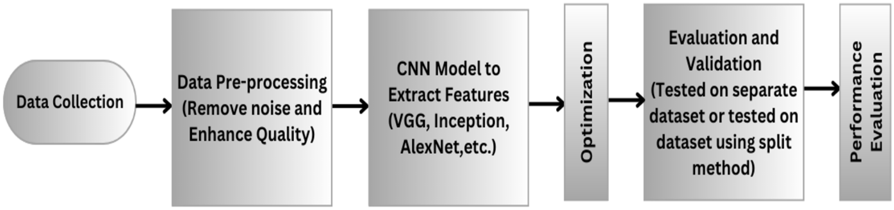

Fig. 1. Deep Architecture for Plant Disease Detection

VGG16, and VGG19 are selected for building deep networks. Each model is known for its effectiveness in processing the images and making the predictions.

Each model is initialized with pre-trained weights on the ImageNet dataset. This initialization provides a good starting point for training on the Plant Village dataset, as the models have already learned general features from a large dataset. Each model's final classification layer is tailored to the number of disease classes in the Plant Village dataset. This layer is in charge of translating the learnt characteristics to particular disease classifications, allowing the models to classify plant diseases. The structures of the models are meticulously constructed to represent complicated patterns and characteristics in plant disease imagery. The utilization of multiple designs allows for a thorough assessment of their accuracy and computing efficiency.

The weights of the pre-trained models are frozen throughout the early training phases, and only the weights of the newly added classification layers are updated. This strategy, known as transfer learning, applies previously trained models' experience while fine-tuning them to the specific job of plant disease classification. The models are built with popular deep learning frameworks like TensorFlow or PyTorch, which offer efficient computation and optimization for the training and assessment procedures. The model architectures were chosen for their popularity, shown effectiveness in picture classification challenges, and applicability for the Plant Village dataset. The inclusion of several designs enables a thorough assessment of their strengths and limitations in the context of plant disease categorization.

4 Results and Discussion

This section illustrates the results of various deep learning models tested on PlantVillage dataset. First up, author reports the performance of VGG16 model as shown in Fig. 2. It shows the ROC and AUC for VGG16 model that is 89.1%.

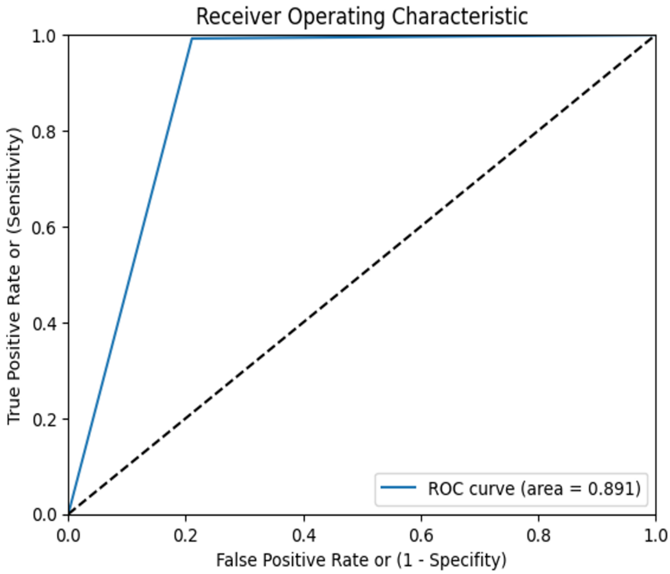

Fig. 2. ROC curve with score for VGG16

Fig. 3 reflects upon the accuracy and loss over the epochs. The reported accuracy of the model is 94.1%

