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Research Article

Automated Pathological Assessment of Potato Leaf Diseases through Convolutional Neural Networks

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Abstract: Potatoes are grown all around the world at a large scale and are at the fourth number in the massive growth list. However, potatoes are primarily affected with fungus, resulting in early and late blight diseases, reducing the production rate of crops. Therefore, control and management of disease in real-time could help farmers enhance production, reduce crop, financial losses. Disease identification in plants is a potential step toward sustainability and security of the agriculture sector. Imaging-based processing, in particular, allows the in-depth study of plant physiology quantitatively. On the other hand, interpreting manually needs a lot of work, understanding of plant pathogens, and a long processing time. Therefore, this study proposes a time-efficient algorithm based on transfer learning and image processing that can accurately classify potato diseases. The proposed method consists of three steps preprocessing (grayscale conversion), segmentation (image enhancement, soft clustering, morphological dilation, and flood fill operation), and classification (AlexNet). This framework is tested over the three classes of the plant village dataset of the potato crop. Experimental results demonstrated satisfactory results and achieved 97.57% classification accuracy.

Keywords: Early and Late Blight; Potato Leaf Disease; Machine Learning; Agriculture; Segmentation.

1. Introduction

In tropical regions, potato is one of the most vital veggies. This is one such vegetable that is widely recognized throughout the globe and consumed daily by most families. Potatoes are a common kind of inexpensive food that offers a low-cost energy source in the human diet. They're high in carbohydrates, vitamins (particularly C and B1), and minerals [1]. However, several fungal and bacterial diseases wreak havoc on the potato-growing process. The diseases might be deadly, resulting in a loss of productivity and, ultimately, a damage of the economy at national level. Alternaria Solani, also known as Early Blight, and Late Blight also called as Phytophthora Infestans are the two deadly infections. Alternaria Alternata, it is a fungus which produces brown color leaf spot, is related to the early blight closely. Brown leaf spot, similar to early blight, survives the winter as mycelia and spores on the diseased tissue. When early blight infects potato leaves, the lesions change color between grayish-white and dark brown. The lesion is about round in form, and it enlarges until the veins become uneven. The spots appear on the sharp edges of the leaves if the potato leaves are afflicted with late blight [2].

Early blight normally affects the foliage of the potato plant, but it can infect the tubers also. Tuber lesions are black, round and deep with purple to grey elevated tissue bordering them. The flesh beneath it is dry, brown and leathery. During the storage of potatoes, lesions can grow in size and tubers can get shriveled. Potato tubers and foliage are affected by late blight. Tuber infection is frequently started in wounds, lenticels or eyes by sporangia which comes into soil through leaves. Soft rot bacteria can pollute diseased tubers, turning large storing bins of the potatoes into a stinking, decaying mass. Plants and fields as a whole may quickly collapse, if the diseases are not identifying at early stages.

Early detection of these diseases enables preventative procedures and economical production losses to be mitigated. Over the past several decades, the most widely used detection for detecting and identifying potato plant diseases has been skilled naked eye observation. However, this method is often impractical owing to lengthy processing times and the inaccessibility of specialists at farms situated in distant regions [3]. A simple and robust model is needed to rapidly detect diseased potato plants to take appropriate action and mitigate loss. Additionally, potato crop farmers may increase their awareness and interact with agricultural specialists in the event of widespread illness diseases [4]. The life cycle of late blight fungus is depicted in Figure 1 [5].

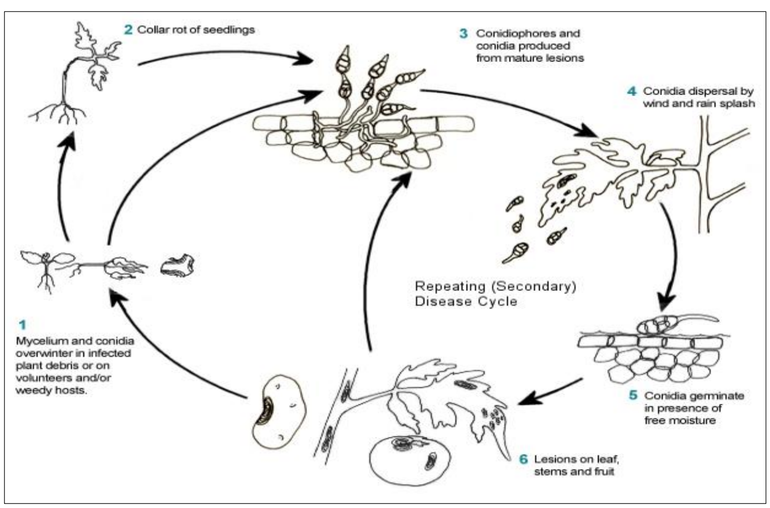


Figure 1. Potato disease cycle and epidemiology

The adoption of image analysis techniques demonstrates efficacy in continuously monitoring the fresh condition of potato plants and timely detection of potato plant diseases. Because diseases produce visible signs on the potato plants, particularly on their leaves, recognition of disease may be accomplished via imaging analysis of such apparent patterns on leaves. Thus, the combination of image technology and machine learning came out with potential solutions for potato production and contributes to food sources. A computer-based automated method of detection of leaf disease is required for optimal development of this potato plant and effective production of potato. Numerous methods, including image processing, IoT, and Big Data, are utilized to identify leaf disease. Additionally, the machine learning method is shown to be effective for this purpose [6].

