Machines and Algorithms
http://www.knovell.org/mna

Research Article

Enhancing Potato Crop Health: Accurate Disease Classification through Deep Learning and Image Processing

Shehzad Akbar[1, *], Dr Asif Raza[2] and Fatima Yousaf[3]

[1]Department of Computing, Riphah International University (Faisalabad Campus), Faisalabad, 38000, Pakistan
[2] Department of Computer Science, Bahauddin Zakariya University, Multan, 60000, Pakistan
[3] Department of Computer Science, Institute of Southern Punjab, Multan, 60000, Pakistan
[*]Corresponding Author: Shehzad Akbar. Email: shahzad.akbar@riphahfsd.edu.pk
Received: 07 June 2022; Revised: 27 June 2022; Accepted: 28 July 2022; Published: 7 October 2022
AID: 001-03-000011

Abstract: Potato plants are primarily affected by fungus, resulting in early and late blight diseases and reducing the production rate of crops. Real-time identification and management of diseases could help farmers enhance production and reduce financial losses. This study introduces a time-efficient algorithm using image processing to accurately classify diseases caused by Alternaria Solani and Phytophthora Infestans in potatoes. Our methodology comprises three steps: pre-processing (grayscale conversion, enhancement), image segmentation (soft clustering, morphological dilation, and flood fill operation), and classification (AlexNet). This framework is tested over the three classes of the PlantVillage dataset of the potato crop. Experimental results demonstrated satisfactory results with 97.57% accuracy in 30 minutes and 58 seconds.

Keywords: Image processing; Disease classification; Time-efficient algorithm; Early Blight; Late Blight;

1. Introduction

Potatoes are considered an essential vegetable in tropical regions as they offer a cheap energy source. They are high in carbohydrates, vitamins (particularly C and B1), and minerals [1]. They are widely recognized throughout the globe and consumed daily by most families. However, several bacterial and fungal diseases severely impair potato growth, which in turn causes damage to the national economy. Among such diseases, early blight and late blight are common but deadly infections caused by fungus-like organisms called Alternaria solani and Phytophthora infestans, respectively. They produce distinctive spots of various colors on potato leaves and often cause stem lesions, eventually leaving a tuber blight on the potato [2].

Early detection of these diseases enables preventative procedures and economic production losses to be mitigated. Over the past several decades, skilled naked-eye observation has been the most widely used detection for detecting and identifying potato plant diseases. However, this method is often impractical owing to lengthy processing times and the inaccessibility of specialists at farms situated in distant regions [3]. Therefore, an automated detection mechanism is needed to detect infected potato plants rapidly.

Adopting image processing and machine learning (ML) techniques has shown great potential in addressing the challenges of disease detection in various plants [4, 5]. As the potato diseases mentioned above produce visible signs on the plants, particularly on their leaves, they can be recognized efficiently via imaging analysis to spot such apparent patterns on leaves.

Deep learning is an emerging theme in ML that has shown high accuracy in pattern recognition problems. It utilizes multiple layers of high-dimensional data handling to perform automatic (unsupervised or supervised) extraction of features, image classification, and object detection [6]. Recently, the application of image-processing techniques in agriculture has gained traction [7]. Several researchers have used computer vision techniques for the classification of fruits [8, 9] and vegetables [10], checking their freshness [11] and detecting diseases [12, 13]. Existing works have also addressed identifying potato plant diseases [14]. Despite the results reported by the methods above, there is a need to explore this domain further to propose more efficient models for the task.

We propose deep learning to identify two common diseases in potato plants, namely early and late blight. The current study also distinguishes between the infected and the healthy potatoes. To this end, the proposed method employs image segmentation comprising various ingredients of image enhancement, soft clustering, morphological dilation, and flood-fill operation. Then we use AlexNet model for the classify the image. We used the PlantVillage dataset to train and test the proposed model. The rest of the paper is organized as follows. Section 2 explains the earlier works completed by other researchers on detecting leaf disease. Section 3 represents the description of the proposed method. Section 4 summarizes the model's results, and Section 5 concludes the key findings.

2. Related Work

There are numerous initiatives to deploy ML technology for detecting various plant diseases. Poornima et al. [15] employed machine learning to evaluate and identify plant diseases. Using color and edge-based image processing methods, the symbols of plant diseases are detected and segmented. The segmented infected part of the leaf is analyzed for appropriate characteristics, and the disease kind is identified through a Support Vector Machine. Too et al. [16] fine-tuned a deep-learning model to identify plant diseases. The study empirically examined various deep learning architectures, including VGG16, ResNet (152, 101, and 50 layers), DenseNet (121 layers), and Inception-v4. The study used images of healthy and disease-affected plants from PlantVillage for training and testing purposes. Another study [17] segmented 450 images of plant leaves from the PlantVillage dataset and used seven classifier methods to recognize and classify infected and healthy leaves. A random forest classifier was found to be the most accurate algorithm for this purpose.

