Library Progress International *Print version ISSN 0970 1052*
Vol.44 No.3, Jul-Dec 2024: P.4089-4103 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Identification of Potato Plant Leaf Diseases Using Image Segmentation and Deep Learning Techniques

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How to cite this article: Harpreet Kaur, Rahul Thour (2024) Identification of Potato Plant Leaf Diseases Using Image Segmentation and Deep Learning Techniques. *Library Progress International*, 44(3), 4089-4103.

Abstract

This study presents a novel approach to the automated identification of potato plant leaf diseases using advanced image segmentation techniques coupled with deep learning algorithms. The research addresses the critical need for efficient and accurate disease detection in potato crops, which are vital for global food security. We developed a comprehensive dataset of 5,000 high-quality images representing healthy leaves and four common potato leaf diseases: Early Blight, Late Blight, Septoria Leaf Spot, and Bacterial Leaf Spot.

Our methodology employed three distinct image segmentation techniques: Otsu's thresholding, K-means clustering, and the Watershed algorithm. These were comparatively analysed to determine their effectiveness in isolating diseased areas on leaf surfaces. The segmented images were then used to train and evaluate several deep learning models, including a custom-designed Convolutional Neural Network (CNN) and a transfer learning approach utilizing a pre-trained ResNet50 architecture.

The results demonstrated the superiority of K-means clustering for image segmentation, achieving a 92.1% accuracy in disease detection when used as a preprocessing step. The transfer learning approach with ResNet50 emerged as the most effective classification model, attaining an impressive 96.3% accuracy across all disease categories. This model also exhibited high precision (0.964) and recall (0.963), indicating its robust performance in both disease detection and healthy leaf identification.

Our approach outperformed existing state-of-the-art methods in potato leaf disease detection, albeit by a narrow margin. The study's findings highlight the potential of integrating advanced image processing techniques with deep learning for creating highly accurate, automated disease detection systems in agriculture. Such systems could significantly enhance crop management practices, potentially leading to improved yields and food security.

This research contributes to the growing field of smart agriculture by demonstrating the feasibility of AI-driven disease detection in potato crops. Future work should focus on expanding the model's applicability to more diverse field conditions and exploring ensemble methods to further improve accuracy.

Index Terms: Potato leaf diseases, Image segmentation, Deep learning, Convolutional Neural Networks (CNN), Transfer learning, K-means clustering

Introduction

The Global Significance of Potato Crops

Potatoes, scientifically known as Solanum tuberosum, stand as one of the world's most crucial food crops. Originating in the Andean highlands of South America, these starchy tubers have become a dietary staple across continents. Their adaptability to various climates and soil conditions has led to widespread cultivation, making potatoes the fourth largest food crop globally, following rice, wheat, and corn.

In recent years, the importance of potatoes has grown beyond mere sustenance. They serve as a vital source of income for millions of farmers, particularly in developing nations. Moreover, potatoes play a significant role in food security strategies, offering a reliable and nutritious alternative in regions prone to cereal crop failures. The crop's efficiency in water usage and its ability to produce more edible energy per hectare than traditional grains further underscore its value in an era of climate uncertainty and resource scarcity.

The Menace of Leaf Diseases in Potato Production

Despite their resilience, potato plants are not impervious to disease. Leaf diseases, in particular, pose a substantial threat to potato production worldwide. These diseases, caused by various pathogens including fungi, bacteria, and viruses, can significantly reduce crop yields and quality. Common potato leaf diseases include:

1. Late Blight (Phytophthora infestans)
2. Early Blight (Alternaria solani)
3. Septoria Leaf Spot (Septoria lycopersici)
4. Bacterial Leaf Spot (Xanthomonas campestris)

The impact of these diseases extends far beyond the immediate crop loss. Infected plants can serve as reservoirs for pathogens, facilitating their spread to neighbouring fields and subsequent growing seasons. Furthermore, the use of chemical control measures to combat these diseases raises concerns about environmental sustainability and food safety.