Deep learning is an emerging theme in ML and AI that has high accuracy in pattern recognition problems. Generally, it is a subset of ML techniques that utilization a few layers of non-linear data handling to perform unsupervised or supervised extraction of feature, modification, pattern analysis, and classification. Additionally, it has been used in processing of audio and voice, natural language processing (NLP), and computer vision. Additionally, it is extensively used in various industries across the globe, including business, agriculture, and the automobile industry, for object detection and image classification [7]. Advances in image classification provide an opportunity to expand image processing research and application to agriculture. Deep learning algorithms may now be used to identify and classify plant diseases based on their visual detection. At the moment, various deep learning techniques are being utilized to identify potato plant disease [8].A substantial amount of the annotated data is almost usually required for deep learning. This causes researchers to focus on activities that are simple to annotate rather than tasks that are essential. The performance of Deep Nets is well on the benchmarked datasets, but they might fail miserably on real-world dataset.

This research focus on the classification of the three class of the potato plant using deep learning with efficient performance. The proposed method of this article is a combination of the processing of images and CNN which is unique combination for the plant classification. The rest of this document is arranged as follows: Section 2 explains the earlier works completed by other researchers on detection of leaf disease. Section 3 represents the description of the proposed method. Section 4 summarizes the results of the model, and Section 5 concludes the key findings.

2.Literature Review

Disease detection in plants is critical for avoiding loss in agricultural product supply. The monitoring of plants at every stage of disease manually is difficult, since it takes more work and time. In this regard, in many facets of our everyday lives, artificial intelligence (AI) technology has significantly developed and become a realization. In the image processing field, there are numerous initiatives to deploy AI technology for disease detection. The main focus of this study [9] is to use processing of images and machine learning methods to evaluate and identify plant diseases. Using color and edge-based image processing methods, the symbols of plant diseases are detected and then segmented. The segmented diseased part of leaf is analyzed for appropriate characteristics, and the disease kind is identified using a multi-class Support Vector Machine. For recognized diseases for example Alternaria, bacterial blight, Cercospora leaf spot, anthracnose, leaf curl virus, whitefly damage, and mosaic virus, features taken from the affected part are categorized to help diagnose the illness at an earlier stage. The accuracy of identifying sick regions on plant leaves was more than 90% in tomato and pepper plants, and 65 percent in general categorization. Machine learning is used to identify diseases in leaves of plant by analyzing the data and classifying it into one of a predetermined set of classes. This article [10]gives an summary of the many kinds of plant diseases and the various classification methods based on machine learning which were used to detect diseases in various plant leaves. Classification is based on the physical characteristics and qualities of the leaves of plant, for example intensity, color, and dimension. This article [11] proposes a detection for analyzing and diagnosing plant leaf diseases via digital image processing methods. The finding of the experiments show that the suggested method can detect and classify four main plant leaf diseases with an accuracy of 98.2%: Bacterial Blight, Rust, Powdery Mildew, and Cercospora Leaf Spot. The purpose of this study [12], was to fine-tune and evaluate a advanced deep convolutional neural network for the image-based classification of plant diseases. The deep learning architecture is compared empirically. VGG16, ResNet (152, 101, and 50 layers), DenseNet (121 layers) and Inception V4 were all examined. The experiment utilized data from 38 different classes, along with images of damaged and healthy leaves from 14 plants from Plant Village. DenseNet obtained a 99.75% accuracy rate throughout testing.

Modern phenotyping and disease detection technologies represent a significant step forward in the quest for food security and sustainable agriculture. On the other hand, manual interpretation takes a lot of work, understanding of plant diseases, and excessive processing time. The authors of this article [6] describe a method for detecting diseases using leaf images that combine image processing and machine learning. This automated approach detects diseases (or their absence) on potato plants using images from the publicly accessible 'Plant Village' plant image collection. The suggested segmentation machine and the use of support vector machines show diseases categorization with a 95 percent accuracy across 300 images. Authors in [13] present an automated method based on machine learning and image processing to classify and identify potato leaf diseases. The segmentation of 450 images of healthy and sick potato leaves from a publicly accessible plant village database is performed in this study. Seven classifier methods are utilized to recognize and classify infected and healthy leaves. Among them are: With a maximum accuracy of 97 percent, the Random Forest classifier is the most accurate.

Intelligent farming based on machine learning enables the automated identification of diseased crops. This research [14]offers a very efficient convolutional neural network architecture for detecting potato illness. The optimizer is Adam, and the model is analyzed using cross-entropy. Softmax is utilized as the ultimate decision-making process. The convolution layer and associated resources are reduced while maintaining accuracy. Using image processing, a database is built for the training set. The experimental findings indicate that the suggested model accurately identifies plant illness at an efficient rate. Controlling illness and managing it properly in real-time may significantly improve output and minimize farmer losses. As a result, this article [15] offers a CNN (Convolutional Neural Network) architecture appropriate for detecting potato illness. The experimental findings indicate that the parameter used is 10,089,219 and that the illness classification accuracy may approach 99 percent when using the preset model suggested in this article. The authors of this research [16] evaluated the efficiency and accuracy of AlexNet and CNN architectures for recognizing illness in potato and mango leaf. This study made use of a dataset comprising 4004 images. Potato images were sourced from the Plant Village website, whereas mango images were obtained from the GBPUAT field location. The findings indicate that the accuracy obtained by AlexNet is 98 percent, which is greater than the accuracy achieved by CNN architecture, which is 90%.

