# Segmentation of Potato Plants: Leveraging OpenCV and Deep CNNs for Pathogenic Degradation Analysis

Kajal Kaul[1,*], Amit Prakash Singh[1], Anuradha Chug[1]
[1]University School of Information, Communication and Technology, New Delhi, India
*Corresponding Author: Kajal Kaul. Email: kajalkaulphd@gmail.com, amit@ipu.ac.in, anuradha@ipu.ac.in

**Abstract.** There is an increasing need for improving plant health against pathogenic degradation in the potato crop and preventing morphological degradation of Potato plants. In this paper, the exploration of the integration of Deep Convolution Neural Network models for the segmentation and severity estimation of various Plant Diseases in potatoes is focused. Potato plants' leaf surfaces have been specifically picked for this study. Potatoes are a staple food crop consumed globally. Its production is significantly threatened by various diseases, leading to substantial economic losses. Disease lesion segmentation is crucial for disease management for preserving the morphology of the biological potato plant leaf surfaces. Using OpenCV-based image segmentation and UNet segmentation, analysing the methodologies, datasets, performance metrics, and challenges is crucial. The average severity scores for Potato Early blight, late blight and healthy leaves are 0.0431, 0.0567 and 0.0427 for Plant Village and 0.0449, 0.0508, and 0.0428 for Plant Doc, respectively. Several other segmentation performance metrics for the UNet model achieved are IoU of 0.735 and a Dice Coefficient of 0.847. The testing pixel accuracy came out to be 0.98 for the Plant Village dataset and 0.89 for the Plant Doc dataset.

**Keywords:** Potato Plant Disease, Deep CNN, UNet Segmentation, OpenCV

## 1. Introduction

Potato plants comprise cellulose, lignin, pectin and other proteins. The plants go through mechanical stressors, environmental degradation, varied temperatures in various seasons and oxidative stress, etc. The potato plant, being an important food crop, provides essential nutrients and contributes significantly to food security. The yield of the potato plant is hindered by different diseases caused by pathogens like fungi, bacteria, and viruses. Pathogen-associated molecular structures bind to plant receptors, which cause immunological responses. These diseases can incur huge yield losses. Conventional ways of disease visual inspection are error-prone. Hence, the budding of efficient disease segmentation techniques is quintessential. Some pathogens produce effectors that disrupt host biological process pathways. Cellulases, pectinases, and lignin peroxidases ruin the cell edges, which causes cell lesions. The infected bio-tissues form crevices, dehydration and pore rupture. This affects the color, texture of the potato plant leaf surfaces, and also the lighting may be affected while capturing complex leaf surface structures. Hence, several imaging techniques and their analysis and processing via image processing, segmentation and deep learning are utilised[1], [3].

Deep Convolutional Neural Networks (DCNNs) and Image Processing on Potato plant leaf structures and surfaces have shown exceptional abilities[5], [8]. In the context of plant pathology, the plant images are trained on large datasets of leaf images to recognise subtle morphological deviations indicative of disease. This paper presents an implementation of Image Segmentation and DCNN techniques for Morphological Plant Leaf surfaces pathogen and disease segmentation.

## 2. Implementation

In this paper, **Arjun Tejaswi's** Plant Village dataset, comprising 2152 plant images, is used. Also, the Plant Doc dataset with 512 images is used. The three class labels are Potato Early Blight, Potato Late Blight and Healthy. The dataset split ratio for the train, test and validation datasets is 80:10:10. The Python script is run for coding purposes with NVIDIA GPU configuration. The organic materials, such as Potato plant leaf surfaces, are segmented based on their color, texture and lighting feature. The binary color-segmented masked images are generated using OpenCV. The yellow and brown colored lesions are pathogenic and diseased. While the Green segmented ones are healthy, pathogen-free leaves. Hence, color plays a crucial role in the identification of diseases in plant organic matter. There is a multilevel semantic segmentation in this paper based on color, texture and lighting, etc. feature levels shown in Table 1 as follows:


M. Kaushik et al. (eds.), *Proceedings of the International Conference on Responsible, Risk-aware, and Regulated AI (RRRAI 2026)*, Advances in Intelligent Systems Research 210,
https://doi.org/10.2991/978-94-6239-723-1_24

**Table 1:** Multi-Level semantic segmentation

| Mask Type | Purpose of Potato Plant Leaf Analysis | Key Metric |
|---|---|---|
| Binary | Identifies the total area of degradation vs. healthy material. | Diseased area |
| Color | Categorises specific morphology (cracks, voids, erosion). | Mean IoU |
| Adaptive Overlay | Validates segmentation accuracy against raw organic textures. | Visual Inspection |

