Fine Tuning based Inception v3 for the Prediction of Diseases in Paddy Leaves

Gayatri Parasa

Department of Computer Science & Engineering, Annamalai University, Tamilnadu.

gayathriparasa20@gmail.com

M. Arulselvi

Department of Computer Scie

nce & Engineering, Annamalai University, Tamilnadu.

marulcse.au@gmail.com

Abstract—

The algorithms of transfer learning techniques have developed as a strong picture for recognition strategic algorithms in the current era. Crop diseases pose a significant threat to rice crop yield. However, recent advancements in deeper layered architectures particularly in the domain of image classification and recognition, have presented an opportunity to address the challenges of overfitting, high computational resources etc. With the ease of obtaining rice crop leaf images, deep learning techniques can be leveraged to automatically detect and identify crop diseases from these images. This study focuses on the analysis and research of identifying leaf diseases in rice plants using a transfer learning and fine-tuning approach based on the Inception-V3 neural network model. By utilizing this methodology, the paper aims to contribute to the effective and efficient management of rice crop diseases, thereby safeguarding agricultural production activities.

Keywords: Inception-v3, Fine tuning, Transfer Learning, Leaf Smut, Bacterial Leaf Blight, Leaf Blight.

1. INTRODUCTION

Nowadays, rice crop diseases pose a serious risk to agricultural productivity and causes large financial losses every year. The agricultural sector is severely impacted by it due to its diverse nature, wide range of effects, and frequent large-scale outbreaks [1]. A few of the most common illnesses that impact rice crop diseases are Bacterial Leaf Blight, Leaf Blight and Brown Spot.

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The fact that these agricultural illnesses have resulted in significant financial losses highlights the urgent need for solutions in the detection and control of crop diseases in the context of agricultural production. The early diagnosis and treatment of unhealthy plants is necessary to improve crop production which further be helpful in global. These automated technologies can assist to prevent the illness from spreading to other healthy plants and reduce crop loss efficiently [2]. For plant disease identification, a wide variety of techniques were utilised, including manual inspection, laboratory testing, and the use of technology like as imaging processing techniques and sensor systems [3]. Visual inspection is the primary method used in conventional plant disease detection. This involves examining indicators such as discoloration, wilting, and the presence of disease-causing chemicals in plants. The rice leaf disease system has been continuously improved in the context of changing technology [3]. Numerous well-known pre-trained image classification networks, such as VGG-16 [4], ResNet50 [5], and GoogleNet [6], are available in MATLAB. The system's leaf disease monitoring has been made more accurate and efficient by the implementation of VGG and ResNet [5]. Brown spots, leaf blast, hispa, leaf smut, and healthy paddy leaf photos were collected from the rice fields and carefully arranged in a folder as part of the first phase of this technique.

2. Related study on Inception v3:

Shrivastava et al., (2020) introduced the Inception V3 architecture. It discusses the design principles behind the Inception network and its improvements over previous versions. The study [3] compared different deep learning architectures, including Inception V3, for the identification of plant diseases. It explored the effectiveness of these models in classifying images of diseased plant leaves. The paper explored the application of deep learning techniques, including Inception V3 [4], for the detection and classification of various plant diseases. It discusses the performance of different architectures on datasets containing images of diseased plants. While not focused on plant diseases, this study showcases the application of transfer learning using Inception V3 for classifying cellular morphological changes. It provides insights into the versatility of Inception V3 in different image classification tasks. The survey paper [5] provided an overview of various deep learning architectures, including Inception V3, for image retrieval tasks. It discusses the strengths and weaknesses of these models in the context of content-based image retrieval. This recent study [6] explored the use

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of deep neural networks, including Inception V3, for image-based plant disease detection. It discusses the challenges and opportunities in applying these models to agricultural settings.

3. Proposed Methodology:

The proposed approach employs the CNN image classification technique for the categorization of rice leaf images. By leveraging information extracted at each convolution layer, the system is adept at automatically detecting and identifying various diseases affecting rice leaves. The architectural representation of this proposed system is illustrated in the accompanying diagram. To facilitate disease identification, image processing techniques are incorporated into the system. Users are required to upload an image of a rice plant leaf, after which the algorithm undertakes preprocessing before applying the CNN algorithm for disease detection. The network is constructed using a hybrid of pre-training on ImageNet and the Inception component, demonstrating superior performance compared to other contemporary techniques. Notably, each convolution layer within the dense block focuses on minute details, allowing the convolution kernels to effectively learn subtle features. The block diagram and flowchart presented below provide a visual overview of our project's structure and workflow in the context of rice leaf diseases.