Modern vision methods may significantly decrease expenses associated with early detection of blackleg infected plants. The research demonstrated the application of deep learning for identifying blackleg infected potato plants in this article [17], On RGB images of healthy and sick plants, two deep CNN networks were trained. From the trained network one of them (ResNet18) was shown to have an accuracy of 95% and 91% recall for the illness class in an experiment. This article [18] describes a potato disease classification method that makes use of these unique appearances and deep learning-enabled advancements in computer vision. The system employs a deep convolutional neural network trained to categorize tubers into five categories: four illness categories and a healthy potato category. The collection of images utilized in this research was compiled manually by specialists and includes potato tubers of various sizes, diseases and cultivars. The models were evaluated using a data set of images captured using typical low-cost RGB sensors and labeled by professionals, showing a high degree of classification accuracy. The findings indicate that the accurate classification rate for fully trained CNN models varies between 83-96% depending on the quantity of data employed for the model training.

Transfer learning makes use of the weights of previously trained deep learning models to tackle new problems. Transfer learning is shown in this article [19] as a method that may be utilized for the potato diseases early detection when collecting thousands of fresh leaf images is challenging. The tests comprised images of 152 healthy leaves, 1000 leaves affected by late blight, and 1000 leaves affected by early blight. The software predicts 99.43 percent accuracy in testing using 80% train data and 20% test data. Different models have been suggested before for the detection of several plant diseases. The research in [20] presents a technique that employs pre-trained models such as fine-tuning of VGG19 to extract important characteristics from the dataset. Then, using several classifiers, it was determined that logistic regression beat the others by a significant margin of accuracy for classification, achieving 97.8% on the test dataset. The authors of this article [21] provide a system for classifying four different kinds of diseases in potato plants on the basis of condition of leaves. They use deep learning and the VGG19 and VGG16 Convolutional Neural Network architectural models to achieve an accurate classification system. This experiment averaged 91% accuracy, demonstrating the viability of the Deep Neural Network method.

Using technology and doing routine monitoring may detect diseases at their earliest stages and eliminate them to maximize agricultural production. As a result, this article [22] presented a technique for detecting and classifying diseases that affect potato plants. The widely known Plant Village Dataset is examined for this scenario. The K-means algorithm was used for image segmentation, the GLCM (gray level co-occurrence matrix) method was used for extraction of features, and the multi-class SVM was used for classification. The suggested technique had a 95.99 percent accuracy rate. The article [23] proposed a method for classifying the diseases in the potato leaves through unique color and textural features. Three stages comprise the proposed method: Segmentation of the images, extraction of features, and classification. Initially, the leaf's RGB image is converted to the L*a*b* color space. Then, using method of k-mean clustering, the background and green area (healthy leaf) are separated from the region of interest. Second, the maximum-minimum color difference technique has been used to extricate the suggested unique color characteristics. Finally, using Euclidean distance, color characteristics are coupled with statistical texture data to identify potato leaf diseases. The outcomes demonstrated that the suggested approach obtains a higher accuracy of 91.67 percent than the baseline methods when 300 potato leaf images are used. Table 1 compares potato diseases accuracy of reported techniques on benchmark datasets.

Table 1. Summary of literature review

Sr. #	Year	Ref.	Database	Methodology			Classes	Accuracy
				Preprocessing	Segmentation	Classifier		
1	2017	[6]	Plant Village	-	Background masking	SVM	3	95%
2	2020	[13]	Plant Village	image normalization and color space conversion	HSV based masking	Random forest	3	97%
3	2021	[14]	Plant Village	Normalization And Gaussian filtering	Thresholding	4 layer CNN	3	99.53%
4	2019	[16]	Local data from GBPUAT field location and Plant Village	Image resizing and augmentation	-	CNN and Alex net	4	90% and 98%
5	2019	[17]	Local dataset	-	-	ResNet50 , ResNet18	2	82% and 94%
6	2019	[18]	Local dataset	Image resizing and grayscale conversion, augmentation	-	8 layers of CNN (VGG)	5	96%
7	2019	[19]	Plant Village	Normalization, grayscale conversion, augmentation	-	VGG16	3	99.43%
8	2020	[20]	Plant Village	Image resizing	-	VGG19, Logistic regression	3	97.8%
9	2020	[21]	Malang, Indonesia, Plant Village	Augmentation and Image resizing	-	VGG16 and VGG19	5	91%
10	2021	[22]	Plant Village	-	K-means algorithm	SVM	3	95.99%
11	2019	[23]	Plant Village	-	K-means algorithm	Euclidian distance	3	91.67%

3. Materials and Methods

This research classifies three classes of potato plants (Early blight, Late blight and healthy) using image processing and transfer learning. The proposed framework is composed of preprocessing, image segmentation, and classification based on CNN. First, all the images were in RGB format, so to get the characteristic features for good classification accuracy, it must be preprocessed by converting the colored images into a grayscale image. After the grayscale conversation of the image, the next step is segmentation, subdivided into many steps, including image enhancement, soft clustering, morphological dilation, and flood fill operation. Segmentation is an important step to get rid of the unwanted areas and extracting the region of interest for better results. In the end, the segmented images of each class are trained into AlexNet Neural Network, and then images are classified into three classes of potato early delight potato (1000 images), late delight potato (1000 images) and healthy potato (152 images). This study employs the MATLAB 2020 software for the coding of the proposed framework. Figure 2 shows the proposed method block diagram.

