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Predicting and Classifying Potato Leaf Disease using *K*-means Segmentation Techniques and Deep Learning Networks

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Abstract

Potato is one of the most cultivated crops. Worldwide potatoes have its own cultivation priority as a staple food. For a successful potato production, we can develop a strong food security system as it is the great source of vitamins and minerals. However, several diseases affect potato production and degrade agricultural development. Therefore, diseases detection in early stage can provide a better solution for a successful crop cultivation. In this study, our aim is to detect and classify potato leaf diseases using deep learning algorithm. We applied *K*-means clustering segmentation and to increase model's efficacy, numerous data augmentation techniques have been applied on the training data. We have selected VGG16, VGG19, and ResNet50 network model. However, by using VGG16 we achieved 97% accuracy which is the best provided results among three networks. The recommended method outperforms several current methodologies as we compared the performances of the recent models according to relevant parameters.

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Keywords: Potato Leaf Disease, Deep Learning, VGG16, Image Segmentation, Data Augmentation;

1. Introduction

Agriculture is one of the crucial tools to alleviate poverty and also helps to achieve the economic growth. Insecurity of food can create a huge risk of several malnutrition. Therefore, food production is a powerful

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component in the whole world. People in rural areas are mostly dependent on agriculture, World Bank reported that approximately 80% people in rural areas are involving in farming [1].

Potato is a highly-successful and most favorite garden vegetable in the world. Actually, it is a widely cultivated October-March winter crop. After rice and wheat, potato is the 3rd most important crop in Bangladesh to enhance economic growth. Bangladesh is the 4th potato-producing country in Asia and hold 7th position throughout the world [2]. However, several diseases attack potato plants during harvesting. Therefore, detecting the conditions of potato fields and taking early treatment according to the results could be a great solution to increase potato production, and that was the aim for doing this study.

Several traditional machine learning algorithms already used to classify potato leaf disease. This study for combining segmentation techniques and deep learning algorithms together to improve classification results. Image segmentation to mask the images of the potato leaves can produce a better image dataset. Computerized pictures are transformed into different picture sections using the method of image segmentation. This technique is ordinarily utilized to find objects and boundaries in pictures. It is the method of relegating a name to each pixel in a photo such that pixels with the same name share specific characteristics. However, several algorithms for image segmentation are Otsu's Binary threshold algorithm, Contour Detection, and K-means clustering Algorithm.

K-means algorithm is one of the most popular segmentation algorithms. This algorithm uses different K values and cluster the objects according to closet neighbor where neighbor objects considered based on k value. Euclidean distance used to calculate similarity distance of K-means algorithm. Usually K value varied between 2 to 10 [3]. Different traditional machine learning algorithms was popular to predict plant diseases as well as to perform several computer vision tasks. For example, Md. Asif Iqbal and Kamrul Hasan Talukder proposed a model where they applied seven popular traditional machine learning algorithms. In this study they also used image segmentation techniques on 450 images collected from PlantVillage dataset. Among seven algorithms random forest provided 97% accuracy as the best model [4]. Another relevant work by Chaojun Hou et al. reported several machine learning algorithms and used graph cut segmentation techniques to predict early and late blight diseases on potato leaf. After image segmentation, they achieved 91% accuracy from SVM classifier [5].

However, deep learning algorithms are now appropriate to improve performance accuracy. Several deep learning algorithms are available to complete different experiments on different agricultural yields, such as rice, tomato, bell pepper, potato [6]. Along with these algorithms, image segmentation techniques also help to achieve most prominent result. Therefore, in this study image segmentation techniques and deep learning algorithms used together to predict potato leaf disease with an enhanced performance results.

