Potato Plant leaf disease detection using CNN Model

Varsha P. Gaikwad[1*] , Dr. Vijaya Musande[2]

[1]Asst. Prof., Information Tech. Govt. College of Engg. Aurangabad (MH)

*Research Scholar at Dr. Babasaheb Ambedkar Marthawada University, Aurangabad (MH)

[2]Prof. & Head CSE dept., Jawaharlal Nehru college of Engg. Aurangabad (MH),

Abstract

Agriculture productivity plays a very significant role in the Indian economy. It contributed more than 17-18% to our country's GDP. Agriculture is the major occupation in India. The economy of our country highly depends on agriculture and its associated products. India stood first in the world with the highest net cropped area followed by US and China. Various pests and diseases affect the plant growth quantity and quality of the product. So it is very necessary to detect the disease at an early stage of the growth of the plant. Plant disease and pests identification are carried out by image processing. In recent years there is the use of machine learning, computer vision, and deep learning to detect and identify plant disease. These automated techniques are very beneficial to monitor large farms in less time period. In this research we worked with potato plant leaves to detect healthy leaf, early blight, and late blight diseases, and also calculated the infected area of the plant leaf. We used a customized convolutional neural network to classify the leaf disease and achieved 96.0% accuracy for the CNN model.

Keywords: pests, disease, Plant damage detection, Deep learning, Machine learning

1. Introduction

India is a cultivation nation; more than 60% of the population of India has agriculture and its productivity as their main occupation. In India agriculture is dependent on the monsoon. When the monsoon is good agriculture productivity is good, when the monsoon is less than productivity is less or not in good condition. Worldwide India stood second in the population. Due to the increase in population farm holding is subdivided and fragmented and becomes uneconomical. In India, traditional methods and traditional equipment were used for agriculture production. This is due to the poverty and illiteracy of the people. Farmers took diversified crops in their farms. Here 75% of the cultivated area is under food crops and the remaining 25% is under commercial crops. India has two cropping seasons 1) Kharip 2) Rabi-

based on monsoon. Cropping patterns of any region depends upon many factors such as soil, climate, irrigation facility, economic motivation, infrastructure facility, and social activity.

Agriculture faces many problems some of these are listed as

1. Old method: In India agricultural practices were self-sufficient but the production remains resource-dependent, cereal-centric, and regionally biased, so these deficiencies raised sustainable issues.

2. Increase use of Fertilization and pesticides: To increase crop productivity farmers were using more and more fertilizers and pesticides which have two disadvantages, 1) It will affect on human body and they become sick 2) Tolerance of the pests to the pesticides develops and slowly they become ineffective.

3. Increased water demand: We are using 10% of water for agriculture purposes. New production techniques require more water.

4. Stagnation (lack of growth): In India production of the major crops becomes stagnant for some time. Police makers and planners are worried about the country as there is an enormous gap between the requirements and supply of rising inhabitants and production.

5. Soil Exhaustion: The farmer took the same crop again and again on the same farm.

6. Costly Farm inputs: Increase in the price of agricultural inputs.

7. Effect of Global climate change: Global climate change has a great effect on agricultural practices.

8. Decrease in fresh groundwater

More than 10-15% of crop productivity losses occur due to various diseases affecting the plants.

The necessity of this research Plants growth study requires observation of biochemical and biophysical attributes of plants. Plants leaf chlorophyll and nitrogen plays a very vital role in plants' growth as well as get information about stress and availability of nutrients in the leaf of the plants. We can get this information by two methods. 1) Traditional method where farmers used their naked eyes to observe the plant growth, but they were not having expertise in this area as well as it is not suitable for a large area. So this is a time-consuming and cost-effective technique. 2) Taking the help of current technologies like computer vision, AI, and remote sensing.

Plant leaf diseases have an unfavorable effect on plant and farming lands. Various diseases such as microorganisms, genetic disorders, and transferable agents like germs, fungus, and viruses. In this research, potato plant leaves were used. Fungi and bacteria diseases are mostly accountable on potato leaf.. Late blight and premature blight are fungal bacterial diseases. Potato is the most important crop in the world. Potato crop grows under the subtropical condition in India. It is a cost-effective food; it provides fewer price celeries for the human diet. Potatoes are reached sources of Vitamin C and B1 and starch. Potatoes are used for several industrial purposes. In potato plants, healthy leaves play a very important role, in a later stage plants can make plenty of food to store underground in structures that will swell into potatoes.