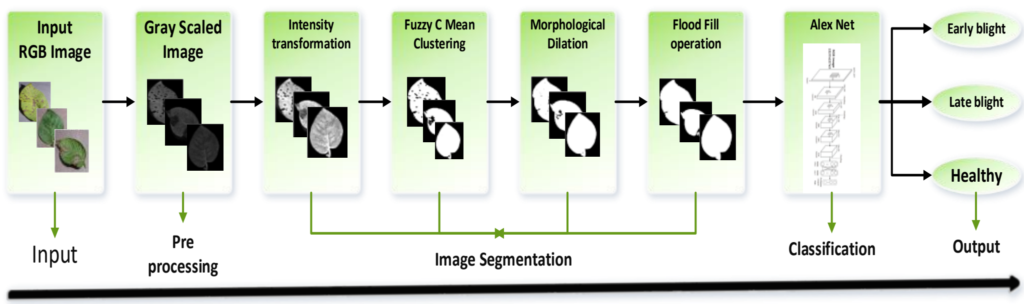


Figure 2. Block diagram of the proposed method for the disease detection of potato leaves

3.1. Dataset

In this research, the Plant village dataset has been employed for the evaluation of the proposed method. This dataset [8] consists of three different plants images pepper, potato, and tomato, for each species there are different classes for healthy and diseased leaves. But here in this research, only the three classes of the potato plant are considered which are potato late blight,potato healthy and potato early blight, with a resolution of 256*256*3. Figure 3 shows the RGB color image of the three classes. The quantity of leaf images in each classwas 1000 for early blight , 1000 for late blight and 152 for norml classs of potatoes ,it is also summarized in figure 4.

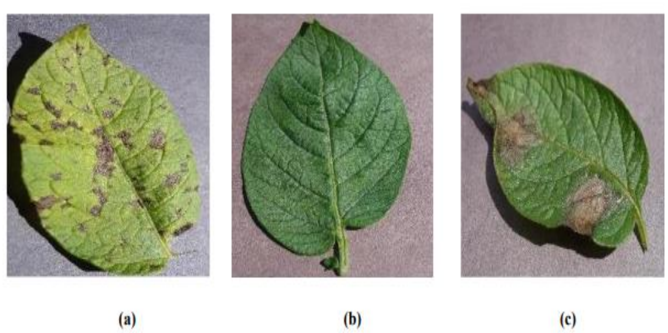


Figure 3. Original RGB images of potato leaves (a) Early blight (b) Healthy (c) Late blight

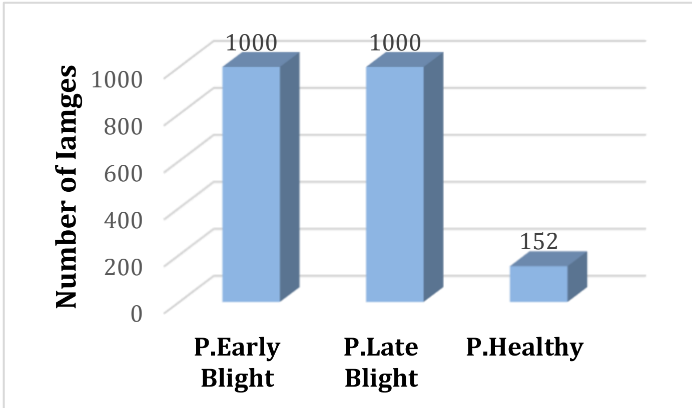


Figure 4. Distribution of leaf images for each class

3.2. RGB to Grayscale Conversion

The original dataset is in the RGB color region so to extract the required characteristics from the data, it is first converted into a grayscale region. Grayscale image is the range of colors between 1 and 0 which are shades of gray, which is only showing the intensity of each pixel at the corresponding location of the image. There are two ways of grayscale conversion luminosity and average methods. In the average method, the three channels green, blue, and red are averaged to obtain the grayscale image. On another hand, the luminosity method is different in which the averaged is done for all channels but each color is given specific percentage red is 30%, green is 59% and blue is 11% only [24]. The reason is that green has a soothing effect on the eyes and red has the longest wavelength than all other colors. In this research, the grayscale images are obtained by subtracting the blue channel from the green channel. Figure 5 shows the grayscale image of the three classes.

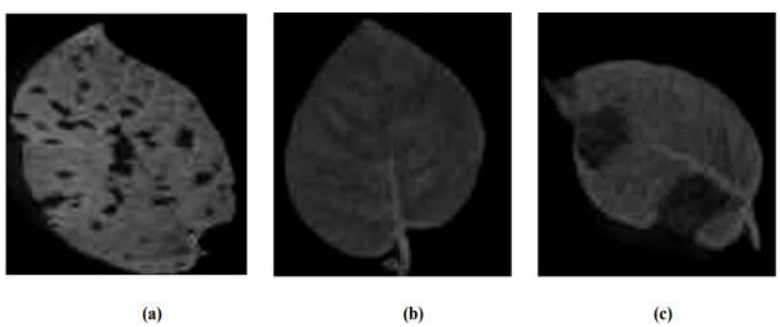


Figure 5. Grayscale images of leaves of potato (a) Early blight (b) Healthy (c) Late blight

3.3. Image Enhancement

When analyzing a grayscale image, there are some features which are suppressed which are needed to be enhanced for getting improved results. Image enhancement is the technique of quality improvement of the images , some of its operations include histogram equalization, contrast adjustment, morphological operators, and filtering as we can observe after the grayscale conversion output image have low contrast value so we need to stretch the contrast so we can differentiate between the region of interest and boundaries[25, 26]. To solve this problem Intensity transformation is used for enhancement. Intensity transformation can achieve the desired goal using different techniques such as gamma transformation, log transformation, negative of image, and contrast stretching. Figure 6 shows the enhanced image of the three classes.