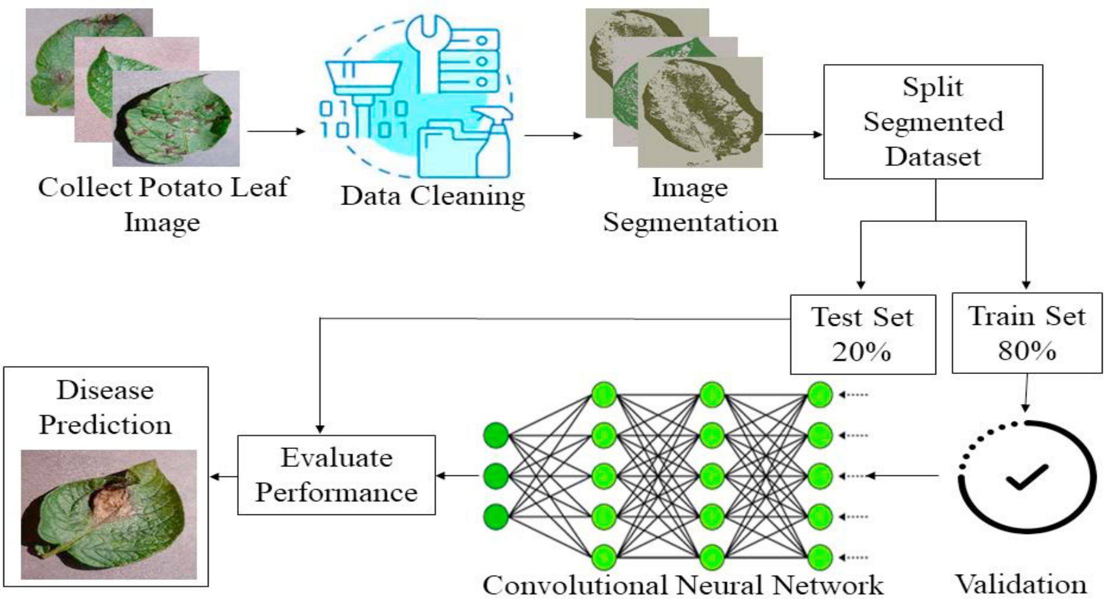

Fig. 1. Deep Learning based Proposed System to Predict Potato Leaf Diseases.

Finally, a deep learning-based system was proposed to predict potato leaf diseases from PlantVillage and Mendeley dataset. A great illustration is shown in Fig. 1. Agricultural development is necessary for every country. Deep learning algorithms and modern technology can alleviate several problems which is crucial to build digital farming. The contributions of this study are listed below-

- We proposed a pre-processed PlantVillage and Mendeley potato leaf dataset.
- Applied *K*-means clustering segmentation approach for three different values.
- Dataset is classified according to three respective classes, such as early-blight, late-blight, and healthy leaf.
- Finally, to achieve prediction results applied different deep networks including VGG19, VGG16, and ResNet50.

2. Literature Review

Several research has done on agricultural development. It can enhance economic growth as well as can provide a healthy environment for human beings. To increase crop production speed already deep learning model and computer vision based studies have been got huge attention. In this section, an impressive summary is presented to know about previous research work.

M. Islam et al. in 2017 [7] performed image segmentation-based potato leaf detection model and they used PlantVillage dataset. They utilized a multiclass Support Vector Machine on that segmented image to classify the diseases, finally achieved 95% accuracy. Samajpati et al. [8] introduced a hybrid model to recognize the disease of apples. The author segmented the images using k-means clustering after that classified the images using random forest algorithm. Their accuracy varied between 60 to 100%. For agricultural research PlantVillage dataset is one of the most popular public dataset sources. Many researches used this dataset to analyze agricultural data to improve production quality and amount.

In 2021, Hassan Afzaal et al used PlantVillage dataset to classify early blight potato disease from real-time system. Here, they used few recent network model, such as GoogleNet, VGGNet, and EfficientNet. A total of 5199 dataset collected from four fields. Selected models were performed better in different situations. Their highest accuracy was from EfficientNet that was 99-100 % for two classes [9]. Widiyanto et al. claimed a decent CNN model to classify four diseases including one healthy class. The author utilized 1000 images for every class and obtained 96.6% accuracy from the plantVillage dataset [10]. Kulendu et al. proposed VGG16 as a better model to detect early and late blight potato leaf diseases. Initially, they applied VGG16, VGG19, MobileNet and ResNet50 on PlantVillage dataset where they achieved better results from VGG16 after fine-tuning the model. Approximately 97.89% accuracy achieved to classify between two classes [11].

