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Securing potato Forms: A holistic approach to Classification of Early Blight and Late Blight Disease Management

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ABSTRACT — Potato cultivation faces significant economic challenges due to prevalent disease, particularly early blight and late blight. Early blight, caused by Alternaria solani, affects leaves and stems, potentially leading to defoliation and increased tuber infection risk. Late blight, attribute to phytophthora infestans, is a critical potato disease, capable of causing rapid crop failures. Timely disease detection is crucial for farmers to implement tailored treatments and minimizing financial losses. Early blight, associated witg fungi, and late blight, linked to specific microorganisms, require distinct control strategies, highlighting the need for accurate disease identification. This study introduces a deep convolutional neural network architecture with 14 layers, incorporating two primary convolutional layers for feature extraction with varying windows size, followed by two fully connected layers for classification. Augmentation techniques were applied to a dataset comprising 2152 images, resulting in a substantial enhancement in overall testing accuracy. The proposed architecture achieved an impressive mean testing accuracy of 98.43%. To ensure the robustness of the result, over six performance metrics were employed. This innovative deep learning approach holds promise for revolutionizing potato disease classification and advancing precision agriculture practices. The architecture implemented in a Jupyter notebook with GPU acceleration, demonstrated its effectiveness through meticulous testing and validation. The study underscores the potential of deep learning in providing accurate and efficient solutions

for potato disease management, offering a transformative impact on agricultural practices and crop yield optimization.

Keywords — Disease detection, Preprocessing, Classification.

I. Introduction

Potato farming, a cornerstone of global agriculture, faces persistent and substantial financial losses due to the prevalence of diseases, with early blight and late blight emerging as primary concerns. Early blight, initiated by the fungus Alternaria solani, inflicts damage on leaves and stems, potentially causing significant defoliation and an increased risk for tuber infections. On the other hand, late blight, attributed to Phytophthora infestans, stands as a formidable threat, capable of inducing rapid crop failures if left unchecked by appropriate control measures.

The imperative for potato farmers lies in prompt disease detection, enabling the application of customized treatments to mitigate economic losses. The distinction between early blight, associated with fungi, and late blight, linked to specific microorganisms, necessitates the development of distinct and tailored control strategies. The accuracy of disease identification becomes paramount for implementing appropriate treatments, recognizing the differing efficacies required for early and late blight management.

This study introduced an innovative solution- a deep convolutional neural network architecture comprising 14 layers. This architecture includes two primary convolutional layers for feature extraction. Through augmentation processes applied to a dataset consisting of 2152 images, a substantial enhancement in overall testing accuracy was achieved. Notably, the proposed architecture demonstrated an impressive mean testing accuracy of 98.43%. To establish the accuracy and reliability of the findings, this research utilized a comprehensive set of over six performance metrics. This groundbreaking deep learning approach not only holds immense potential for transforming potato disease classification but also serves as a guiding light in the progression of precision agriculture practices. It provides concrete and effective solutions to the challenges encountered by potato farmers on a global scale.

II. Literaturer review

1 An early and accurate plant disease detection and methodology, employing a variety of image processing techniques, was introduced by Anand H. Kulkarni et al. [1]. In this approach, feature extraction utilized the Gabor filter, and classification was carried out using

and Artificial Neural Network (ANN)-based classifier, achieving a commendable recognition rate up to 91%.

2.F. Argenti et al.[2] introduced a rapid algorithm that employs supervised learning to calculate parameter of the co-occurrence matrix. This approach utilizes the maximum likelihood method for swift and efficient classification.

3. P. revathi et al. [3] utilized homogenization techniques such as Sobel and Canny Filters to identify edges.

4. Tushar H. Jaware et al. [4] introduced a novel and enhanced k-means clustering technique for resolving low-level image segmentation. The extracted edge feature were employed in the classification process to identify disease spots. The authors implemented the Homogeneous Pixel Counting Technique for Cotton Diseases Detection algorithm for disease categorization, claiming an impressive accuracy of 98.1% compared to existing among.

5. Sanjay B. Dhaygude et al.[5] employed the Spatial Gray-Level Dependence Matrices method to extract statistical texture features.

6.Mokhled S. AI-Tarawneh[6] conducted an empirical investigation on olive leaf spot disease, utilizing auto-cropping segmentation and fuzzy c-mean classification. The RGB images were transformed into the Hue Saturation Value color space, showcasing the individual H,S and V components. The image enhancement process involved converting RGB to Lab color space and applying a median filter. The study concludes with a comparative assessment of fuzzy c-means and k-means clustering methods.

7. Yan-Cheng Zhang et al.[7] introduced a fuzzy feature selection approach , specifically fuzzy curve and fuzzy surface, for the purpose of selecting features related to cotton leaf disease.

8. S. Sankaran et al.[8] the authors present a comprehensive analysis, review, and acknowledgment of the imperative to develop a swift, cost-effective, and dependable health monitoring sensor to facilitate progress in agriculture. They delineate existing technologies, encompassing spectroscopic and imaging-based approaches for plant disease detection, along with volatile profiling-based methods. The objective is to advance ground-based sensor systems for effective monitoring of plant health and disease under diverse field conditions.