Objectives of this Research

Plant leaves play an important role to monitor the health condition of the plant. The aim of this research is to build up a system that is able to find out and recognize the type of infection of plant leaf disease, based on a convolutional neural network.

1. Literature Survey

Ghosh etl.[1] did an experimental study using RGB potato plant leaf images. They captured images in the laboratory under controlled conditions and did a series of experiments to train CNN and SVM models. They observe that the same type of images perform differently when they are captured under different environmental conditions. From this research, they also got the information to generate an image dataset, which leads to an unswerving categorization accuracy. Tiwari etl [2] used the Kaggle dataset of potato plant leaf and did the classification as healthy leaf, early blight, and late blight. They used the VGG19 pre-trained model and achieved 97.8% accuracy. Sumit Kumar etl. [3] Proposed deep learning based on CNN model as well as reign-based fully connected RCNN network to detect various complex diseases of the plant leaves. This model achieves 94.6% validation accuracy. Shrivastav etl. [4] Developed a model of DCNN and worked with the Kaggle dataset of the PlantVillage dataset. Due to the novelty of this model plant, health identification becomes very easy. This model achieves 88% accuracy. Shrestha etl[5]. Developed a CNN-based model to detect plant disease at an early stage. They worked with different species of plants by implementing the model in Python programming. This model achieves 88.8% accuracy. Rangaraju etl.[6] worked with maize plant leaf with a computer vision system to detect the disease of plant leaves. Maize crop leaf images were captured with 13 MP cameras. Total 750 images were captured with white backgrounds among which 600 images were used for training and validation purposes and 150 images were used for testing purposes. This model achieved overall testing accuracy of 86.70%. Sk Hassan[7]In this paper DCNNs are implemented to detect plant leaf disease at an early stage. They used the Kaggle PlantVillage dataset with 14 different crops and 38 classifiers including the healthy class. They achieved accuracy 98.42% for InceptionV3, 99.11%, InceptionResNetV2 and 97.02% for, MobileNetV2 and 99.56% using EfficientNetB0 model. Pranay etl.[8] worked with an open-source dataset of a corn leaf. CNN model trained by using4000 images and tested using 2000 images. This model optioned 98% accuracy. Mangal etl. [9] Used peeper bell plants from the PlantVillage dataset to discriminate between healthy and diseased plant leaves. First, they used the canny edge technique for segmentation and GLCM technique for extracting features from the image. Finally, they applied CNN classifier and achieved 97.82% accuracy. Gaikwad etl. [10] captured wheat plant leaf images with the camera and also took some images from the internet, they used the KNN cluster method to segment the images, used texture, shape and color features for the classification of damage symptoms. These features

were applied to Feed Forward Neural Network and SVM and received 80.21% and 89.23% accuracy respectively.

1. Methodology Used

Convolutional Neural Network: CNN is a class of DNN used to identify and categorize exacting features from imagery. It is used to analyze visual images. As shown in Fig1. CNN holds two main parts.

1. Feature Extraction: this is a tool used to separate and recognize various features of the image.
2. An FC layer: used to envisage the group of the image based on features extracted in the previous stage

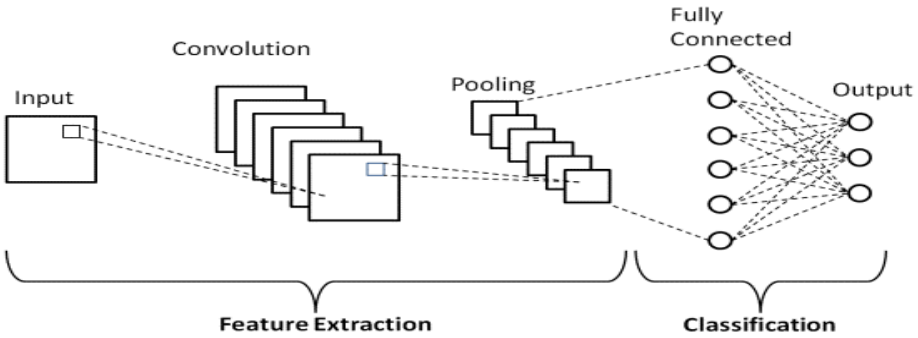

Figure 1. CNN model with two parts

CNN holds 03 types of layers convolutional layers, pooling layers, and fully-connected (FC) layers. There are 02 additional layers one is the dropout layer and another is the activation layer. When these entire layers combined together it formed CNN architecture as shown in fig2.