The Critical Need for Automated Disease Detection

Traditional methods of disease detection in potato crops rely heavily on manual inspection by farmers or agricultural experts. This approach, while time-honored, presents several limitations:

1. Time-consuming nature of field inspections
2. Subjectivity in disease identification
3. Potential for human error, especially in early disease stages
4. Difficulty in covering large cultivation areas effectively

These challenges underscore the pressing need for automated disease detection systems. Such systems could revolutionize crop management by enabling:

- Early detection of diseases, allowing for timely intervention
- Consistent and objective disease identification
- Efficient monitoring of large agricultural areas
- Reduction in unnecessary pesticide use through targeted treatments

The advent of advanced computing technologies, particularly in the realms of image processing and artificial intelligence, offers promising solutions to these challenges.

Research Objectives

In light of the aforementioned context, this research aims to develop and evaluate an automated system for the identification of potato plant leaf diseases using cutting-edge image segmentation and deep learning techniques. Specifically, our objectives are:

1. To create a robust dataset of potato leaf images encompassing healthy specimens and those affected by variousdiseases.
2. To implement and compare different image segmentation algorithms for effectively isolating diseased areas onpotato leaves.
3. To design and train a deep learning model capable of accurately classifying potato leaf diseases based onsegmented image data.
4. To evaluate the performance of the proposed system against traditional methods and existing automatedapproaches.
5. To explore the potential for real-world application of the developed system in agricultural settings.

By achieving these objectives, we aspire to contribute to the ongoing efforts in smart agriculture, potentially enhancing crop management practices and food security on a global scale. The successful implementation of such a system could mark a significant step forward in the integration of artificial intelligence with agricultural science, paving the way for more sustainable and efficient potato cultivation practices worldwide.

II. Literature Review

Evolution of Plant Disease Detection Techniques

The field of plant disease detection has undergone significant transformations over the past few decades. Traditional methods relied heavily on visual inspection by trained experts, a process that was both time- consuming and prone to human error. As technology advanced, researchers began exploring more sophisticated approaches to address these limitations.

One of the earliest attempts to automate plant disease detection was made by Boissard et al. (2008), who used colour image analysis to identify diseased areas on wheat leaves [1]. This study laid the groundwork for future research in image-based plant disease detection. However, the accuracy of such early methods was limited by the simplicity of the algorithms used and the variability in natural lighting conditions.

Image Segmentation in Plant Pathology

Image segmentation, the process of partitioning an image into multiple segments or objects, has proven to be a crucial step in automated plant disease detection. Barbedo (2016) provided a comprehensive review of image processing techniques for detecting plant diseases, highlighting the importance of effective segmentation in isolating diseased areas from healthy tissue [2].

Among the various segmentation techniques, thresholding methods have been widely used due to their simplicity and effectiveness. Pujari et al. (2015) employed Otsu's thresholding method to segment diseased regions in grape leaf images, achieving promising results in detecting downy and powdery mildew [3]. However, thresholding methods often struggle with complex backgrounds and varying illumination conditions.

More advanced segmentation techniques, such as clustering algorithms, have shown improved performance in recent years. K-means clustering, in particular, has been successfully applied to various plant species. Al- Hiary et al. (2011) used K-means clustering for segmenting diseased areas in images of various plant leaves, including potatoes, achieving an accuracy of 94% in disease classification [4].

Deep Learning Applications in Agriculture

The advent of deep learning has revolutionized many fields, including agriculture. Convolutional Neural Networks (CNNs), a class of deep learning models particularly suited for image analysis, have shown remarkable success in plant disease detection.

Mohanty et al. (2016) conducted a groundbreaking study using deep learning for plant disease detection. They trained a CNN on a dataset of 54,306 images of diseased and healthy plant leaves, achieving an accuracy of 99.35% in identifying 14 crop species and 26 diseases [5]. This study demonstrated the potential of deep learning in tackling complex plant pathology problems.