Zhou et al., [12] came up with a restructured residual dense network, a hybrid deep learning model that encompasses the upper hand of deep residual and dense networks, reducing the training process. The author applied this model to the Tomato leaf dataset from AI Challenger and identified the 9 classes of tomato leaf diseases with an accuracy rate of 95%. Farah Saeed et al. in 2021 [13] proposed a different approach to detect plant diseases. In their study they used deep neural model along with partial least squares (PLS) feature selection approach. They experiment on PlantVillage dataset for three popular crops (tomato, corn and potato) and the accuracy was 90.01%. In another promising work where author proposed a MobileNet to detect potato leaf diseases. Lightweight MobileNet V2 achieved 97.73% accuracy to predict potato leaf diseases. In this study again PlantVillage dataset was used to generate an average accuracy [14]. Ali Arshaghi et al. in 2022 [15] worked on five different potato diseases. As like potato leaf diseases detection potato diseases is also crucial to detect and classify for betterment of production proportion. In his study the used transfer learning and got around 100% accuracy.

Md. Khalid Rayhan Asif et al. [16] claimed CNN model to classify potato leaf images for several diseases. They divided the dataset into two classes: normal and disorder-impacted leaf. After applying five transfer learning algorithms they achieved 97% accuracy to classify the provided dataset. Image segmentation also used to detect disease region and predict leaf diseases. PlantVillage dataset used by Aditi Singh and Harjeet Kaur in 2021 [17], where they applied K-means segmentation and SVM was selected as a classification algorithm and 95.99% accuracy was achieved to detect potato leaf diseases. Hong H et al., [18] introduced a deep learning method to classify tomato leaf disease and other 8 types of disease leaves. Here applied transfer learning to reduce the size of train data, computational time, and model complexity. Five deep network structures were used, while Densenet_Xception offered the highest accuracy. Another impressive work proposed by Trong-Yen Lee et al in 2021 [19]. They also used PlantVillage dataset and applied effective CNN model to predict and classify potato leaf diseases and achieved 99.53% accuracy. Though several review paper already available on plant diseases prediction and classification [20, 21], still there are many scope to study on this field because early prediction and disease classification is necessary to enhance agricultural production. The major problem is appropriate dataset for agricultural development.

Several researches used PlantVillage dataset to preform unique experiments, only few research performed on own collected dataset but those datasets are not available for experiment. Yogeswararao, G e al. in 2022 [22] combined own collected data and PlantVillage dataset to predict and classify different crops diseases. They considered five most popular plants to improve economic growth. However, in future, research on making large and public dataset will be effective.

After observing several previous studies, we have chosen potato leaf diseases prediction as our research topic. In addition, listed few recent papers on classification and prediction in Table 1.

Table 1. Summary of Recent Papers for Potato Leaf Disease Prediction.

Author	Algorithm	Dataset	Plants/ Classes	Accuracy
Iqbal et al., 2020 [4]	Random Forest	Private dataset, 450 images	2 class problems	97%
Kulendu et al, 2022 [11]	VGG19, ResNet50, MobileNet and VGG16	PlantVillage	3 classes of potato leaf diseases	97.89%
Zhou et al, 2021 [12]	Restructured residual dense network, Deep CNN, RestNet50, DenseNet121	AI CHALLENGER Dataset (13185 images)	9 classes of tomato leaf diseases	95%
Weirong Chen et al, 2022 [14]	MobileNet-V2	PlantVillage		97.73%
Md. Khalid Rayhan Asif, 2020 [16]	CNN	Kaggle, Dataquest and Other	2 class problems	97%
Lee et al, 2021 [19]	CNN	PlantVillage	3 classes of potato leaf diseases	99.53%

3. Methodology

3.1. Data Collection

Models are trained and assessed on a specific dataset to produce an accurate leaf classification and disease diagnosis algorithm. In this paper, two distinct datasets such as PlantVillage and Mendeley, and three classes are gathered. Early and late blight are two frequent potato diseases; however, we also included healthy leaf as a class in the total three classes. The dataset has been divided into 80:20 ratios for models train and test purpose that provided the decent performance of our proposed network. Table 2 represents the exact data volume for each class and Fig. 2 for representing a sample data.

Table 2. Dataset for Three Categories Potato Leaf.