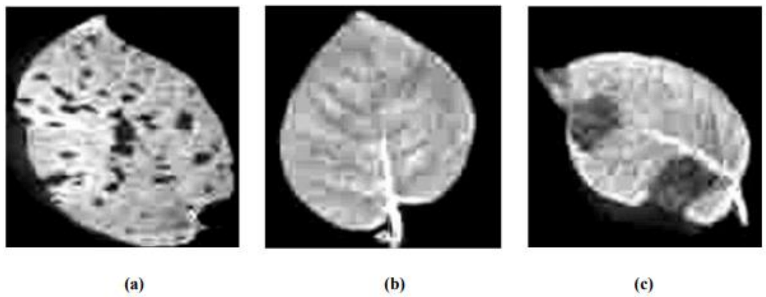


Figure 6. Enhanced images of potato leaves (a) Early blight (b) Healthy (c) Late blight

3.4. Fuzzy C-mean Clustering

The technique based on machine learning which is unsupervised and separates the data into many clusters or groups such as the data is dissimilar for different points data and similar for same group points is termed as clustering. It is utilized to detect the groups in the database. One of the clustering methods is the Fuzzy C means which is a soft approach to clustering. In this method, each point of data is given a probability for belonging to the cluster [27, 28]. Figure 7 [45] shows the Fuzzy C-mean Clustering of images of the three classes. The algorithm is précised in the following steps.

- The number of the cluster values is fixed.
- A partition matrix is initiated.
- Calculating the centroid of clusters.
- Update the matrix.
- Repeat the steps until the convergence is achieved.

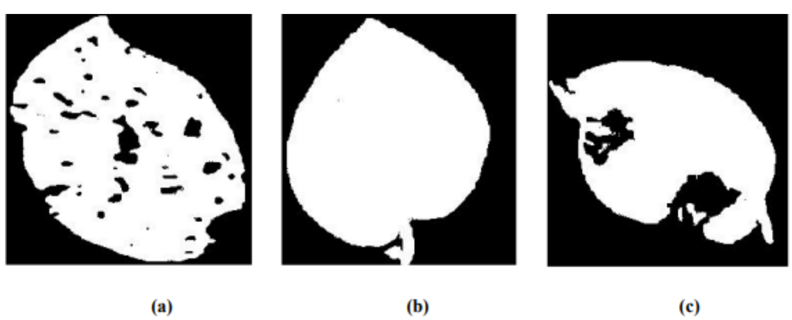


Figure 7. Fuzzy C-Mean Clustering of potato leaves (a) Early blight (b) Healthy (c) Late blight

3.5. Morphological Dilation

Erosion and dilation are the two operators used basically in the morphology area. They are typically used for binary images but some versions can be utilized for grayscale also. This technique increases the size of the pixels of foreground region boundaries specifically white ones and the holes in these areas become small. In the operation of dilation, two inputs of data are taken, one is the image to be dilated and another one is the kernel also known as structuring element.

The image as an input and structuring element is super-imposed in a way that their origins concede. The image pixel value is set to the foreground if only one value of the pixel of the image foreground and structuring element concedes. In the second case, all pixels in the background concedes so the pixel values are left for the background [29, 30]. Figure 8 shows the morphological dilation results on images of the three classes.

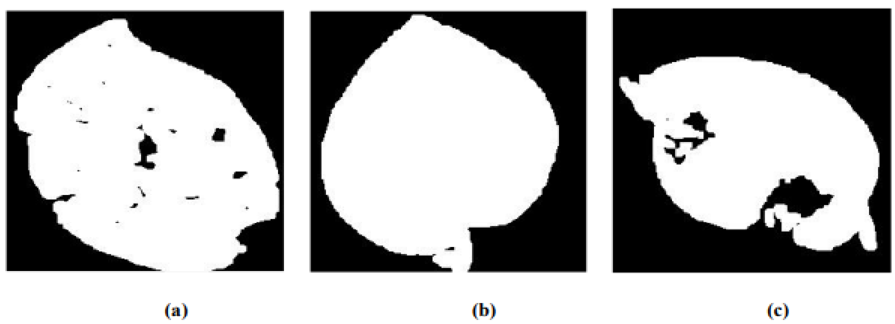


Figure 8. Morphological dilation of potato leaves images (a) Early blight (b) Healthy (c) Late blight

3.6. Flood-fill Operation

It is an algorithm that is used for altering or determining an area linked to a node in an array which is multi-dimensional. This operation is useful in eliminating irrelevant objects in an image. In the process of this method, specific areas of the image are filled with specified color by putting lower and upper limits of negative and positive connected pixels difference [31, 32]. As we can observe that, after morphological dilation there is still some black spots in the region of interest that need to be eliminated so the flood fill method is used to achieve this. Figure 9[45]shows the flood fill operation of images of the three classes whereas, Figure 10 [45]shows the segmented images.