1. Convolutional Layer

The first layer is responsible for extracting different features from the image. Here the arithmetical process of convolution performs between a filter of a particular size NxN and an input image. Output is in the form of a feature map will be the input for the next layer.

2. Pooling Layer

Responsible to reduce the dimension of convolved feature map to overcome the performance cost. Max pooling and average pooling are two types of pooling.

3. FC Layer: The FC layer connect the neurons between 02 different layers.
4. Dropout

This layer is used to drop a few neurons, to overcome the problem of overfitting.

5. Activation Functions

This layer plays a very important role to make the decision as to which information should be used to forward direction and which one is not.

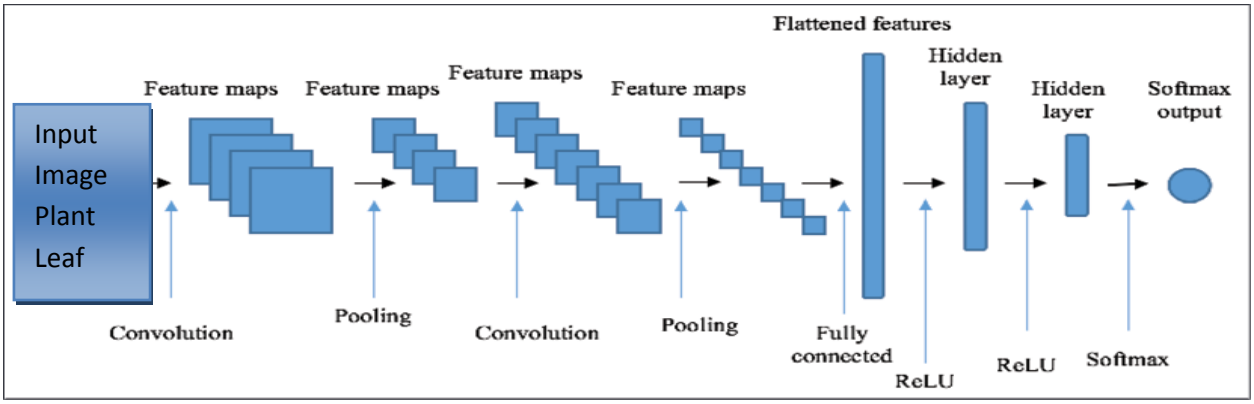

Figure 2. Architecture of Convolutioal Neural Network for classification

2. System Architecture

The proposed System design includes data acquisition, Data Preprocessing, and classification of the leaf as a healthy leaf, early blight, and late blight leaf. Fig3. Shows the proposed architecture of our research.