Serial No.	Class	Number of Samples	Training Sample	Test Sample
1	Healthy	514	411	103
2	Late Blight	1066	853	213
3	Early Blight	1000	800	200
Total		2580	2064	516

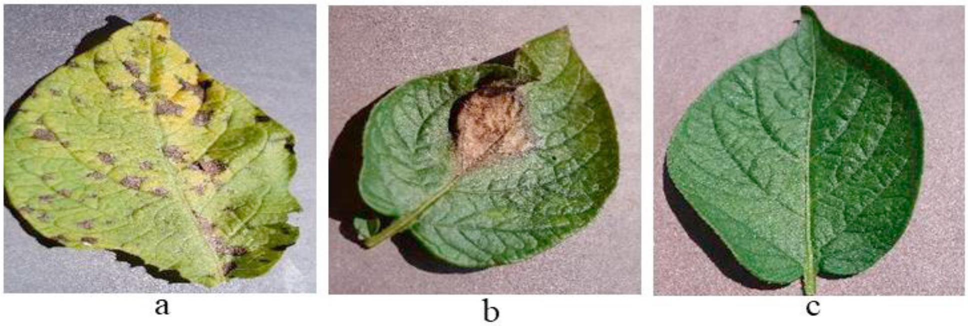

Fig. 2. Example of Collected Dataset (a) Potato Early Blight, (b) Potato Late Blight, (c) Potato Healthy Leaf.

3.2. Augmentation

Data augmentation is a powerful method for increasing the accuracy of modern image classifiers [23]. We applied several augmentation techniques to the raw dataset to improve our model performance and recognition capability. On training images with one axis fixed and the other stretched to a predetermined angle, a shear range of 0.2 is applied. Shear refers to an axis-based distortion of the image, usually done to produce or correct the perception angles. Typically, it is utilized to enhance photos so that computers may observe how humans perceive things from various perspectives. Zooming was done with a 0.2x range, and the raw images were rotated horizontally with a horizontal flip. The augmentation methods that we used in this research are listed below and depicted in Fig 3. A total of 10320 images were generated after data augmentation where 8256 and 2064 data were considered for training and testing the model.

- Shear range 0.2.
- Zoom range 0.2.
- Horizontal flip.

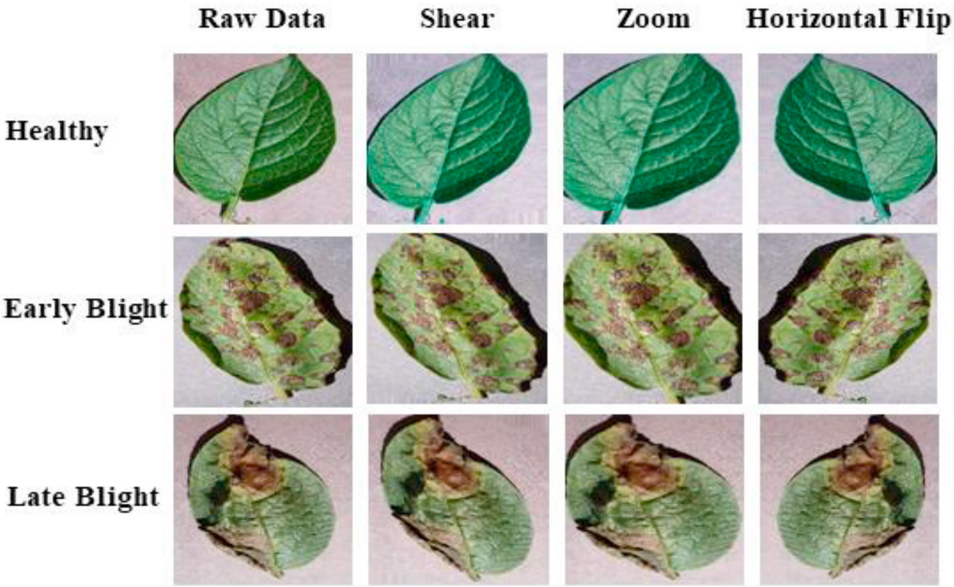

Fig. 3. Sample Dataset after Applying Augmentation Techniques.

3.3. Segmentation

Segmentation is to standardize and change an image's visualization and it make easier to understand the images. We chose *K*-means clustering with three different *K* values: 3,5 and 7 by analysing different segmentation techniques as it offers excellent efficiency.

The *K*-means clustering algorithm is shown in Fig. 4. *K*-means clustering seeks to achieve the least sum of squared distances between all locations and the cluster centre, as shown in equation (1) [24].