The binary segmented masks are depicted in the given Figure 1(a-f) as follows:

***Figure 1(a):*** *The Plant Village Brown-color binary segmented mask samples*

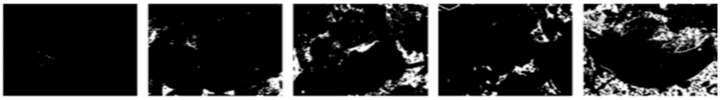

***Figure 1(b):*** *The Plant Doc Brown-color binary segmented mask samples*

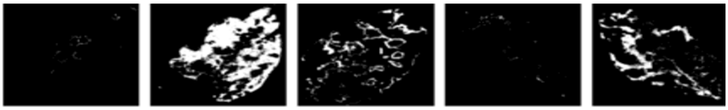

***Figure1(c)****: The Plant Village Yellow-color binary segmented mask samples*

***Figure 1(d)****: The Plant Doc Yellow- color binary segmented mask samples*

***Figure 1(e):*** *The Plant Village Green-color binary segmented mask samples*

***Figure 1(f):*** *The Plant Doc Green-color binary segmented mask samples*

Similarly, for potato plant leaf texture visualisation, adaptive masks are used to detect the plant leaf surface texture and shape. These masks also cater to the appropriate lighting requirements for the surfaces. Since the leaf areas are porous and have shadows, lighting should be appropriate for capturing the complexities of the plant leaf images, as shown in Figure 2(a-b):

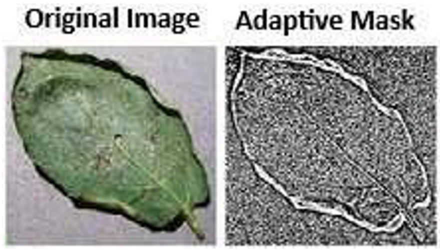


**Figure 2(a):** The Plant Village dataset Adaptive Overlay mask

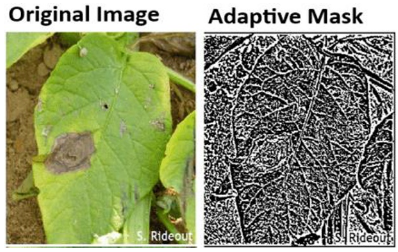


**Figure 2(b):** The Plant Doc dataset Adaptive Overlay mask

The overlay mask samples are also visualised based on the colour as given in Figure 3(a-f); the segregation of brown, yellow and green plant leaf areas is visualised. Similarly, any organic matter surface areas such as plant stems, roots, etc. can be visualised. In this research, the primary emphasis is on organic plant leaf surfaces.

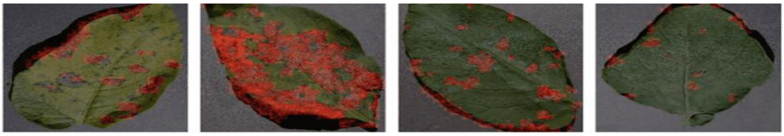

**Figure 3(a):** The Plant Village dataset Brown color segmented overlay masks

**Figure 3(b):** The Plant Doc dataset Brown color segmented overlay masks

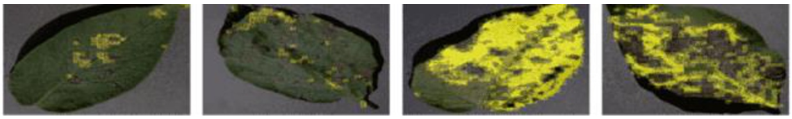

**Figure 3(c)**: The Plant Village dataset Yellow color segmented overlay masks

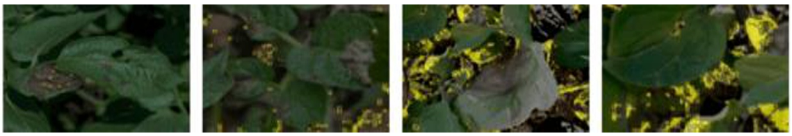

**Figure 3(d):** The Plant Doc dataset Yellow color segmented overlay masks

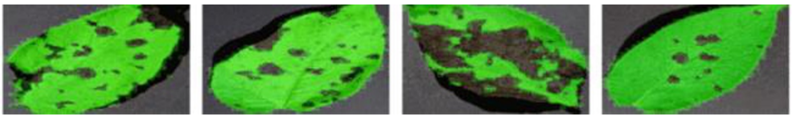

**Figure 3(e):** The Plant Village dataset Green color segmented overlay masks

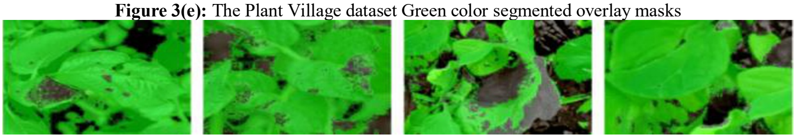

**Figure 3(f):** The Plant Doc dataset Green color segmented overlay masks

The overlay mask generation is based on illumination, texture factors. The edges are also sharp and well seen under the mask. It helps us gain insights of the organic matter under the mask. Therefore, visualisation for the same is shown in the Figure 4(a-b) below:

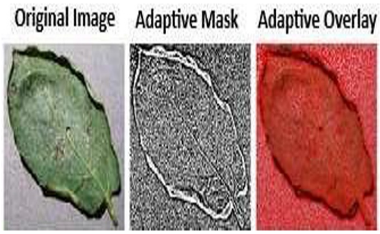


**Figure 4(a):** Plant Village dataset Adaptive Overlay mask

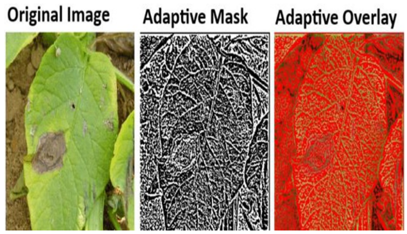


**Figure 4(b)**: Plant Doc dataset Adaptive Overlay mask

The adaptive overlay merged mask is the combination of color, illumination, texture features to analyse the plant leaf surfaces. The prominent lesions, leaf spots and other degradation on the potato plant leaf surface are focused on as shown in Figure 5(a-b) below:

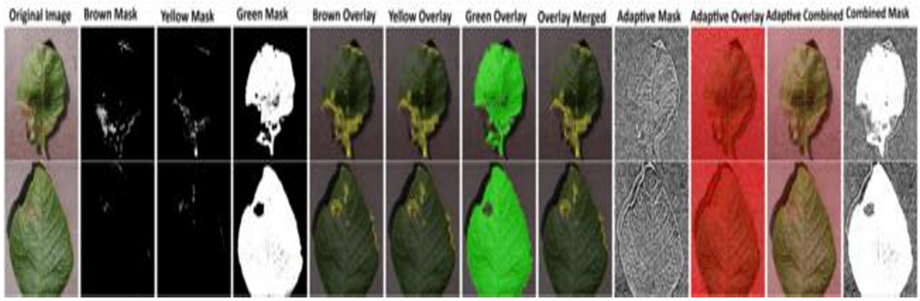


**Figure 5(a):** Plant Village dataset Combined Ground Truth Masks

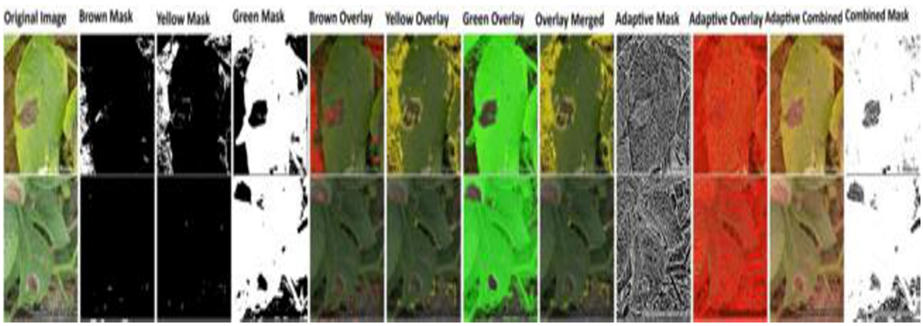


**Figure 5(b):** Plant Doc dataset Combined Ground Truth Masks

Deep Convolution Networks(DCNNs) also play a pivotal role in checking if the final Ground truth masks are serving their purpose. So, for that UNet model is used to check them against refined predicted masks as shown in the Figure 6(a-b) given below:


**Figure 6(a)**: U-Net based Segmented Predicted Mask for Early Blight disease


**Figure 6(b):** U-Net based Segmented Predicted Mask for Late Blight disease

The hyperparameters tuned for UNET-based segmentation used are shown in Table 2:

**Table 2:** Hyperparameters Tuned for Plant Village Dataset & Plant Doc Dataset

| Hyperparameters | Plant Village Dataset & Plant Doc Dataset |
|---|---|
| Optimiser | Adam |
| Learning Rate | 0.0001 |
| Epochs | 20(with early stopping) |

