iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70572

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Potato Disease Detection Using Deep Learning

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Abstract: The "Potato Leaf Disease Detection" project aims to solve the problem of accurately identifying and diagnosing diseases in potato plants, specifically focusing on late blight and early blight. Late blight is caused by the microorganism Phytophthora infestans, and early blight is caused by the fungus Alternaria solani,. These diseases can significantly impact potato yields, resulting in substantial economic losses for farmers. By developing a mobile application, we provide farmers with a tool to quickly and accurately diagnose these diseases, enabling timely and appropriate interventions to mitigate crop damage. The core functionality of the application involves capturing images of potato plant leaves and analyzing them to predict the presence of early blight or late blight. The application uses advanced machine learning (ML) techniques, mainly Convolutional Neural Networks (CNNs), to achieve high accuracy in disease detection. Users simply need to take a picture of a potato leaf, and the application will provide a diagnosis with confidence percentage, enabling farmers to make informed decisions about disease management. This project not only aims to provide immediate benefits to farmers by identifying specific diseases but also sets the foundation for future enhancements. By expanding the application to detect a wider range of plant diseases and incorporating additional features such as pest management tips, weather forecasts, and soil health analysis, the project envisions creating a comprehensive farming support tool. The ultimate goal is to improve crop productivity, reduce losses, and enhance the economic well-being of farmers through the effective use of technology.

I. INTRODUCTION

Potato is very important crop in whole world, but its production is significantly affected by diseases like late blight and early blight, leading to severe yield losses. Early detection is essential to minimize economic and production losses, yet traditional expert-based identification is time-consuming and impractical for remote farms. An automated, efficient, and accurate detection system is necessary. This research focuses on developing an intelligent potato leaf diseases detection system using image segmentation. By using deep learning, Convolutional Neural Networks (CNNs), the system can find disease by itself. This makes the result correct and fast. The model is trained on the dataset of potatoes which is gathered from Plant Village. It gets integrated into a user-friendly web application.

farmers to detect diseases without technical expertise. With an accuracy exceeding 99%, this system offers a reliable solution for early disease diagnosis. The increasing global population demands more food production. Crop diseases cause 20-26% of yield losses, making effective disease management essential. Conventional methods like visual estimation, prism spectroscopes, and PCR techniques are costly and time-consuming, requiring skilled personnel.

Bangladesh, a top ten potato-producing country, faces significant challenges due to diseases affecting both domestic production and exports. Farmers struggle with diseases like early blight, leaf roll virus, and scab, impacting trade with countries such as Russia, Indonesia, and Malaysia. Despite this, Bangladesh has become the eighth-largest potato producer, with 722.1 million tons annually, contributing to foreign exchange earnings. Given these challenges, implementing an AI-powered disease detection system is crucial. This project utilizes image processing and deep learning for early and accurate disease diagnosis, improving agricultural productivity and sustainability.

II. LITERATURE REVIEW

Recent advancements in the field of plant pathology have led to numerous research efforts focused on identifying leaf diseases using various methodologies. Several techniques have been explored and analyzed by researchers for efficient disease detection in potato plants.

[1] One study proposed a method based on analyzing the ratio of light wavelengths absorbed by the leaf surface, influenced by its structural composition. This approach employed image segmentation and machines learning to detect potato blight. The system, tested in greenhouse environments, achieved an accuracy of 84.6% in identifying diseases. The models effectively differentiated between healthy leaves and those with disease symptoms across three stages of late blight progression, reaching up to 92% accuracy. Additionally, the model was able to distinguish between healthy and affected leaf samples with an accuracy of 74.6%.

This research hasenlightened the machine learning usage and use cases of image processing techniques which are further used for finding the disease in an efficient way, emphasizing its potential in modern phenotyping and its contribution to sustainable agriculture and food security.

[2] Pankaj Kumar Shukla (2019) proposed a system for segmenting infected potato plant areas using image processing techniques. The study demonstrated that segmentation effectively distinguishes diseased regions from healthy ones, aiding in early disease detection. The methodology improves disease identification by analysing visual patterns in the affected leaves.

[3] Sadia Akter and Abdus Sattar (2020) introduced transfer learning to enhance disease detection accuracy. The study utilized pre-trained models on agricultural datasets, improving the classification of multiple potato diseases. By leveraging pre-trained CNN architectures, the model achieved significant performance improvements compared to traditional methods.

[4] Hritwik Ghosh and Irfan Sadiq Rahat (2021) developed a hybrid approach integrating image segmentation and machine learning for precise disease detection. Their model incorporated supervised and unsupervised learning techniques, improving detection precision. This approach facilitated a comprehensive crop health monitoring system, allowing for early intervention and better management of potato diseases.