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} || x_i^{(j)} - c_j ||^2, \tag{1}$$

here, J = objective function., k = number of clusters, n = number of cases, x_i = case I, c_j= centroid for cluster j, and ||xi(j) - cj || is the distance function.

Algorithm of *K*-means clustering:
Let X = {x_1, x_2, x_3, ……., x_n} be the set of data points and C = {c_1, c_2, ……., c_k} be the set of centres.
1. Randomly select *'k'* cluster centres.
2. Calculate the distance between each data point and cluster centres.
3. Assign the data point to the cluster centre whose distance from the cluster centre is minimum of all the cluster centres.
4. Recalculate the new cluster centre.
5. Recalculate the distance between each data point and new obtained cluster centres.
6. If no data point was reassigned then stop, otherwise repeat from step 3.

Fig. 4. Algorithm of *K*-means Clustering Segmentation.

Dataset was segmented using *K*-means clustering technique. Fig. 5 presents a sample dataset for *K*-means clustering algorithm. Here, three different classes were presented.

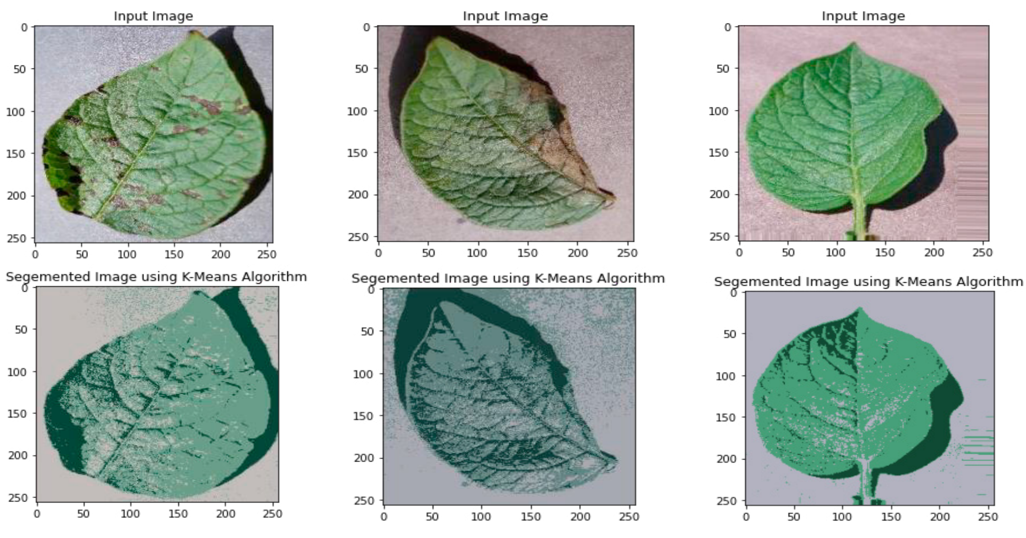

Fig. 5. Sample Dataset after *K*-means Segmentation.

3.4. Proposed Network

In this section we are going to discuss proposed network models. In this paper study, we applied VGG19, VGG16 and ResNet50 network; however, pre-processed dataset performed better with VGG16. Fig. 6 to illustrate the basic block diagram of VGG16 as the best model. VGG16 works 97% accurately on pre-processed dataset.

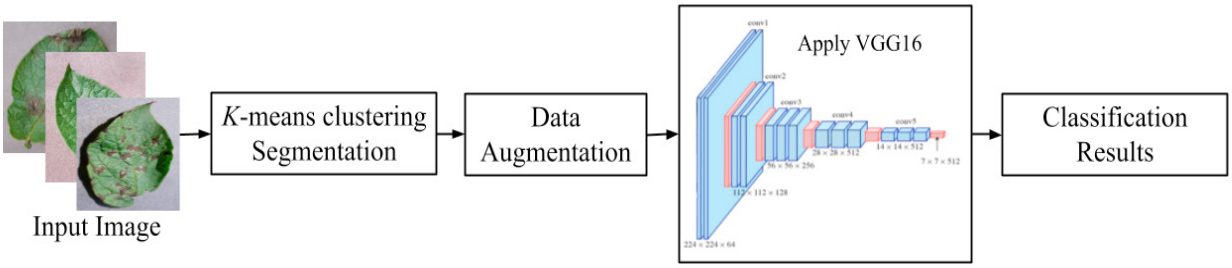

Fig. 6. Block Diagram of Proposed Work using VGG16.