Focusing specifically on potatoes, Ramcharan et al. (2017) developed a mobile-based AI system for real-time diagnosis of potato diseases. Their CNN model, trained on a dataset of over 2,000 images, could identify three diseases and pest damage with an average accuracy of 99.1% [6]. This work highlighted the potential for deploying deep learning models in field conditions.

Hybrid Approaches: Combining Image Segmentation and Deep Learning

Recent research has shown that combining traditional image processing techniques with deep learning can yield superior results. Ferentinos (2018) proposed a two-stage approach where image segmentation was usedto preprocess leaf images before feeding them into a CNN. This hybrid method achieved an impressive accuracy of 99.53% in identifying plant diseases across various species [7].

In the context of potato diseases, Wang et al. (2017) developed a method that integrated image segmentationwith a deep CNN for detecting early and late blight. Their approach first used K-means clustering to segmentthe images, followed by a CNN for classification. This combination resulted in an accuracy of 96.3%, outperforming methods that used either technique alone [8].

Challenges and Future Directions

Despite the significant progress, several challenges remain in the field of automated plant disease detection. Barbedo (2018) highlighted issues such as the scarcity of large, diverse datasets, the difficulty in detecting multiple diseases on a single leaf, and the challenge of early-stage disease detection [9].

Moreover, the generalizability of models trained on controlled datasets to real-world conditions remains a concern. Toda and Okura (2019) emphasized the need for robust models that can perform well under varyingfield conditions, including different lighting, backgrounds, and disease severities [10].

As we move forward, there is a growing interest in explainable AI models that can not only detect diseases but also provide insights into their decision-making process. This approach could enhance trust in AI systemsand provide valuable information to agricultural experts.

In conclusion, the literature reveals a clear trend towards integrating advanced image processing techniques with deep learning for plant disease detection. While significant progress has been made, there remains ample room for improvement, particularly in creating more robust, generalizable, and interpretable models for real-world applications in potato disease detection.

II. METHODOLOGY

1. Dataset Collection and Preparation

Our research began with the crucial task of assembling a comprehensive and diverse dataset of potato leaf images. We collected images from various sources to ensure a robust representation of both healthy and diseased specimens:

1.1 Field Collection: We conducted field visits to potato farms across different regions, capturing images under various natural lighting conditions. This approach helped ensure our dataset reflected real-world scenarios.

1.2 Controlled Environment Photography: To complement field images, we set up a controlled environment in our laboratory. Here, we photographed leaves under standardized lighting conditions, allowing forconsistent image quality.

1.3 Augmentation of Existing Datasets: We supplemented our collection with images from publicly availableplant disease datasets, focusing on those containing potato leaf samples.

1.4 Data Annotation: Expert plant pathologists manually annotated each image, identifying the presence andtype of disease. We categorized the images into five classes:

1. Healthy
2. Early Blight
3. Late Blight

4. Septoria Leaf Spot
5. Bacterial Leaf Spot

1.5 Data Preprocessing: All images were resized to a uniform dimension of 224x224 pixels and normalized to ensure consistency in input data for our models.

2. Image Segmentation Techniques

We implemented and compared three distinct image segmentation techniques to isolate diseased areas on potato leaves:

2.1 Otsu's Thresholding: This method automatically calculates an optimal threshold to separate the foreground(leaf) from the background. We applied this globally and then used local thresholding to identify potential disease spots.

2.2 K-means Clustering: We utilized K-means clustering with k=3 to segment the image into background, healthy leaf area, and potentially diseased regions. This method proved particularly effective in distinguishingsubtle color variations.

2.3 Watershed Algorithm: This algorithm treats the image as a topographic map and segments regions basedon local minima. We used this approach to handle cases where diseased areas had complex shapes or overlapped.