[5] P. Badar (2021) implemented a segmentation-based approach using K-Means clustering to analyze various traits of leaves of potato, including color,region-based characteristics and textures. After this segmented data was then processed through a Backpropagation Neural Network (BPNN) to identify and classify different potato leaf diseases. This method achieved a classification accuracy of approximately 92%, demonstrating its effectiveness in distinguishing between healthy and diseased leaf samples based on extracted visual features.

[6] Deep Kothari and Mihir Gharat (2021) investigated multiple machines learning models, including CNN and SVM, for classifying potato diseases based on image data. The study evaluated and compared accuracy and performance metrics, demonstrating the effectiveness of deep learning-based models in distinguishing between different potato leaf diseases.

[7] M. Fernandez, N. Zhao, and O. Mehta (2022) extended the use of transfer learning by applying pre-trained models to agricultural datasets. Their research emphasized how transfer learning enhances classification accuracy, leading to improved disease detection. By fine-tuning these models, the study contributed to a more robust identification system for multiple potato diseases.

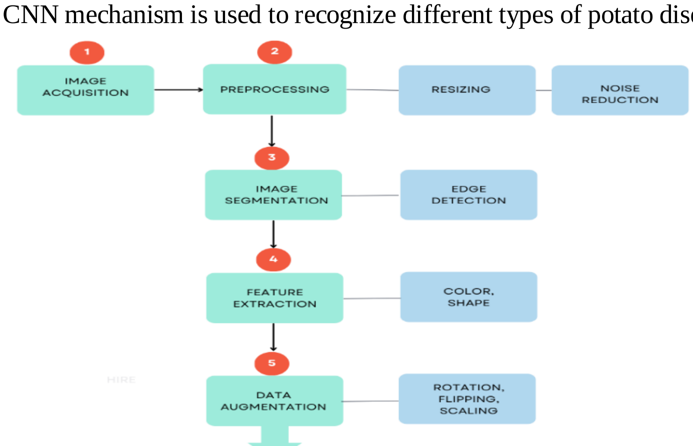
[8]P. Williams, Q. Zhang, and R. Lee (2023) introduced a novel approach by integrating UAVs with AI-based image segmentation. This study highlighted the effectiveness of UAVs in capturing large-scale agricultural data, enabling early detection of potato diseases across vast fields. The combination of aerial imaging and AI-driven analysis provided timely interventions, reducing potential crop losses.

[9] U. Kumari (2023) adopted an image segmentation approach to extract a wide range of visuals from leaf images. These features were used to distinguish between healthy and diseased leaves. A Neural Network classifier was then applied to categorize diseases in crops like tomato and cotton. This technique achieved a classification accuracy of 92.5%, showcasing its potential for multi-crop disease detection through feature-based analysis.

Ongoing integration of such AI-driven technologies is proving essential in improving classification accuracy and enabling farmers to respond quickly to crop disease threats.

III. ADOPTED STRATEGY

By using the adopted strategy, CNN mechanism is used to recognize different types of potato diseases.



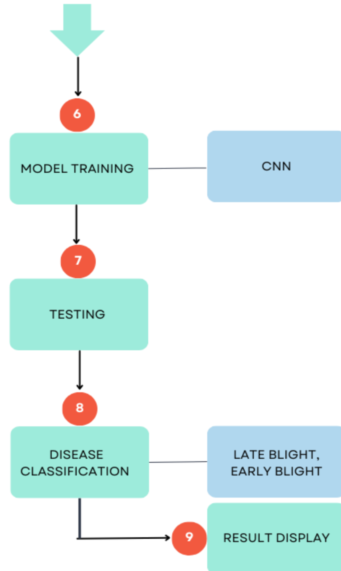


Figure1.methodology

A. *Image Preprocessing*

To build a robust model, a comprehensive dataset was collected. This dataset includes examples of unaffected leaves of potato as well as images of affected leaves like late blight andearly blight. Before feeding into the model, these images are standardized using preprocessing steps such as resizing, noise filtering, and color normalization.