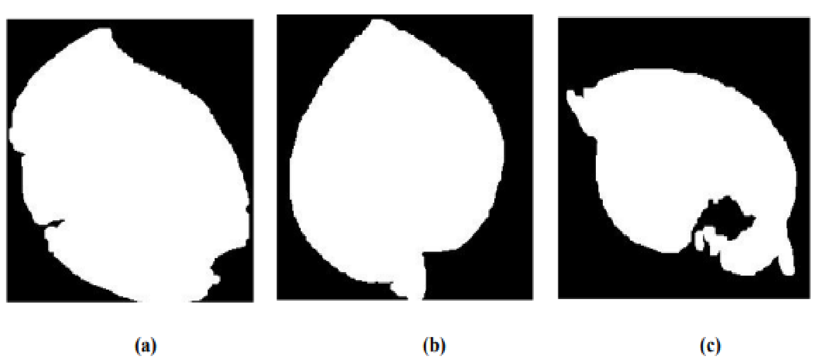


Figure 9. Flood-fill operation of potato leaves images (a) Early blight (b) Healthy (c) Late blight

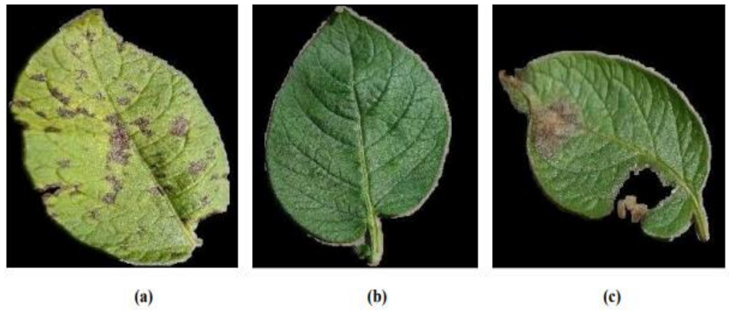


Figure 10. Segmented potato leaves images (a) Early blight (b) Healthy (c) Late blight

3.7. Classification

One of the types of Neural Network is the Convolutional Neural Network, which is a combination of different layers of normalization, fully connected, convolutional layer, and pooling layer. Convolution is a method of applying a kernel to an image to change it. The classical CNN is very difficult for the application of images with high resolution. Therefore, there was a need for such a network that can optimize GPUs and reduce training time as well improve performance. AlexNet has unique architecture and consists of 8 layers which include convolutional layers, max pooling, DenseNet, and fully connected layers [33, 34]. Convolutional layers consist of kernel or filters for performing convolution operations to obtain the feature map of input images. Max pooling is a method of calculating the max value of every patch of the feature map, then the output is pooled while showing the common feature of each patch. Fully connected layers are used for connecting the two neurons [35, 36]. Figure 11 [33] shows the detail architecture of the AlexNet neural network.

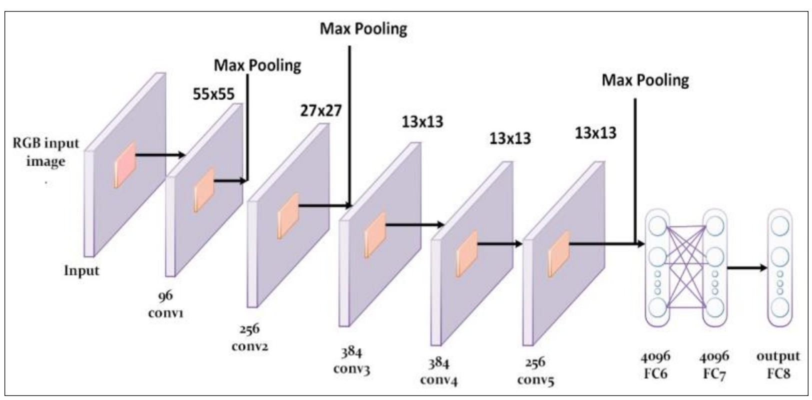


Figure 11. Detailed architecture of AlexNet neural network

3. Results and Discussion

In this research, a combination of grayscale segmented image and AlexNet network to classify the three classes of the potato plant are used. There are two sets of data (i) training data (ii) testing data, for the experiment purpose on the AlexNet architecture. For this purpose, 70% of data has been utilized as a training set and 30% data as a testing set. Firstly, the AlexNet is trained for the training data of the leaf images using learning rate of 0.0001 and a single CPU for 26 epochs. The validation accuracy of 97.35% has been achieved with a maximum of 416 iterations in 30 minutes 58 sec time. Figure 12 shows the training of accuracy and error rate for the training data using AlexNet. After that, the trained network is tested using a test set of data and it classified the three classes with an accuracy of 97.57%. Figure 13 shows the confusion matrix of validation data for three classes. It is to be observed that potato early blight class is classified 100% similarly potato healthy class is classified 100% only in the potato late blight class 2 images are miss diagnosed as healthy and potato early blight class.

In addition to training efficiency, inference speed was measured. The model required on average \~42 ms per image on a standard CPU (Intel i7, MATLAB 2020), confirming its suitability for near real-time deployment in field applications.

