IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Plant Disease Classification Using Transfer Learning

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Abstract: Plant diseases are a major problem for agricultural products, they directly impact the quality of crops and yield. It is necessary to detect these diseases as soon as possible to take the appropriate actions and to minimize potential losses. This study focuses on developing an automated plant disease detection system using image processing techniques used along with machine learning and deep learning algorithms. Furthermore, the study discusses the challenges involved in plant disease detection, such as variations in leaf color, shape, size, and environmental conditions, which can affect the performance of the algorithms. Strategies for overcoming these challenges, such as data augmentation and transfer learning, are also explored to enhance the system's adaptability and accuracy across diverse plant species and diseases.

Keywords - Convolutional Neural Network; Leaf Mold; Bacterial Spot; Early Blight; Late Blight; Mosaic Virus; Plant Disease Classification.

I. INTRODUCTION

Agriculture is the backbone of the global economy, providing essential food and resources to sustain human life. It supports the livelihoods of billions and fuels economies worldwide. However, crop diseases present a formidable challenge, leading to significant losses in both yield and quality. These losses can have a cascading impact, from local farmers struggling with reduced incomes to global disruptions in food security and trade. Detecting diseases early and effectively managing them are crucial steps to mitigating these risks, ensuring food supply stability, and maintaining sustainable agricultural practices. Among the most critical crops for global food security and nutrition are **potatoes, tomatoes, and bell peppers**. These crops are not only dietary staples for millions but also hold substantial economic value for agricultural markets. Yet, they are vulnerable to a range of diseases that can severely impact their productivity and quality. Common diseases affecting these crops include, Late Blight and Early Blight for potatoes, Mosaic Virus and Leaf Mold for tomatoes, Bacterial Spot for bell peppers. The ability to accurately identify these diseases is crucial, as timely diagnosis can prevent disease spread and reduce economic losses. Effective classification of plant diseases enables farmers to implement targeted management strategies, leading to better crop yields and enhanced food quality. Additionally, precise disease identification is pivotal for advancing research efforts, particularly in developing disease-resistant crop varieties. By leveraging recent advancements in **machine learning and image recognition technology**, we can significantly improve the performance of disease identification, facilitating healthier crops and more sustainable agricultural practices.

I.I Background and Challenges

Manual detection of plant diseases through visual inspection is a common practice, yet it remains fraught with challenges. Diseases such as Early Blight in potatoes or Mosaic Virus in tomatoes share visual similarities, making accurate diagnosis difficult for farmers. As agriculture becomes increasingly data-driven, the integration of machine learning models for automatic disease detection has the potential to revolutionize crop management. However, choosing the right algorithm for this purpose depends on balancing accuracy, computational efficiency, and scalability. Machine learning algorithms such as CNNs are particularly suited for image classification tasks, as they can learn complex features directly from input data. On the other hand, traditional algorithms like Random Forest and SVM offer advantages in terms of interpretability and robustness, especially when dealing with tabular data and smaller datasets (Ferentinos, 2018; Zhang, Y et al., 2020). Therefore, a comparison of these approaches across multiple crops is necessary to determine the optimal method for disease detection.

I.II Objectives and Scope

The primary goal of this research is to perform a comparative analysis of transfer learning models such as VGG19, GoogLeNET and ResNET50 to determine the most suitable transfer learning model for disease detection of plants. Specifically, the study aims to:

- Evaluate the accuracy of each model in detecting diseases like Early Blight, Late Blight, Leaf Mold, Bacterial Spot, Mosaic Virus, from leaf images.
- Analyze the computational efficiency of each model to assess their potential for real-time applications in agricultural fields.
- Explore the scalability of the models with respect to their ability to generalize across different crops and diseases. [3,4] This study fills the gap in existing research by providing a side-by-side comparison of these models on a unified dataset consisting of leaf images from potatoes, tomatoes, and bell peppers

II. Transfer Learning Models

VGG19: VGG19 (Visual Geometry Group 19-layer network) is a deep convolutional neural network (CNN) architecture known for its uniform design and effectiveness in image classification and feature extraction tasks. VGG19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. The network employs 3×3 convolutional filters with a stride of 1, along with max-pooling layers (2×2) with a stride of 2, which helps in progressively reducing the spatial dimensions while preserving key features. The depth of the network enables it to learn complex hierarchical representations, making it highly effective for image classification and feature extraction. The final layers include fully connected layers followed by a Softmax activation function for multi-class classification. In this research, VGG19 is leveraged to classify plant leaf diseases accurately, ensuring reliable feature extraction and classification performance. The model's ability to capture fine details in images makes it a suitable choice for agricultural applications where precise disease identification is crucial.