## 3. Mathematical Severity Calculation

The Disease Severity percentage has been calculated by dividing the Disease_Pixel_Area by the leaf's Total_Pixel_Area, and is represented in the formula given in Eq. 1 as follows:

$$Disease\ Severity\ (\%) = (\frac{DiseasedArea}{TotalLeafArea}) * 100 \quad (1)$$

## 4. Results

The Average Disease Severity Estimation based on the above potato plant leaf segmented surfaces visualised above are shown in Table 3 as below:

**Table 3:** Average Disease Severity Estimation

| Class Labels | Plant Village Dataset | Plant Doc Dataset |
|---|---|---|
| Potato Early Blight | 0.0431 | 0.0449 |
| Potato Late Blight | 0.0567 | 0.0508 |
| Potato Healthy | 0.0427 | 0.0428 |

The U-Net segmentation model performance metrices are as given in Table 4 as below:

**Table 4:** U-Net Segmentation Evaluation Metrics

| Evaluation metrics | Plant Village Dataset | Plant Doc Dataset |
|---|---|---|
| IOU | 0.735 | 0.810 |
| Dice Coefficient | 0.847 | 0.894 |
| Testing Precision | 0.947 | 0.959 |
| Testing Recall | 0.895 | 0.902 |
| Testing F1 Score | 0.920 | 0.929 |
| Testing Specificity | 0.881 | 0.870 |
| Testing Pixel Accuracy | 0.981 | 0.894 |

## 5. Conclusion and Future Scope

The implementation of image segmentation of potato plant leaf interfaces was performed appropriately and yielded considerably efficient results for Severity estimation. The papers [2], [10] also emphasized on the severity estimation aspect. The use of dynamic DCNNs and Image Processing techniques in the study and analysis of potato plant leaf surfaces is an asset. In future, it can be compared to other SOTA models like Vision Transformer, SWIN transformer, YOLOv8[4], etc. Also, more aspects like fertilizer use, chemicals and pesticide recommendation, green composites like manure and other organic products can be incorporated into the study[6],[7],[9]. Other parameters such as Temperature, pressure and humidity can also be accommodated into the research. The IoT aspect can also be studied in future.

## References

1. Ranjan RK, Singh D, Baranwal VK. Simultaneous Detection of Brown Rot- and Soft Rot-Causing Bacterial Pathogens from Potato Tubers Through Multiplex PCR. Curr Microbiol. 2016 Nov;73(5):652-659. doi: 10.1007/s00284-016-1110-0. Epub 2016 Aug 1. PMID: 27480266. .

2. S. Biswas, B. Jagyasi, B. P. Singh and M. Lal, "Severity identification of Potato Late Blight disease from crop images captured under uncontrolled environment," 2014 IEEE Canada International Humanitarian Technology Conference - (IHTC), Montreal, QC, Canada, 2014, pp. 1-5, doi: 10.1109/IHTC.2014.7147519.

3. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, *7*, 1419. https://doi.org/10.3389/fpls.2016.01419

4. Yongzheng, M., Wei, M., & Xiaoyu, Z. (2025). SerpensGate-YOLOv8: An enhanced YOLOv8 model for accurate plant disease detection. *Frontiers in Plant Science*, *15*.

5. Polder G, Blok PM, de Villiers HAC, van der Wolf JM, Kamp J. Potato Virus Y Detection in Seed Potatoes Using Deep Learning on Hyperspectral Images. Front Plant Sci. 2019 Mar 1;10:209. doi: 10.3389/fpls.2019.00209. PMID: 30881366; PMCID: PMC6405642.

6. B.P. Singh, P.M. Govindakrishnan, Islam Ahmad, Shashi Rawat, Sanjeev Sharma & J. Sreekumar (2016) INDO-BLIGHTCAST – a model for forecasting late blight across agroecologies, International Journal of Pest Management, 62:4, 360-367, DOI: 10.1080/09670874.2016.1210839

7. Gurjar, M.S., Kumar, R., Singh, D. et al. Development of fungicides spray schedule to manage the late blight of potato in north eastern Himalayan region of India. Indian Phytopathology 71, 505–512 (2018). https://doi.org/10.1007/s42360-018-0082-3

8. S. Durai, T. Sujithra and M. M. Iqbal, "Image Classification for Potato Plant Leaf Disease Detection using Deep Learning," 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 154-158, doi: 10.1109/ICSCSS57650.2023.10169446.

9. Kumar, A., & Singh, B. (2020). Potato: A Comprehensive Review on Nutritional Properties and Role in Human Health. Journal of Agriculture and Food Chemistry, 68(35), 9332-9345.

10. G. Wang, Y. Sun, and J. Wang, "Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning," Comput. Intell. Neurosci., vol. 2017, p. 2917536, 2017, doi: 10.1155/2017/2917536