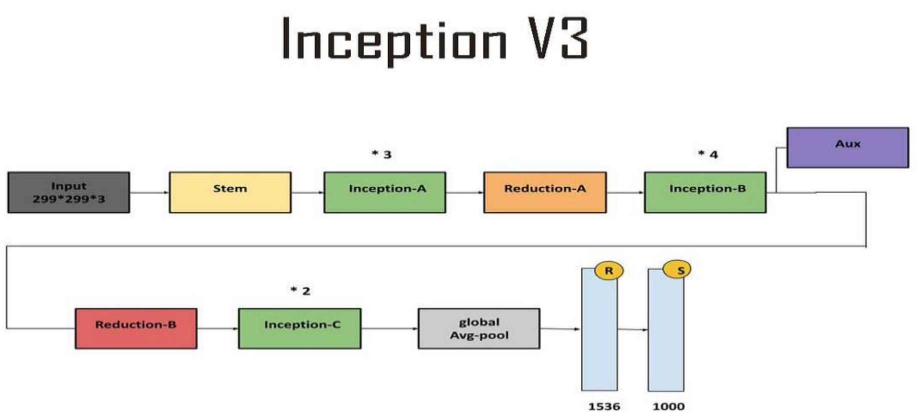

Figure 1.1: Inception v3 block diagram for the prediction of diseases in rice leaves

I. Data Collection: The dataset utilized in this study was sourced from the Kaggle Cotton Disease Dataset available online. The corresponding code was embedded in the Kaggle online kernel, facilitating efficient computation and analysis of training loss and validation.

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II. Data Pre-Processing: To enhance image quality and eliminate undesired distortions, preprocessing of the input images was conducted. This involved clipping the leaf image to focus on the region of interest, followed by image smoothing using a smoothing filter. Additionally, image enhancement techniques were applied to increase contrast.

III. Transfer Learning: Transfer learning is a methodology that involves leveraging knowledge gained from solving one problem and applying it to another related problem. Given the computational challenges associated with the feature extraction phase in Convolutional Neural Networks (CNNs), transfer learning proves valuable by reusing pre-trained feature extraction sections. Users have the option to replace the final layers of the pre-trained model with new layers to construct a customized CNN. Training is specifically carried out on the newly added layers.

IV. Recognition Using Inception V3 Network Transfer Learning: The Inception series of CNNs holds a significant place in the history of neural networks. Unlike conventional networks that deepen by increasing convolutional layers for improved performance, Inception networks introduced a novel approach. The Inception module, proposed within the Inception Neural Network, utilizes filters of different sizes and maximum pooling to reduce data dimensionality. This strategic use of diverse filters and pooling results in richer features with significantly reduced computational requirements and fewer parameters.

4. Results and Analysis:

In machine learning, training loss represents how well a model performs on the training dataset, refining its parameters to minimize errors. This process aims to enhance the model's accuracy in predicting target values for the provided training data. Conversely, validation loss measures the model's ability to generalize to new, unseen data, distinct from the training set. Training loss, often referred to as the training error or training cost, is a measure of how well a machine learning model performs on the training data. During the training phase, the model is exposed to a labelled dataset, and it adjusts its parameters (weights and biases in the case of neural networks) based on the input data to minimize the training loss. The goal is to minimize the training loss, which means the model is becoming more accurate in predicting the target values for the given training data.

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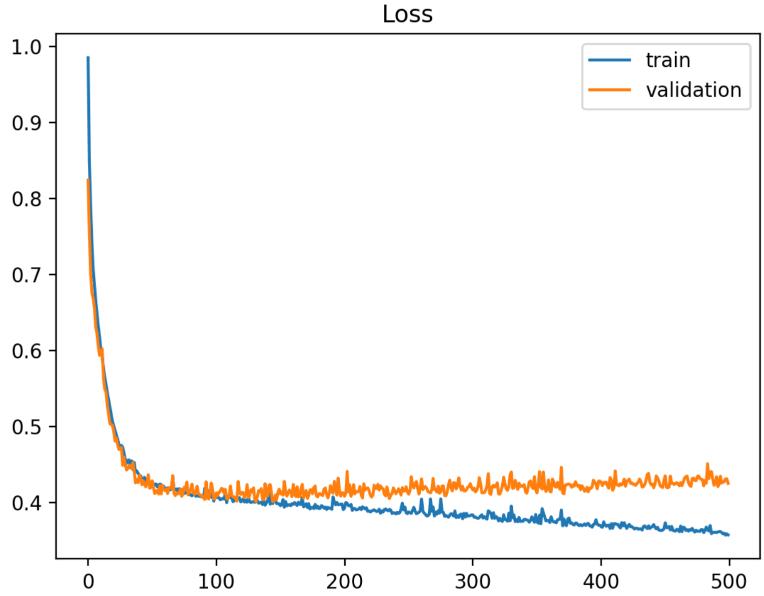

Figure 1.2: Training and validation loss for the proposed model

Training and testing accuracy are pivotal metrics in evaluating the performance of machine learning models. Training accuracy gauges how well a model fits the training data during the learning process. As the model iteratively adjusts its parameters to minimize errors, training accuracy reflects the proportion of correctly predicted outcomes on the training set. While high training accuracy indicates the model's proficiency in learning from the provided data, it does not guarantee robust generalization to new, unseen data. Testing accuracy, on the other hand, assesses the model's performance on an independent dataset not used during training. A high testing accuracy signifies the model's effectiveness in making accurate predictions on new instances, indicating its ability to generalize well. Striking a balance between high training and testing accuracy is crucial, aiming for a model that not only learns intricacies within the training set but also demonstrates reliable predictive power on diverse, real-world data. Monitoring both accuracies helps diagnose issues like overfitting or underfitting and guides the optimization of machine learning models for optimal performance.