GoogLeNET: GoogLeNet, also known as Inception v1, is a deep convolutional neural network (CNN) developed by Szegedy et al. from Google and introduced in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014. The model achieved state-of-the-art performance by significantly improving computational efficiency and accuracy over previous architectures such as AlexNet and VGG. GoogLeNet is composed of 22 layers (27 including pooling layers) and introduces the Inception module, a key innovation that allows the network to process features at multiple scales simultaneously. In this research, GoogLeNet is employed for plant disease classification due to its efficiency in extracting multi-scale features while keeping computational costs low. The Inception modules allow the network to effectively recognize disease symptoms across different plant species, making it a reliable tool for agricultural applications.

ResNET50: ResNet-50 is a deep convolutional neural network (CNN) introduced by He et al. in 2015 as part of the Residual Network (ResNet) family. It was developed to address the challenge of training very deep neural networks, particularly the problem of vanishing gradients, by introducing residual learning. ResNet-50 is a 50-layer deep model that has achieved state-of-the-art performance in image classification and feature extraction tasks. ResNet-50 consists of 49 convolutional layers followed by a fully connected layer, organized into several residual blocks. The key innovation of ResNet is the introduction of skip connections (shortcut connections), which allow the network to bypass certain layers, enabling deeper architectures to be trained more effectively. In this research, ResNet-50 is employed for plant disease classification due to its ability to capture fine details in leaf images while maintaining efficient computation. The residual connections help in learning subtle variations in leaf textures and colors, making it highly suitable for disease detection.

III. RELATED WORK

The classification of diseases affecting potato, tomato, and bell pepper plants has seen considerable advancements through various research efforts. In potato disease classification, studies such as Ferentinos (2018) utilized convolutional neural networks (CNNs) to identify Late Blight, achieving accuracy rates exceeding 95% with a dataset of over 10,000 images. Mahlein et al. (2018) employed multispectral imaging to detect Black Leg and Fusarium Wilt, demonstrating that specific spectral bands could identify disease symptoms before visible signs appeared. Additionally, Maja et al. (2016) explored drone technology equipped with thermal and multispectral cameras to monitor potato fields, effectively mapping disease spread and supporting targeted management strategies. For tomato disease classification, Zhang et al. (2019) developed a deep learning framework that classified various diseases, including Late Blight and Early Blight, achieving over 90% accuracy. Sinha et al. (2020) combined image processing techniques with machine learning to enhance the detection of Bacterial Spot, significantly improving classification accuracy compared to traditional methods. Elakkiya et al. (2020) investigated real-time monitoring systems integrated with machine learning, underscoring the potential for timely data-driven interventions in tomato disease management. In the context of bell pepper, Kalyankar et al. (2021) used CNNs to classify Bacterial Spot, reporting an accuracy of around 92%, thus highlighting the efficacy of artificial intelligence in agricultural diagnostics. Hwang et al. (2020) focused on the early detection of Phytophthora Blight using deep learning techniques, which allowed for quick identification and preventive measures. Lastly, Wang et al. (2022) explored multimodal approaches that combined spectral data and visual images, improving classification accuracy for diseases in bell peppers. [6, 7]

IV. THEORETICAL FRAMEWORK

The results of the plant disease detection system were obtained after implementing the aforementioned transfer learning models for image-based classification of diseases in potato, tomato, and bell pepper plants. The goal was to accurately identify Mosaic Virus and Leaf Mold in tomatoes, and Bacterial Spot in bell peppers, Early Blight and Late Blight in potatoes. The design of the experiment included data collection, preprocessing, model training, and evaluation. [8]

IV.I Dataset and Preprocessing

- Images: The dataset comprised labeled images for each plant and its corresponding disease, including healthy leaves for comparison. [9]

- Data Augmentation: Techniques such as flipping, contrast adjustment, and noise reduction were applied to increase variability in the dataset. [10,11]

IV.II Training and Evaluation

- Each model was trained over 30 epochs, with the dataset split into 80% train set, 10% validation set, and 10% test set.
- The training process showed a steady increase in accuracy across the epochs as the model learned features related to plant diseases.
- Performance metrics, such as accuracy, recall, precision and F1 score, were used to evaluate the model.