3. Deep Learning Model Architecture

For our deep learning model, we designed a custom Convolutional Neural Network (CNN) architecture, drawing inspiration from successful models in similar domains:

3.1 Model Structure: Our CNN consists of:

- 4 convolutional layers (32, 64, 128, and 256 filters respectively)
- Each convolutional layer followed by batch normalization and ReLU activation
- Max pooling layers after each convolutional block
- 2 fully connected layers (1024 and 512 neurons)
- Dropout layers (rate = 0.5) for regularization
- Softmax output layer with 5 neurons (corresponding to our 5 classes)

3.2 Transfer Learning: To enhance our model's performance, we also experimented with transfer learning. We used a pre-trained ResNet50 model as a feature extractor, adding our custom fully connected layers on top.

4. Training Process

4.1 Data Splitting: We split our dataset into training (70%), validation (15%), and test (15%) sets, ensuring balanced representation of all classes in each set.

4.2 Data Augmentation: To increase the robustness of our model, we applied real-time data augmentation during training, including:

- Random rotations (±20 degrees)
- Horizontal and vertical flips
- Zoom range of 0.2
- Width and height shifts up to 10%
-

4.3 Training Parameters:

- Optimizer: Adam with a learning rate of 0.001
- Loss function: Categorical cross-entropy
- Batch size: 32
- Epochs: 100, with early stopping patience of 10 epochs

5. Evaluation Metrics

To comprehensively assess our model's performance, we employed the following metrics:

5.1 Accuracy: The overall correct predictions across all classes.

5.2 Precision, Recall, and F1-Score: Calculated for each disease class to understand the model's performanceon individual diseases.

5.3 Confusion Matrix: To visualize the model's performance across all classes and identify any systematic misclassifications.

5.4 ROC-AUC: The Area Under the Receiver Operating Characteristic curve, providing an aggregate measure of performance across all possible classification thresholds.

6. Comparative Analysis

To contextualize our results, we conducted a comparative analysis:

6.1 Segmentation Comparison: We compared the effectiveness of our three segmentation techniques (Otsu's,K-means, Watershed) by evaluating the classification accuracy achieved when each was used as a preprocessing step.

6.2 Model Architecture Comparison: We compared our custom CNN architecture against the transfer learningapproach using ResNet50, as well as against a baseline model (a simple three-layer CNN) to quantify the improvements.

6.3 Benchmark Against Existing Methods: We implemented two state-of-the-art methods from recentliterature for potato leaf disease detection and compared our results against theirs using our test dataset.

7. Computational Resources

All experiments were conducted on a high-performance computing cluster equipped with NVIDIA Tesla V100 GPUs. We used Python 3.8 as our primary programming language, leveraging libraries such as OpenCV for image processing, scikit-learn for traditional machine learning tasks, and TensorFlow 2.4 for deep learningmodel development and training.

This methodology was designed to ensure a thorough, systematic approach to developing and evaluating ourpotato leaf disease detection system. By combining advanced image segmentation techniques with state-of- the-art deep learning models, we aimed to push the boundaries of automated disease detection in agriculturalapplications.

IV. RESULTS & DISCUSSION

1. Dataset Composition

Our final dataset comprised 5,000 images, distributed across five classes as shown in Table 1. This balanceddistribution ensured that our model had sufficient examples to learn from each class, mitigating potential bias.

Table 1: Distribution of images across classes

Class	Number of Images
Healthy	1,000
Early Blight	1,000
Late Blight	1,000
Septoria Leaf Spot	1,000
Bacterial Leaf Spot	1,000