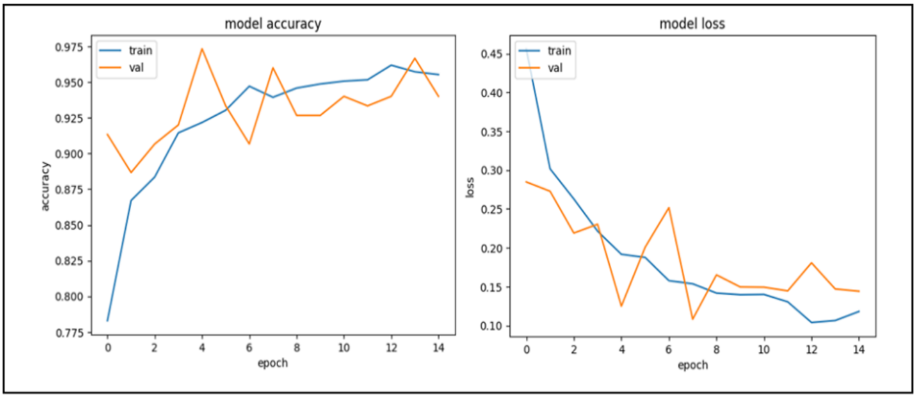

Fig. 3. Accuracy and loss for VGG16

Next, the performance of VGG19 is reported under Fig. 4, and Fig. 5 that represents the AUC-ROC and Accuracy respectively.

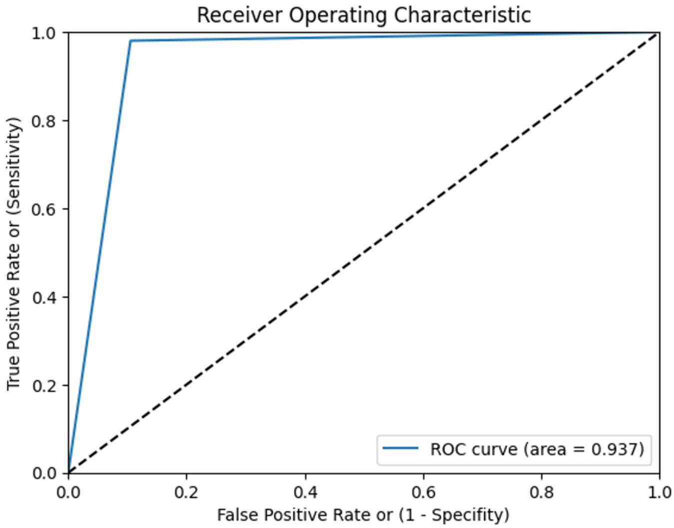

Fig. 4. ROC curve with score for VGG19

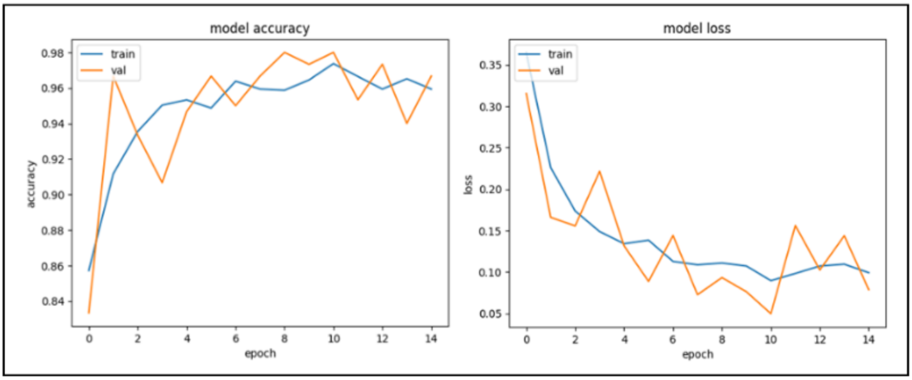

Fig. 5. Accuracy and loss for train and validate in VGG19

To ensure the stability of proposed models, 10-fold cross validation is applied, and values are recorded as Table 1. The results obtained are comparable with the current state-of-the-art models as YOLOv3 contributed by Alhwaiti et al. 2025 [17], shows 97% accuracy for plant disease detection.

Table 1. Cross-Validated Performance of models

Model	Accuracy (%)	F1-Score (%)	AUC-ROC (%)
VGG16	93.12 ± 1.05	91.85 ± 0.98	90.1± 0.02
VGG19	97.05 ± 0.87	95.77 ± 0.91	94.7 ± 0.21

5 Conclusions and Future Scope of the Work

This study contributed an effective and scalable deep model based on VGG19—for accurate plant disease detection. The model is built over the PlantVillage dataset. An empirical comparison, among two architectures, which are VGG16 and VGG19 is also made. It is observed that VGG19 achieved superior classification performance while maintaining computational efficiency. It is noted that Vgg19 based model is suitable to be deployed in the settings with agricultural settings with lesser resources. The proposed approach supports sustainable farming practices by enabling early disease diagnosis, reducing excessive pesticide use, and aligning with multiple SDGs. For future work, the model can be extended to handle real-time detection using mobile applications integrated with edge AI.

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