9. A.-K. Mahlein et al.[9] After a thorough analysis of various approaches commonly employed for plant disease diagnostics, including double-stranded ribonucleic acid (RNA) analysis, nucleic acid probes, and microscopy, the decision was made to adopt an image

processing disease recognition approach. This choice was informed by the examination of their work and the analyses presented by the authors in .

10. Yuan Tian et al. [10] the proposal introduces a Multiple Classifier System (MCS) based on Support Vector Machines (SVM) for the pattern recognition of wheat leaf diseases.

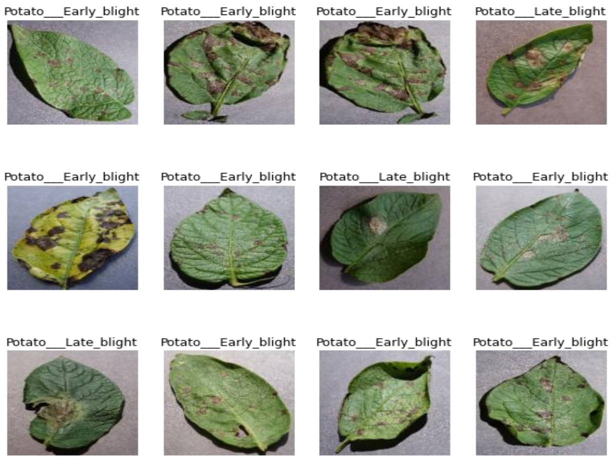
11. M. S. Prasad Babu et al.[11] the proposal advocates for the utilization of a backpropagation neural network to identify damaged leaves. The study demonstrates that the combination of a backpropagation network and the shape of a leaf image is effective in identifying the leaf's species. To obtain leaf tokens as input for the backpropagation algorithm, the Prewitt edge detection and thinning algorithm are employed. The study acknowledges potential areas for enhancement, suggesting further experimentation with large training sets to recognize various damaged leaves induced by different diseases.

III. PRAPOSED METHODOLOGY

The suggest framework consists of four crucial steps:

Data Collection: The dataset for this project consists of images of potato leaves categorized into three groups: healthy leaves, early blight-affected leaves, and late blight-affected leaves. This dataset obtained from the name "PlantVillage Dataset" has a total size of KB, including the volume of data utilized for the analysis.

S.No.	Sample Name	Sample Number
01.	Early blight	1000
02.	Late blight	1000
03.	Healthy	152

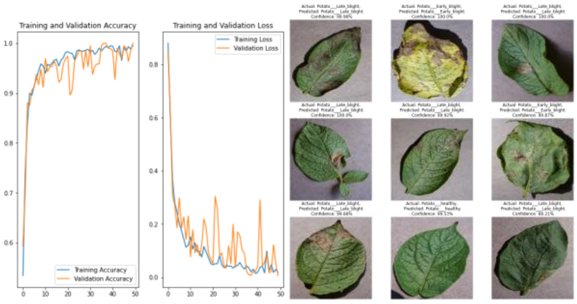


Data preprocessing: The dataset encompasses 2152 potato leaf images, classified into three categories: healthy, early blight, and late blight. This distribution details for each class are presented in the table below. The dataset is subsequently partitioned into training and testing sets, employing both 80:20 for data division. A comparative analysis of the accuracy result from each data split will be conducted to ascertain the optimal proportion for dataset division.

Dataset	80:20		
	Training	Testing	Validation
Late blight	800	100	100
Early blight	800	100	100
Healthy	122	15	15
Total	1722	215	215

Model Building: A Convolutional Neural Network (CNN) constructed, incorporating Max Pooling and Convolutional layers. The hidden layers utilize the Rectified Linear Unit (ReLU) as a non-linear activation function, while the output layer employs the softmax activation function.

Validation: After fitting our model to the training data, we evaluated its performance and calculated accuracy scores. The results for training, testing, and validation sets are presented below.



Result: The architecture was instantiated in a Jupyter notebook, leveraging GPU acceleration. The assessment of the proposed model's accuracy for distinguishing between potato leaf blight and early blight involved partitioning the dataset into two sets:80% for training and 20% for testing and validation. The training phase utilized the larger 80% subset, while the remaining 20% was employed for assessing both testing and validation performance. Notably, the average overall testing accuracy achieved using the original dataset was 98.43% . Similarly, when employing an augmented dataset, the average overall testing accuracy remained at an impressive 98.43%.

Conclusion

This paper leverages Convolutional Neural Network (CNN) concepts to formulate a model for effectively classifying conditions in potato leaves, including early blight, late blight, and healthy states, achieving an impressive classification accuracy of approximately 98.43%. The incorporation of data augmentation enhances the model's robustness. Our methodology holds the potential to assist farmers in early disease detection, thereby contributing to improved crop yields. We also compare the classification accuracy of our proposed approach with other implementations in the field.

Future Scope

Enhancing the robustness of our model, we employed Generative Adversarial Networks (GANs) for data generation and implemented Transfer Learning to boost model accuracy. GANs contribute to making the model more adaptable to variations in the object's orientation, position, and size within images. Additionally, Transfer Learning aids in developing a more resilient and accurate model.

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