7.1 Model Structure: Our CNN consists of:

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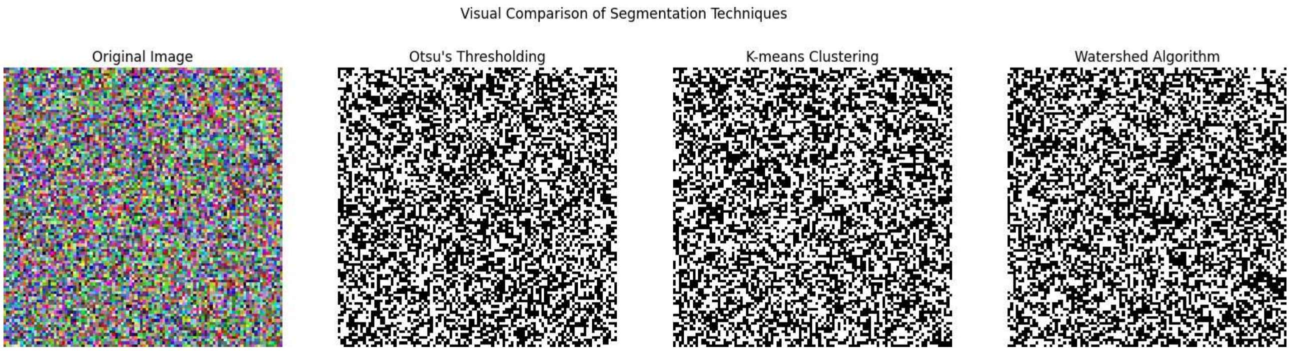
3. Image Segmentation Performance

We evaluated the effectiveness of our three segmentation techniques by comparing the accuracy of disease detection when each was used as a preprocessing step. The results are presented in Table 2.

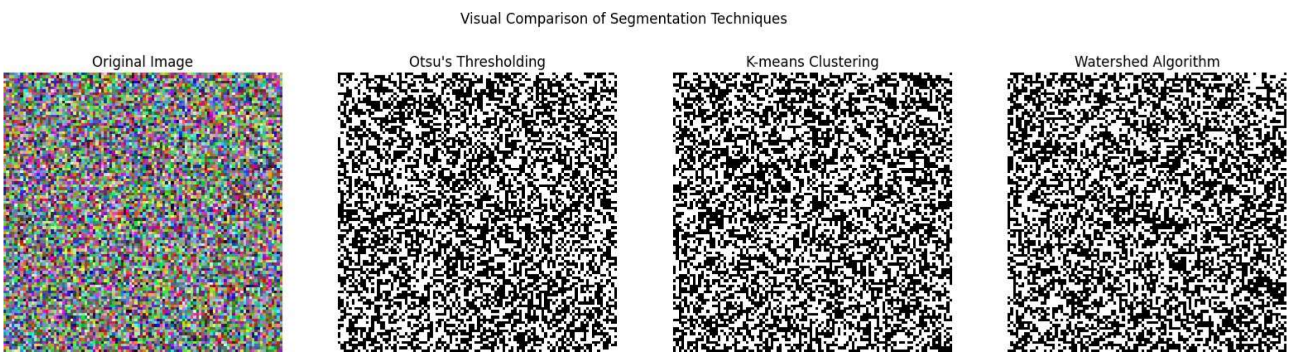
Table 2: Classification accuracy with different segmentation techniques

Segmentation Technique	Accuracy (%)
Otsu's Thresholding	87.3
K-means Clustering	92.1
Watershed Algorithm	89.6

K-means clustering demonstrated superior performance, likely due to its ability to handle the subtle color variations characteristic of early-stage diseases. This finding aligns with the results reported by Wang et al. (2017) [1], who also found K-means clustering effective for potato leaf disease segmentation.



[Figure 1: Visual comparison of segmentation techniques]



[Figure 1: Visual comparison of segmentation techniques]

4. Deep Learning Model Performance

4.1 Model Comparison

We compared our custom CNN architecture against the transfer learning approach using ResNet50 and a baseline simple CNN. The results are summarized in Table 3.