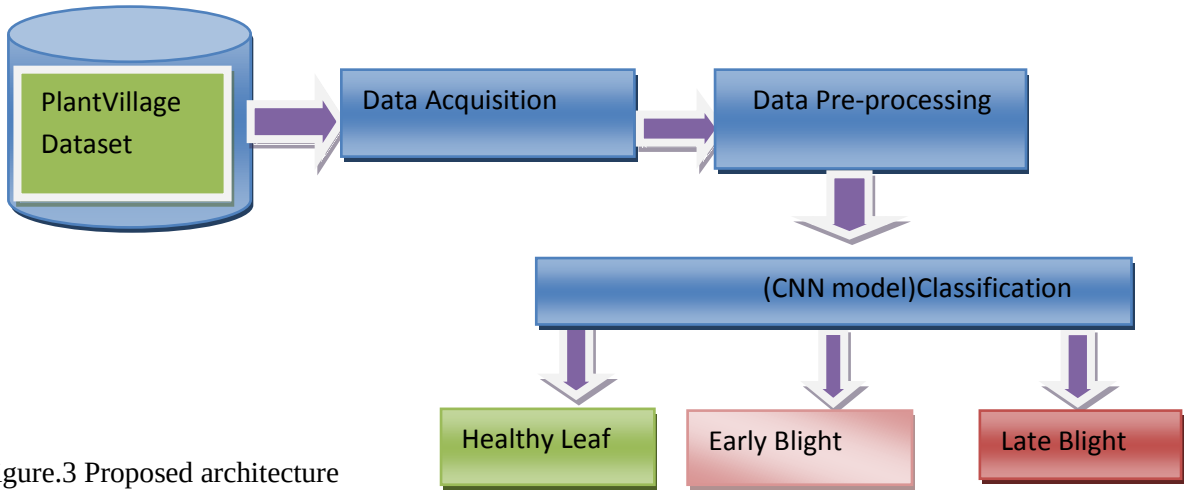

Figure.3 Proposed architecture

4.1 The Dataset

Healthy Leaf Early Blight Late Blight

Figure 4: Sample image of each class

For this research images were taken from Kaggle which is an open basis storehouse, which provides the PlantVillage dataset. This dataset holds more than 55000 plant leaf images of different species including fit and impure plant leaves. The number of leaf imagery in each class is not consistent; it varies from 152 imagery to 1000 imagery. Here we considered only potato leaves, images downloaded from the PlantVillage dataset. All Images were resized with resolution 256×256 pixels, which include healthy leaf, early blight, and late blight leave. Figure4 shows sample image leaf of each class.

2.2 Results

As shown in fig.5 training process includes 02 graphs as accuracy and loss. Graph reaches 100% when epoch reaches its maximum level and loss graph reaches 0%.

Fig.5 shows the training process of potato plant leaf images using a convolution neural network and table 1 shows details of the training process.

CNN confusion matrix is shown in Fig.6 and the table 2 shows the distribution of potato leaves as healthy leaf, early blight, late blight with classification precision.

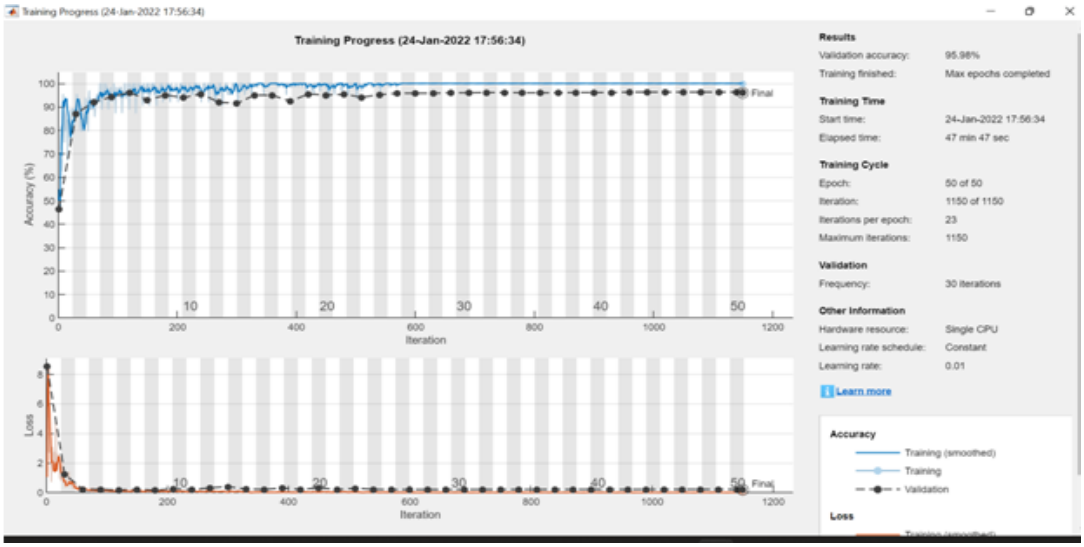

Figure.5 Training Process

Table1. Shows details of training process

Execution Time in minutes	47 minutes 47 seconds
No. of Epoch	50
Total Iterations	1150