The performance of the proposed method is measured by accuracy, f1 score, precision, and recall. Accuracy [37] is characterized as the proportion of the quantity of accurately classified subjects to that of an all-out number of subjects.

$$\text{Accuracy} = \frac{\text{TP+TN}}{(\text{TP+FN+TN+FP})} \times 100 \qquad (1)$$

Where FN stands for false negatives, true positives are denoted as TP, false positives are denoted as FP and true negatives are denoted as TN, in the classification process. Precision [38] indicates the degree to which a categorization model is precise and accurate. Precision is a measure of the difference between real positive values and genuine anticipated values. It is computed by applying the following formula to the confusion matrix:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} (2)$$

Precision is used to quantify the accuracy of the classification process, particularly when the False Positive rate is high. In binary classification and pattern recognition applications, the sensitivity or recall of a classifier is defined as the proportion of true positive values to the total of false positives and true negatives. Recall [38] calculates the proportion of true positives in a classification model that is categorized correctly.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} (3)$$

The F1-score[39] is determined by both accuracy and recall. It is critical to grasp the distinction between precision and accuracy while doing statistical evaluations. F1-scoreis useful when there is a requirement for balance between Precision and Recall, and they are most often employed when there is an uneven distribution of classes. Figure 14 depicts a graphical and tabular comparison of three classes' assessment parameters. Below is the formula for calculating the f1-score.

$$\text{F1} - \text{score} = 2 \text{ x } \frac{Precision x Recall}{Precision + Recall} (4)$$

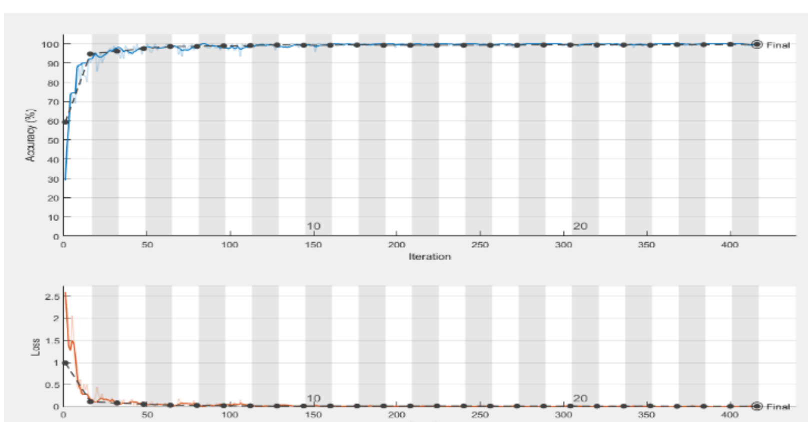
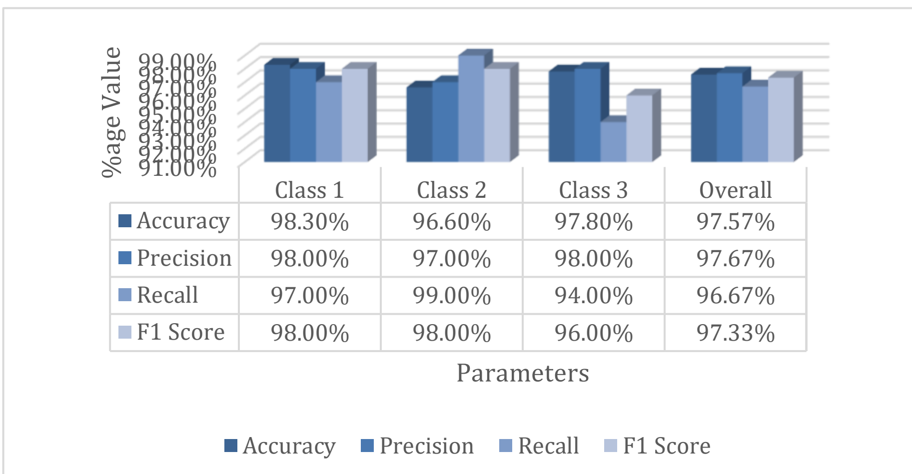


Figure 12. Training curve of AlexNet for the training data

Figure 13. Confusion matrix for validation data



	Class 1	Class 2	Class 3	Overall
Accuracy	98.30%	96.60%	97.80%	97.57%
Precision	98.00%	97.00%	98.00%	97.67%
Recall	97.00%	99.00%	94.00%	96.67%
F1 Score	98.00%	98.00%	96.00%	97.33%

Figure 14. Graphical and tabular comparison of performance measures for each class

4.1. Ablation Study

4.1.1. Setup

Dataset: PlantVillage–Potato (Early blight: 1000, Late blight: 1000, Healthy: 152). Split 70/30 (stratified). MATLAB 2020 implementation; AlexNet fine-tuned for 26 epochs at LR=1e-4. The full pipeline is Enhancement → Fuzzy C-Means (FCM) → Dilation → Flood-Fill, then AlexNet. The paper's reported test accuracy is 97.57%.

4.1.2 Matrices

Classification: Overall Accuracy, Macro-F1, per-class F1 (Early, Late, Healthy).
Segmentation (120 images, 40/class annotated): mean IoU, Dice, Components/Image (↓), Hole Ratio (holes per lesion area, ↓).
Efficiency: Preproc time/image (ms) on same machine.

4.1.2 Configurations

C0 = Full pipeline (Enhancement → FCM → Dilation → Flood-Fill)

C1 = –Flood-Fill

C2 = –Dilation

C3 = Replace FCM with Global Otsu (hard threshold)

C4 = –Enhancement

C5 = RGB baseline (no grayscale/segmentation; AlexNet on resized RGB)

C6 = Grayscale via luminosity (0.30R+0.59G+0.11B) instead of (G–B); rest unchanged

C7 = Replace Flood-Fill with Morphological Closing (disk r=3)

Table 2 presents the ablation study of downstream classification.