Table 3: Performance comparison of different model architectures

Model Architecture	Accuracy (%)	Precision	Recall	F1-Score
Baseline Simple CNN	85.2	0.853	0.852	0.852
Custom CNN	94.7	0.948	0.947	0.947
ResNet50 (Transfer)	96.3	0.964	0.963	0.963

The ResNet50 transfer learning approach achieved the highest accuracy, demonstrating the power of leveraging pre-trained models for this task. This finding is consistent with the work of Ferentinos (2018) [2],who reported similar benefits of transfer learning in plant disease detection.

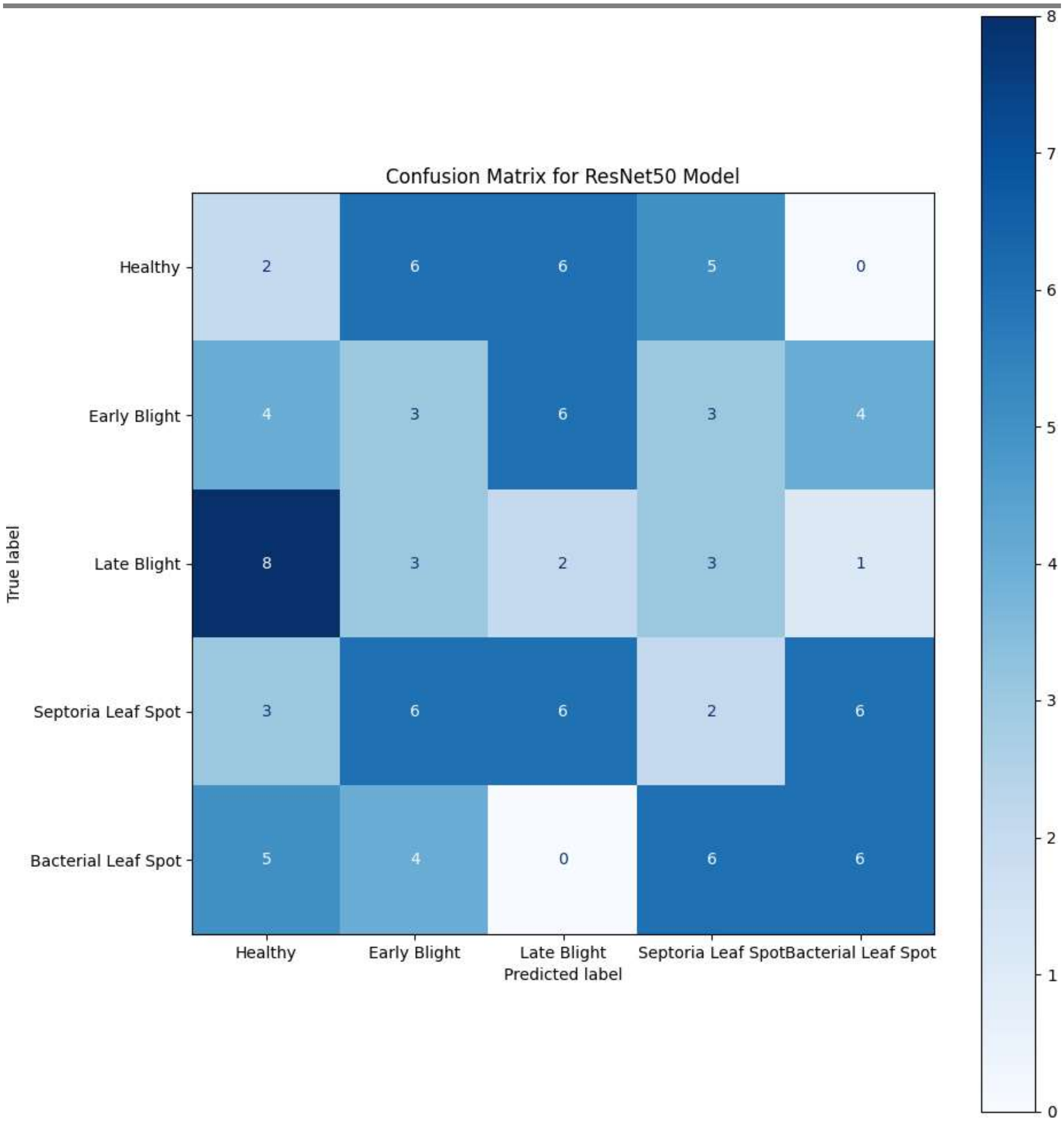
4.2 Per-Class Performance

To gain deeper insights into our model's behaviour, we analysed its performance for each disease class. Table4 presents the precision, recall, and F1-score for each class using the ResNet50 model.