Iteration per Epoch	23
Learning rate	0.01
Accuracy	95.86
Losses	4.14

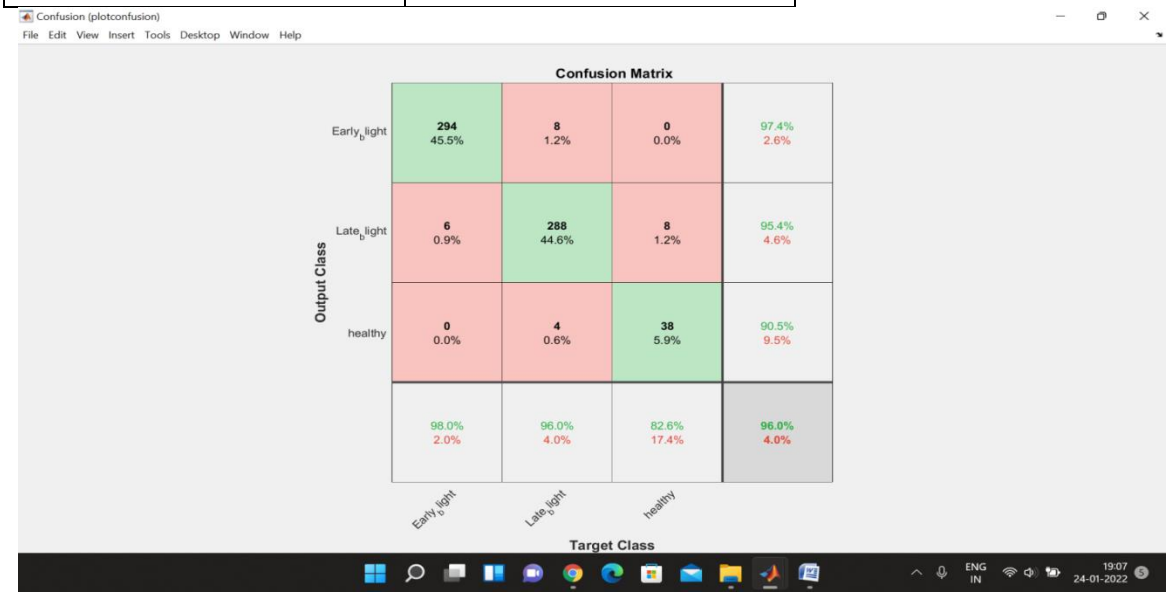

Figure.6 Confusion Matrix

Table 2: Plant leaves used for training and testing

Sr. No	Category	Total Samples	Training Samples	Testing Samples	Accuracy In %	Error Rate %
1	Early Blight	1102	800	302	97.4	2.6
2	Late Blight	1096	800	296	95.4	4.6
3	Healthy	142	100	42	90.5	9.5
	Total	2340	1700	640	96.0	4.0

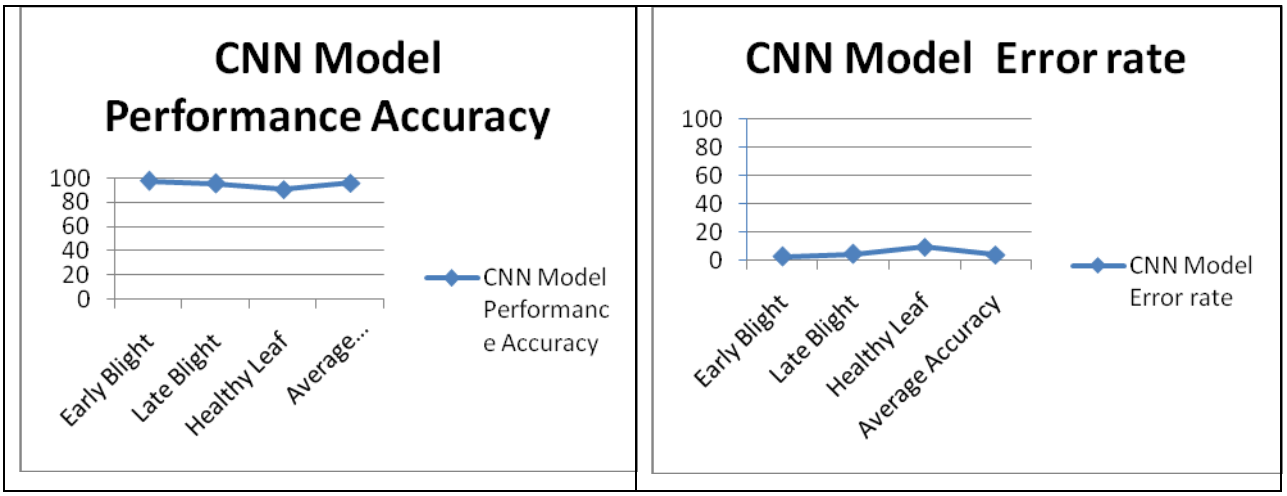

Figure7 Graph represents CNN model accuracy and error rate

This research extended to calculate the infected area of the plant. As shown in Fig.8 original images were segmented using the K-means clustering technique. First the RGB image converted into L*a*b color gap.