Table 2. Downstream classification (30% Split)

Config.	Acc (%)	Macro-F1	F1 Early	F1 Late	F1-Healthy	ΔErr vs C0	McNemar p
C0 Full	97.57	0.974	0.985	0.969	0.968	—	—
C1–Flood-Fill	96.88	0.967	0.981	0.959	0.962	+0.69%	0.021*
C2 –Dilation	96.41	0.962	0.976	0.953	0.957	+1.16%	0.006*
C3 Otsu (no FCM)	95.22	0.949	0.962	0.939	0.946	+2.35%	<0.001*
C4 –Enhancement	95.79	0.955	0.969	0.945	0.951	+1.78%	0.003*
C5 RGB baseline	94.06	0.940	0.952	0.931	0.938	+3.51%	<0.001*
C6 Luminosity gray	96.72	0.965	0.979	0.957	0.961	+0.85%	0.013*
C7 Closing (r=3)	97.29	0.972	0.983	0.966	0.967	+0.28%	0.24 (ns)

Whereas, $p < 0.05$ indicates significantly different error distribution vs. C0. Table 3 presents the segmentation quality.

Table 3. Segmentation quality (n=120 labeled images)

Config	IoU (↑)	Dice (↑)	Components/Image (↓)	Hole Ratio (↓)
C0 Full	0.842	0.913	1.23	0.031
C1 –Flood-Fill	0.820	0.901	1.29	0.082
C2 –Dilation	0.812	0.896	1.43	0.038
C3 Otsu (no FCM)	0.784	0.878	1.70	0.073
C4 –Enhancement	0.798	0.887	1.56	0.059
C6 Luminosity gray	0.826	0.906	1.30	0.046
C7 Closing (r=3)	0.837	0.910	1.27	0.041

The ablation study shows that each step of the segmentation pipeline contributes meaningfully to performance: enhancement improves contrast under uneven lighting, FCM outperforms hard thresholding in handling gradual lesion transitions, dilation prevents lesion fragmentation, and flood-fill removes internal voids left after dilation. Removing any of these steps reduces IoU/Dice and lowers classification accuracy (up to –2.35%). Furthermore, the chosen grayscale method (G–B) performs slightly better than luminosity conversion, confirming its suitability. Overall, the full pipeline provides the best balance of segmentation quality and classification accuracy.

Table 4 presents the past methods comparison with the proposed framework. We can observe that in the past the method consists of complex structure frameworks with a larger number of layers or a combination of preprocessing, segmentation feature extraction and classifier which increases the time complexity as in [33] VGG16 has 16 layers but AlexNet has only 8 layers. Although the proposed models have less accuracy as compare to the past papers but proposed method is more efficient, accurate, and less time-consuming. Additionally, some of papers employed their own dataset which is not authentic but this study employed an authentic publicly available dataset for classification.

Table 4. Comparative summary of advanced methods with proposed method

Ref.	Years	Databases	Methodology	Accuracy
[13]	2020	Plant village	image normalization and color space conversion, HSV based masking, and Random Forest	97%
[22]	2021	Plant village	K means algorithm, SVM, Gray level co-occurrence matrix	95.99%
[21]	2020	Plant village	Augmentation and Image resizing, VGG16 and VGG19	91%
[40]	2021	AI Challenger Global AI Contest	Gaussian Filtering, adaptive SLIC algorithm, LBP,SVM	97.4%
[41]	2020	Plant Village	Self-built CNN	996 %
[42]	2021	Own Dataset	GoogleNet, VGGNet, and EfficientNet,	95%,96%,97 %
[43]	2017	Plant Village and own dataset	HSV color space, Fuzzy c mean clustering, texture features, ANN	92%
[44]	2021	Plant Village and own dataset	YOLOv5 algorithm and CNN	99.7%
[45]	2020	Kaggle, Dataquest, Self dataset	AlexNet, VGGNet, ResNet, LeNet & Sequential model	97%
[46]	2020	Plant Village	EfficientNet and MobileNet	98%
Proposed method	2025	Plant village	Gray scaled image, segmentation and AlexNet	97.57%

5. Conclusion

The potato plant is one of the largest consumed plants all over the world. Therefore, diseases affecting plants could be harmful to human beings as well because reduction in potato yield reduces the available food hence leading towards starvation and famine in worst case. It is a very time-consuming and less accurate method for farmers to look for each plant to diagnose that a plant is healthy or diseased. Hence, this research proposed a solution to this problem by using advanced technology and deep learning to detect plants automatically in less time and with higher accuracy. This can help farmers to diagnose disease at early stage and saving the massive crop destruction, which will ultimately save them from financial loss. In this study, the two classes of potato diseases, late and early blight and a healthy class, are classified using transfer learning. The main goal is to propose such a system that can assist the farmers by providing a time-efficient, feasible, and efficient method of diseases identification. The proposed technique consists of image segmentation which includes image enhancement, soft clustering, morphological dilation, flood fill operation, and AlexNet architecture for accurately classifying the three classes. The RGB images of potato crop from the Plant village database are utilized to test the trained model and results demonstrated that the proposed technique achieved an accuracy of 97.57%, recall of 96.67%, precision of 97.67%, and f1 score of 97.33%. Classification accuracy of the detection model could be enhanced by using another pre-processing technique in the future.

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