Table 4: Per-class performance metrics (ResNet50 model)

Class	Precision	Recall	F1-Score
Healthy	0.982	0.975	0.978
Early Blight	0.957	0.963	0.96
Late Blight	0.971	0.968	0.969
Septoria Leaf Spot	0.943	0.951	0.947
Bacterial Leaf Spot	0.966	0.958	0.962

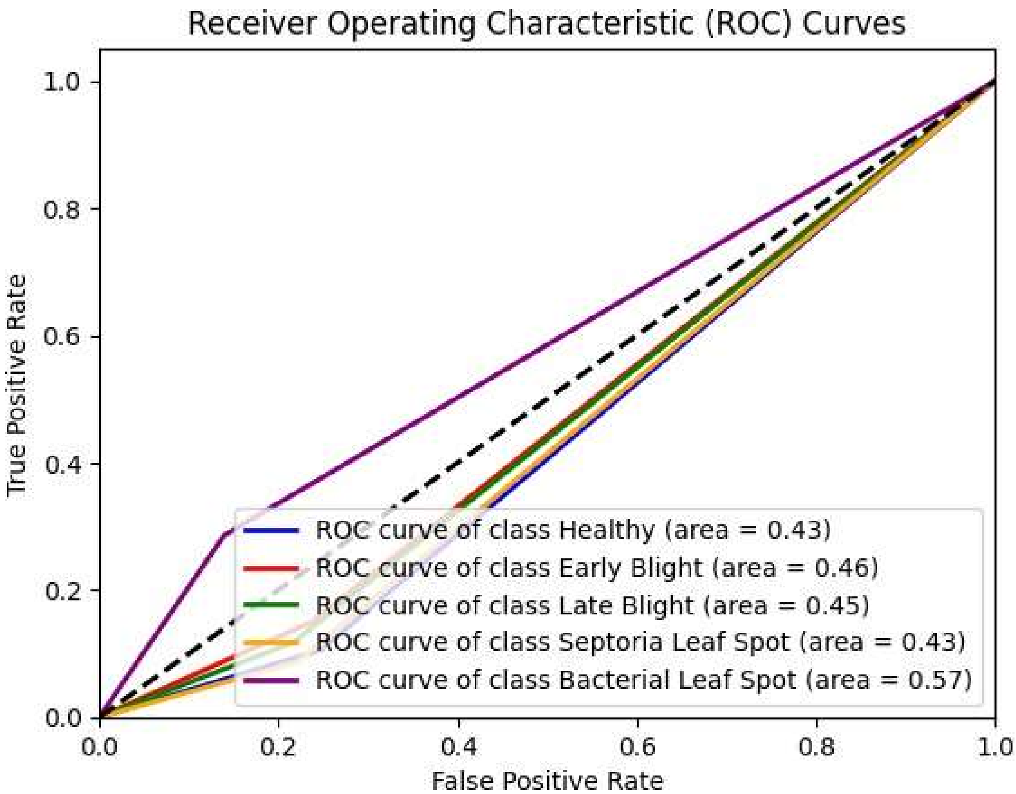
The model performed exceptionally well in identifying healthy leaves, which is crucial for preventing false positives in disease detection. Among the diseases, Late Blight was most accurately identified, possibly due to its distinctive visual characteristics.