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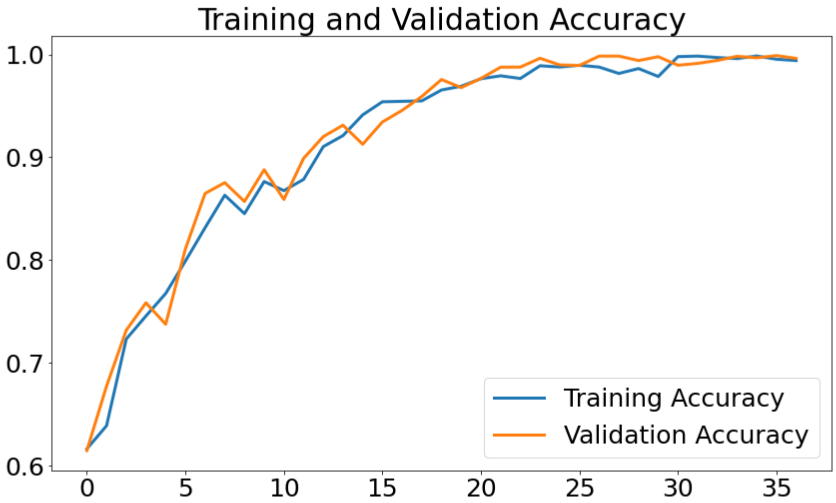

Figure 1.2: Training and validation accuracy for the proposed model

5. Conclusion:

This research paper presents an investigation into diverse approaches for detecting plant leaf diseases through the application of image processing techniques. Recognizing that a singular method may not suffice for identifying all diseases, numerous methodologies have been explored in the context of the diseased plant leaves dataset. Despite the development of several methods for identifying and classifying plant diseases, a reliable and cost-effective commercial technology for disease detection is currently lacking. In this study, we employed a CNN and Inception Model specifically for the detection of cotton diseases. Utilizing the Kaggle dataset, comprising nearly 500 photos taken under laboratory conditions, we trained and tested the model. Our future endeavors include expanding this project by establishing a comprehensive database encompassing various plants and predicting their associated diseases.

References

[1] Shrivastava, Vimal K., and Monoj K Pradhan. n.d. “Rice plant disease classification using color features: a machine learning paradigm.” Journal of Plant Pathology 103.1 (2018): 17-26.

[2] Emma Harte. n.d. “Plant Disease Detection using CNN.” Diss. Ph. D. thesis, 2016.

[3] Ferentinos, Konstantinos P. n.d. “Deep learning models for plant disease detection and diagnosis.” Computers and Electronics in Agriculture 145 (2018): 311-318.

ISSN PRINT 2319 1775 Online 2320 7876

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[4] Gavhale, Ms Gawande,, and Ujjwala. 2014. "An Overview of the Research on Plant Leaves Disease Detection usingImage Processing Techniques." IOSR Journal of Computer Engineering 16. 10-16. 10.9790/0661-16151016.

[5] L. Li, S. Zhang, and B. Wang. n.d. "Plant Disease Detection and Classification by Deep Learning—A Review." IEEE vol. 9, pp. 56683-56698, 2015 (doi: 10.1109/ACCESS.2021.3069646.).

[6] R. R, and M.S H. n.d. "Plant Disease Detection and Classification using CNN." International Journal of Recent Technology and Engineering (IJRTE) vol. 10, no. 3, pp. 152156, Sep. 2014.

[7] Patel, Sneha, Jaliya, and Dr Patel Pranay. n.d. "A Survey on Plant Leaf Disease Detection." International Journal for Modern Trends in Science and Technology 6. 129-134. 10.46501/IJMTST

[8] Warne, Pawan P, and S R Ganokar. 2015. "Detection of Diseases on Cotton Leaves Using K-Mean Clustering Method."

[9] Sumit Kumar. n.d. "Plant Disease Detection Using CNN." Turkish Journal of Computer and Mathematics Education (TURNCOAT) 12.12 (2016) (2106-2112).

[10]Venkataramanan, Aravindhan, and Pooja. 2019. "Plant Disease Detection and Classification Using Deep Neural Networks."

[11]Jiang, Peng, Yuehan Chen, Bin Liu, Dongjian He and Chunquan Liang. n.d. "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks." IEEE Access 7 (2019) (59069-
59080).

[12]Amara, Jihen, Bouaziz, Bassem, and Algergawy, Alsayed. 2017. A Deep Learning-based Approach for Banana Leaf Diseases Classification 79-88.

[13]Mohanty, Sharada, Hughes, David, and Salathe, Marcel. 2016. "Using Deep Learning for Image-Based Plant Disease Detection." Frontiers in Plant Science 7. 10.3389/fpls.2016.01419.