4. Experimental Result Analysis

In this study, we segmented the input images using *K*-means clustering. We employed three classification methods, including VGG19, ResNet50, and VGG16 to predict the classes of the leaf. On the training set, each model was trained for 50 epochs. Fig. 7 shows the confusion matrix for VGG16 as the best model, and Table 3 reports the performance results of our models on different environments. For various choices of *K* values, we also computed performance metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Table 3. Performances of Models according to different Measurement Units.

Dataset Approach		Algorithm	Evaluation Metric			
			ACC	PR	Recall	F1-score
Raw Data		VGG16	0.954	0.954	0.957	0.955
		VGG19	0.906	0.904	0.905	0.905
		ResNet50	0.643	0.635	0.655	0.645
After Data Augmentation		VGG16	0.959	0.959	0.945	0.952
		VGG19	0.925	0.924	0.914	0.918
		ResNet50	0.632	0.631	0.632	0.631
Image Segmentation (*K*-Means) + Augmentation	*K*=3	VGG16	0.971	0.969	0.969	0.970
		VGG19	0.944	0.943	0.943	0.943
		ResNet50	0.675	0.673	0.674	0.674
	K=5	VGG16	0.961	0.961	0.962	0.961
		VGG19	0.947	0.947	0.948	0.948
		ResNet50	0.674	0.673	0.674	0.674
	K=7	VGG16	0.962	0.961	0.961	0.962
		VGG19	0.951	0.951	0.952	0.952
		ResNet50	0.674	0.674	0.673	0.674

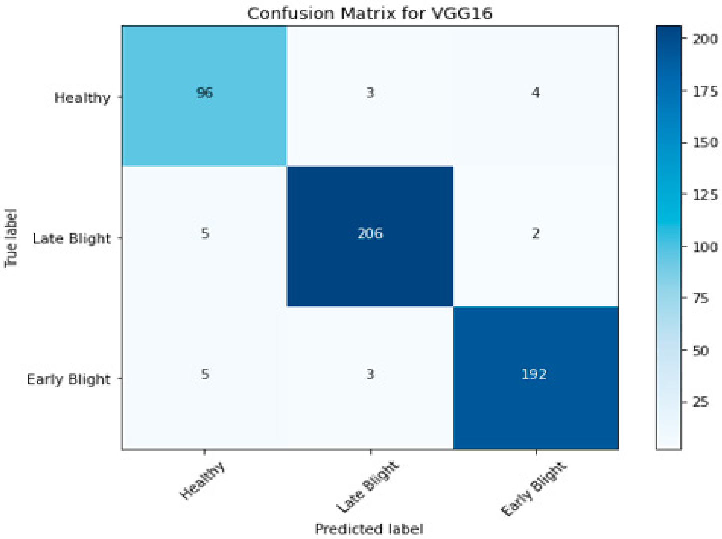

Fig. 7. Confusion Matrix of VGG16.

We obtained 0.954, 0.906, and 0.643 accuracies without data augmentation using the VGG16, VGG19, and ResNet50 models, respectively. Any deep neural network's performance can be improved by data augmentation [25]. As a consequence, we applied a number of augmentation techniques to our dataset, which significantly improved the ability to identify sick images. After augmentation, we obtained accuracies of 0.959, 0.925, and 0.632 using the VGG16, VGG19, and ResNet50 models. The performance of the vgg16 and vgg19 models was enhanced by augmentation, but not the resnet50 model. *K*-means segmentation was then used for various values of *K* after that. The VGG16 model provided us with the best accuracy (97%) for *K*=3. The accuracy of the other two models, VGG19 and ResNet50, peaked at 95% and 67%, respectively, for our dataset. In Fig. 8 shows the accuracy and loss curve according to epochs for the VGG16 model.