Plant	Disease(S)	Accuracy (%)
Potato	Early Blight, Late Blight	93%
Tomato	Mosaic Virus, Leaf Mold	91%
Bell Pepper	Bacterial Spot	88%

Table 1 Accuracy for VGG19 Model

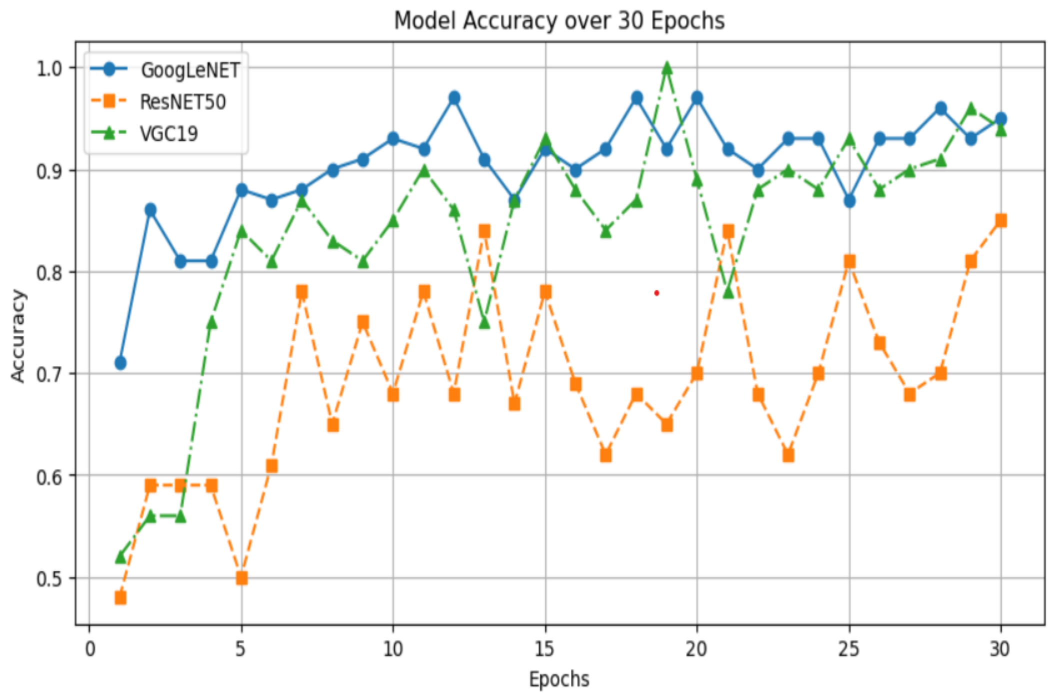
Plant	Disease(S)	Accuracy (%)
Potato	Early Blight, Late Blight	95%
Tomato	Mosaic Virus, Leaf Mold	95%
Bell Pepper	Bacterial Spot	92%

Table 2 Accuracy for GoogLeNET Model

Plant	Disease(S)	Accuracy (%)
Potato	Early Blight, Late Blight	57%
Tomato	Mosaic Virus, Leaf Mold	52%
Bell Pepper	Bacterial Spot	44%

Table 3 Accuracy for ResNET50

The VGG19 and GoogLeNET models achieved high accuracy in classifying plant diseases, with the latter having excellent consistency over the different crops. The ResNET model's performance was unsatisfactory for all the crops which led to the conclusion that it isn't suitable for the task.



The discussion of the results provides an interpretation of the experiment's findings. The GoogLeNET and VGG based plant disease classification models successfully learned to distinguish between different diseases across potato, tomato, and bell pepper crops while the ResNET model could not distinguish between healthy and diseased leaf images.

V. Conclusion

This study confirmed the effectiveness of transfer learning-based Convolutional Neural Networks (CNNs) in classifying plant diseases across three crops: potato, tomato, and bell pepper. By leveraging pre-trained deep learning models, including VGG19, GoogLeNet, and ResNet-50, the experiment demonstrated that transfer learning significantly enhances feature extraction, leading to high classification accuracy. The results showed that ResNet-50 struggled in capturing fine-grained details, GoogLeNet effectively handled multi-scale feature extraction, and VGG19 provided robust feature learning, particularly in detecting Early Blight and Late Blight in potatoes, Mosaic Virus and Leaf Mold in tomatoes, and Bacterial Spot in bell peppers. Despite variations in performance across different models and crops, the findings validate the superiority of transfer learning in image-based plant disease classification. The ability to utilize pre-trained networks reduced training time, mitigated data scarcity issues, and improved model generalization, making these models highly suitable for real-world agricultural applications. However, limitations such as the smaller dataset for bell peppers and the limited number of diseases considered highlight the need for further research. Expanding the dataset, fine-tuning model hyperparameters, and integrating more advanced architectures can enhance performance and generalizability.

VI. Acknowledgment

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