L*a*b space consists of a light layer 'L*', chromaticity layer 'a*'and 'b*'. K means clustering is used to categorize the color in a*b. As the image has 3 colors here formed 3 clusters as shown in Fig9. The distances between two pixels were measured using the Euclidean distance metric to get the infected area as shown in fig 10. Table3 shows a comparative study of potato plant disease classification with our proposed method.

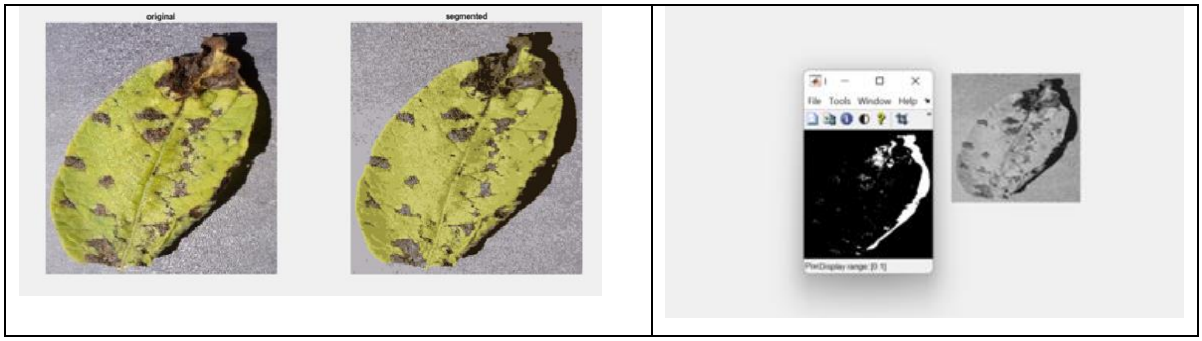

Figure.8 Original image and segmented image with L*a*b image

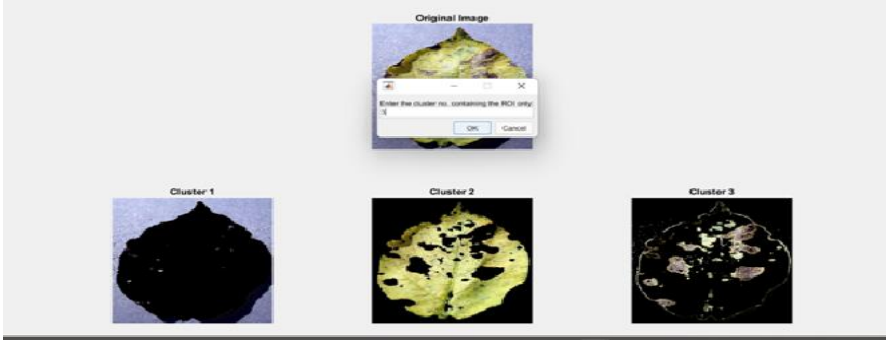

Figure 9. Cluster image

	Healthy Leaf ans = 'Area of the disease affected region is : 161' ans = ' Total leaf area is : 193573' ans = 'Affected Area is: 0.0831728%'
	Early Blight ans = 'Area of the disease affected region is : 88104' ans = ' Total leaf area is : 196568' ans = 'Affected Area is: 44.8211%'
	Late Blight ans = 'Area of the disease affected region is : 93476' ans = ' Total leaf area is : 195950' ans = 'Affected Area is: 55.704%'

Figure.10 Shows area of the plant leaf diseased affected region over total area of leaf

Table3. Comparative analysis of various methods used in plant damage detection.

Author, Year	Vegetable/ plant leaf	No of samples	Methodology Used /Classifier	Accuracy (%)
Mohanty etl.[11]2016	PlantVillage dataset for 26 different disease with 38	54,306 images of 14 different plant	AlexNet	85.53%

	classes			
Manya etl.[13] 2019	RTK-GNSS Potato leaf	532 of six different dates	ResNet 18	95%
Ghosh etl.[14] 2021	Potato Leaf	In-field images 3387 Open source 2152	Pre-trained SNet	93.78
Islam M. etl[15] 2017	Potato leaf	PlantVillage Dataset	Segment and Multi SVM	95.0%
Proposed System	Potato Leaf	2340	CNN	**96%**

3. Conclusion

Every year more than 20% of losses of crop production occur due to various diseases that affect plants. Deep learning methods play a very important role to detect disease at an early stage and help to improve the productivity and quality of the product. In this research, a fast and customized CNN model is used to detect and classify diseases from potato plant leaves. The accuracy of the CNN method for our work is found as 96.0%.This research also identifies the infected area of the plant over a total area of the plant leaf.