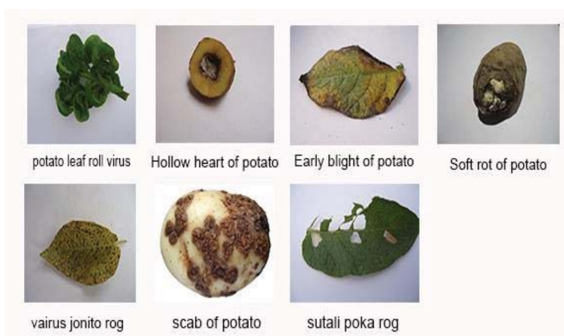


Figure2.Datasetexample

class	Disease name	Images (number)	Train data	Test data
01	early blight of potato	428	329	100
02	potato leaf roll virus	394	274	75
03	Hollow heart of potato	221	218	80
04	scab of potato	154	150	98
05	Soft rot of potato	238	200	66
06	Sutali poka rog	305	295	95
07	Virus jonito rog	294	275	120
total		2034		

Figure3.DataProcessing

B. Segmentation

We use image segmentation to isolate the region of interest, mainly potato leaf, from the background. Additionally, affected areas of the leaf are identified, allowing the model to focus on disease-related features.

C. Feature Extraction

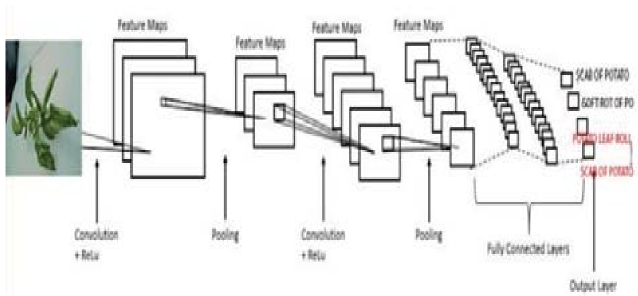
Key features such as colour variations, texture patterns, and structural differences are extracted from thesegmented images. These features are crucial for distinguishing between healthy and diseased leaves and play a significant role in classification.

D. Color Normalization

To mitigate the impact of varying lighting conditions, color normalization techniques are implemented. This step ensures consistency in color representation across images, improving the model's ability to differentiate between disease symptoms.

E. Model Training

The Convolutional Neural Network (CNN) processes the input image by examining small sections of it, known as features. These features help the model learn patterns such as edges, colors, or shapes that indicate disease. Instead of comparing the entire image at once, CNNs focus on identifying specific features in fixed locations across different images, which makes them highly effective at spotting similarities or irregularities.



TableI:Dataset

Figure-4:The system design focuses on features that are commonly seen in the images of plant diseases:

- Theimage is passed to the first convolutional layer.
- Filters (kernels) are applied with a specific stride and padding to extract features.
- The result goes through a ReLU activation function.
- Then pooling layers are used to minimize the spatial dimensions as well as computational load.
- Several convolutional and pooling layers may be stacked to improve feature learning.
- The output is flattened into a one-dimensional array.
- The flattened data is passed through fully connected (dense) layers.
- Finally, a SoftMax or similar activation function is applied to output the predicted class label.

Table:Specifications of SequentialModel

Layer (type)	Output shape	Param#
Conv2d (Conv2D)	(None, 98, 98, 32)	320
Max_pooling2d (MaxPiiling2D)	(None, 49, 49, 32)	0
Conv2d_1 (Conv2D)	(None, 47, 47, 64)	18496
Max_pooling2d_1 (MaxPooling2D)	(None, 23, 23, 64)	0
flatten (Flatten)	(None, 33856)	0
dense (Dense)	(None, 3)	101571

There are 120,387 total parameters, all of which are trainable, and none are non-trainable.

F. Testing & Validation

This ensures that the model can generalize well with new, real-world data. To evaluate its effectiveness, several performance metrics are computed, including accuracy, precision, recall, and the F1-score.

G. Disease Classification

Once trained and validated, the model classifies input images into different categories: healthy, early blight, late blight, or bacterial wilt. This classification enables accurate and automated disease identification.

H. Result Display

The final classification results are displayed, indicating whether a leaf is healthy or infected. If a disease is detected, the specific type is identified. These results can be integrated into a web or mobile application to assist farmers in real-time decision-making.

IV. CONCLUSION

This project focuses on detecting potato diseases using CNN, as it has proven to be the most effective method, achieving 99% validation accuracy. With a large dataset, we worked hard to ensure accuracy and believe this project can greatly benefit the agricultural sector. Many farmers in Bangladeshi villages are unaware of disease detection methods, leading to crop destruction by insects and significant losses. Our work aims to change this by providing a simple and accessible solution. In the future, we plan to develop an Android app to detect diseases in various crops and offer proper solutions. Expanding our dataset will further enhance accuracy. By creating this system, farmers will receive instant advice and take quick action to protect their crops, improving agricultural productivity and reducing losses.

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