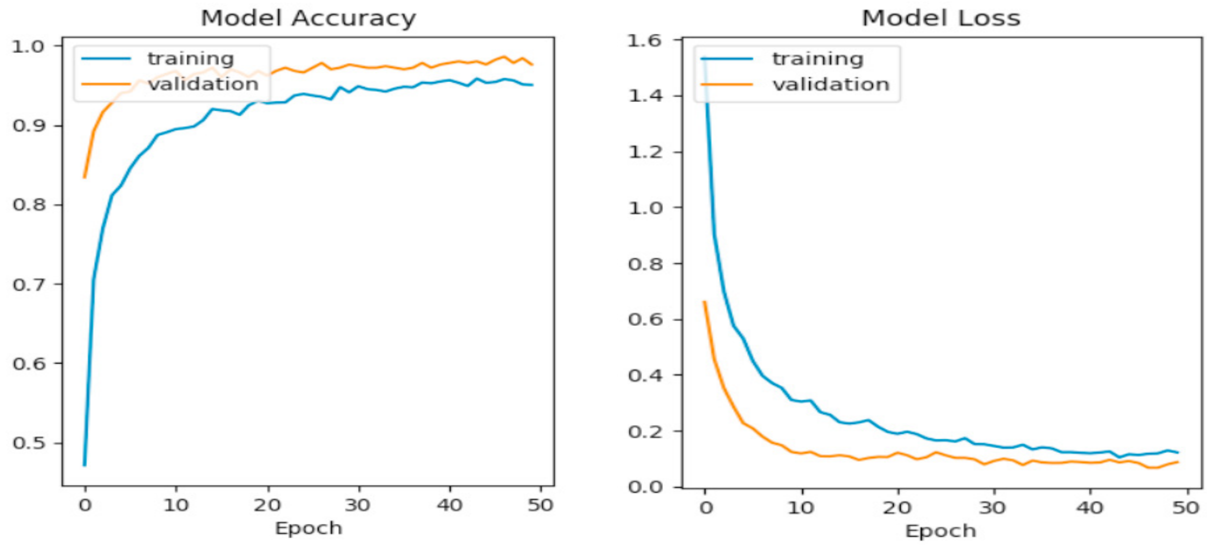

Fig. 8. Training and Validation Results of VGG16.

4.1. Performance comparison

Comparisons are made between the proposed VGG16 model and earlier proposed networks such the VGG19, Novel CNN, PDDCNN, MCD (Minimum-Maximum Distance), and SVM. Each model was trained on the original PlantVillage and Mendeley dataset several of the approaches contained augmentation and segmentation. Table 4 demonstrates a basic comparison of several models for potato leaf diseases classification, except Rashid et al. [27], the presented VGG16 model outperformed all other proposed models for the "augmented + segmented" dataset. Future research on this topic with local and huge dataset may provide a great outcome.

Table 4. Previous Work vs. Proposed Model.

Reference	Model	Segmentation	Augmentation	Dataset	Accuracy
Sholihati et al. (2020) [26]	VGG16, VGG19	N/A	Yes (Translations, rotation, change in scale, shearing, vertical and horizontal flips)	PlantVillage	91%
Rashid et al. (2021) [27]	Novel CNN, PDDCNN	YOLOV5	Yes (Scale transformation, rotation, shearing, vertical flips, zoom)	PlantVillage, PLD	99.75%
Aditi Singh and Harjeet Kaur. (2021) [17]	SVM	K-Means Clustering	N\A	PlantVillage	95.99%
Proposed	VGG16	K-Means Clustering	Yes (Rescale, horizontal flip, sheer, zoom)	PlantVillage, and Mendeley	97%

5. Conclusion and Future Work

This study has been introduced a deep learning-based method to classify potato leaf diseases. For performing this experiment, we collected dataset from two individual sources: PlantVillage and Mendeley. Thereafter, several pre-processing steps considered to achieved a decent outcome. Image segmentation is one of the steps. *K*-means clustering with k value three provided the best result where applied three augmentation techniques. VGG16, VGG19 and ResNet50 were applied to complete this study and finally from VGG16 we obtained 97% accuracy for classifying potato leaf diseases. We summarized the study as follows-

- We applied a k-means clustering segmentation approach for three different values.
- Prepared dataset using three augmentation techniques.
- After final experiment got VGG16 as the best model.

In our future work, we will create a tool to identify the type of leaf disease and incorporate other algorithms to improve the performance of the model. enabling a consequence, farmers working in the agricultural sector will be able to recognize particular diseases early on, which will enable them to take the appropriate action.

- By implementing certain new algorithms, we will enhance the research.
- To improve the results, utilize a wide range of dataset types.
- Lastly, provide a more effective application for crop fields.

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