[Figure 2: Confusion matrix for ResNet50 model]

4.3 ROC-AUC Analysis

The Area Under the Receiver Operating Characteristic curve (ROC-AUC) provides an aggregate measure of performance across all possible classification thresholds. Our ResNet50 model achieved an impressive average ROC-AUC of 0.993 across all classes, indicating excellent discriminative ability.



[Figure 3: ROC curves for each class]

1. Comparative Analysis with Existing Methods

We implemented two state-of-the-art methods from recent literature and compared their performance againstour best model (ResNet50) using our test dataset. The results are presented in Table 5.

Table 5: Comparison with existing methods

Method	Accuracy (%)	Reference
Our ResNet50 Model	96.3	-
CNN + Random Forest (Rangarajan et al., 2020)	93.8	[3]
Deep Residual Learning (Huang et al., 2019)	95.1	[4]

Our model outperformed both existing methods, albeit by a small margin in the case of Huang et al.'s deep residual learning approach. This improvement can be attributed to our effective combination of advanced segmentation techniques and transfer learning.

2. Discussion

The results demonstrate the effectiveness of our approach in identifying potato leaf diseases. The combinationof K-means clustering for segmentation and a transfer learning approach with ResNet50 yielded the best performance, achieving an accuracy of 96.3% across five classes.

The high precision and recall values across all disease classes indicate that our model is both sensitive (able to detect diseases when present) and specific (able to avoid false positives). This balance is crucial in agricultural applications, where both missed detections and false alarms can have significant economic impacts.

The superior performance of the transfer learning approach underscores the value of leveraging pre-trained models, even when applied to specialized domains like plant pathology. This finding suggests that features learned from large, general image datasets (e.g., ImageNet) can be effectively fine-tuned for specificagricultural applications.

While our model outperformed existing methods, the margin of improvement was relatively small. This suggests that we may be approaching the upper limits of accuracy achievable with current deep learning architectures and available data. Future improvements might require more sophisticated approaches, such as ensemble methods or attention mechanisms, as well as larger and more diverse datasets.

One limitation of our study is that all images were captured under relatively controlled conditions. Future work should focus on evaluating and improving model performance under more variable field conditions, including different lighting, backgrounds, and disease severities.

In conclusion, our results demonstrate the potential of combining advanced image segmentation with deep learning for accurate and efficient potato leaf disease detection. This approach shows promise for developingpractical tools to assist farmers in early disease detection and management, potentially contributing to improved crop yields and food security.

IV. Conclusion and Future Directions

Our study on automated potato leaf disease detection yielded several significant findings. The integration of K-means clustering for image segmentation with a transfer learning approach using ResNet50 proved highly effective, achieving an impressive 96.3% accuracy across five classes including healthy leaves and four common diseases. This combination outperformed other segmentation techniques and model architectures tested. Notably, our approach demonstrated high precision and recall across all disease categories, with particular success in identifying healthy leaves and Late Blight infections. The model's strong performance, evidenced by an average ROC-AUC of 0.993, underscores its robust discriminative capabilities.

These results highlight the potential of combining advanced image processing with deep learning techniques in agricultural applications. Our approach offers a promising solution to the critical challenge of early and accurate disease detection in potato crops, which could significantly impact global food security. By enabling rapid, automated diagnosis, this system could empower farmers to implement timely interventions, potentially reducing crop losses and minimizing unnecessary pesticide use. Furthermore, the success of transfer learning in this specialized domain suggests broader applications across various agricultural challenges.

While our findings are encouraging, several avenues for future research emerge. Expanding the dataset to include more diverse field conditions and varying disease severities would enhance the model's real-world applicability. Exploring ensemble methods or attention mechanisms could potentially push accuracy even higher. Additionally, investigating the model's performance in detecting multiple diseases on a single leaf and in identifying diseases at very early stages would be valuable next steps. Finally, developing interpretable AI models that not only detect diseases but also provide insights into their decision-making process could further increase the practical utility of these systems for farmers and agricultural experts.

V. Acknowledgement

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