4. **Future Work:**

Plant disease detection in the early stage is a very challenging task. We wanted to implement the same system on smart phones; it will be easy for the farmers to get results in stipulated time.

5. **Financial and ethical disclosures**: Directly or indirectly funding organizations or agencies are not involved during this research.

6. References

1. Soma Ghosh, Renu Rameshan and and Dileep A. D. “An Empirical Study on Machine Learning Models for Potato Leaf Disease Classification using RGB Images”, ICPRAM 2021 - 10th International Conference on Pattern Recognition Applications and Methods.
2. Divyansh Tiwari, Mritunjay Ashish etl.” Potato Leaf Diseases Detection Using Deep Learning”, Proceedings of the International Conference on Intelligent Computing and Control Systems (ICICCS 2020) IEEE Xplore Part Number:CFP20K74-ART; ISBN: 978-1-7281-4876-2

3. Sumit Kumar et., Plant Disease Detection Using CNN, Turkish Journal of Computer and Mathematics Education Vol.12 No.12 (2021), 2106-2112
4. Prakanshu Shrivastav , Vaibhav Avsthi etl, "Plant Disease Detection using Convolutional Neural Network", Internation Journal of Advanced Research(IJAR) January 2021
5. Garima Shrestha, Deepsikha etl. "Plant Disease Detection using CNN", Proceedings of 2020 IEEE Applied Signal Processing Conference (ASPCON), ISBN: 978-1-7281-6882-1
6. Gokaraju Rangaraju, VNR Vignana Jyothi, Plant Disease Detection Using Convolutional Neural Networks , International Journal of Advanced Trends in Computer Science and Engineering, ISSN 2278-3091, June 2020
7. Sk Mahmudul Hassan , Arnab Kumar Maji etl. "Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach", Electronics 2021, 10, 1388. https://doi.org/10.3390/electronics10121388, June 2021
8. Garlapati Pranay, Aditya Kuruba etl. Detection of Disease and Damage Control for Crops using Convolution Neural Networks, Journal of Xi'an University of Architecture & Technology, ISSN No : 1006-7930, Volume XII, Issue XI, 2020
9. Sakshi Mangal and Pratiksha Meshram, PLANT DISEASE IDENTIFICATION USING DEEP LEARNING CLASSIFICATION MODEL: CNN, Journal of University of Shanghai for Science and Technology, ISSN: 1007-6735, Volume 23, Issue 1, January – 2021
10. Varsha P. Gaikwad and Dr. Vijaya Musande,Wheat Disease Detection using Image Processing, 2017 1st International Conference on Intelligent Systems and Information Management(ICSIM),978-1-5090-4264-7/17/$31.00©2017IEEE, 10.1109/ICISIM.2017.8122158
11. Shrad P. Mohanty, David P. Hughes and Marcel Salathe, Sept 2016 "Using Deep Learning for Image-Based Plant Disease Detection" Front. Plant Sci 7:1419 doi: 10.3389/fpls.2016.01419, Volume 7.
12. Varsha P. Gaikwad, Vijaya Musande, 2020, "Plant leaf damage detection based in colour and texture using deep learning – ALEXNET", Solid State Technology Volume: 63 Issue: 2 Publication
13. Manya Afonso, Pieter etl. Blackleg Detection in Potato Plants using Convolutional Neural Networks, https://doi.org/10.1016/j.ifacol.2019.12.481
14. Soma Ghosh, Renu Rameshan and Dileep A. D ,An Empirical Study on Machine Learning Models for Potato LeafDisease Classification using RGB Images, , ICPRAM 2021 - 10th International Conference on Pattern Recognition Applications and Methods

15. Islam, M.; Dinh, A.; Wahid, K.; Bhowmik, P. Detection of potato diseases using image segmentation and multiclass support vector machine. In Proceedings of the 2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE), Windsor, ON, Canada, 30 April–3 May 2017; pp. 1–4.