Several existing works have explicitly focused on detecting potato plant diseases. Sinshaw et al. [14] comprehensively reviewed different computer vision techniques for detecting potato early and late blight. Mahum et al. [18] employed DenseNet to classify the visual features of potato leaves pertaining to various diseases into five classes. Lee et al. [19], [20] proposed CNN architecture for detecting potato illness. The convolution layer and associated resources are reduced but accuracy is maintained to enhance computational efficiency. A customized dataset was also developed to enhance the training process. The research in [21] presents a technique that employs pre-trained models such as VGG19 to extract important features from the dataset. Then, several classifiers were adopted to identify potato plant diseases. Sholihati et al. [22] provided a system for classifying four potato diseases based on leaf analysis. They fine-tuned the VGG-based architectural models to develop an accurate classification model. Using technology for routine monitoring may detect diseases at their earliest stages and eliminate them to maximize agricultural production. To this end, Singh and Kaur [23] proposed a novel technique for potato plant disease identification and classification. The PlantVillage dataset was used along with a clustering algorithm used for image segmentation. The GLCM (gray-level co-occurrence matrix) method was utilized to extract various features, and a multi-class Support Vector Machine was used for classification.

3. Materials and Methods

This research identifies three classes of potato plants; healthy, infected with early blight, and infected with late blight using image processing and image classification. The proposed framework comprises pre-processing, image segmentation, and classification based on CNN. Initially, all the images were in RGB format. In order to extract characteristic features for improved classification accuracy, pre-processing was performed by converting the colored images into grayscale. This step was taken because the color channels are not as informative, and concurrently, we are developing a time-efficient technique. After the grayscale conversion 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 a crucial step to eliminate unwanted areas and extract the region of interest for better results. In the end, the segmented images of each class are trained into AlexNet Neural Network. Then images are classified into early blight potato (1000 images), late blight potato (1000 images), and healthy potato (152 images). Fig. 1 shows the proposed method block diagram. The details of each step of the methodology are given below.

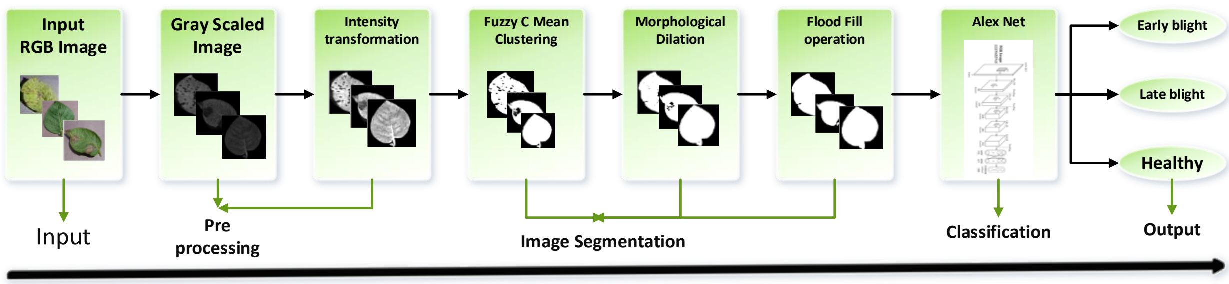

Figure 1: Block diagram of the proposed method for the disease detection of potato leaves

3.1. Dataset

We used Plant Village dataset to evaluate our technique. This dataset [24] comprises various plant images, but for our analysis, we specifically focus on potatoes**.** For each species, there are different classes of healthy and diseased leaves. In this research, only the three classes of the potato plant are considered: healthy potatoes and potatoes affected by early and late blight, with a resolution of 256*256 *3. The number of leaf images was 1000 for each early and late blight and 152 for healthy potatoes. The original images of the three target classes are shown in Fig. 2.

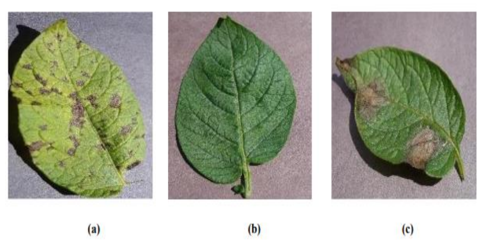

Figure 2: Original RGB Images of Potato Leaves with (a) Early Blight, (b) Healthy, and (c) Late Blight

3.2. RGB to Grayscale Conversion

The original dataset is in the RGB color region. The images are first converted into grayscale to extract the required characteristics from the data. There are two ways of grayscale conversion: luminosity and average methods. The average method averages the green, blue, and red channels to obtain the grayscale image. In the luminosity method, an average is calculated for all channels, but each color is given a specific percentage, i.e., red is 30%, green is 59%, and blue is 11% [25]. 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 3 shows the grayscale image of the three classes after blue channel subtraction.

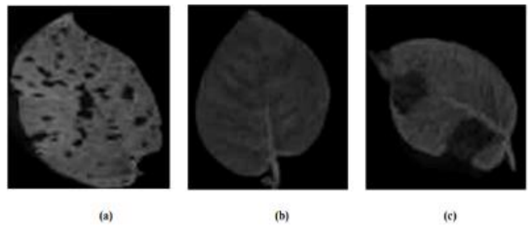

Figure 3: Grayscale Images of Leaves of Potato (a) Early Blight, (b) Healthy and (c) Late Blight

3.3. Image Enhancement

When analyzing a grayscale image, some features are suppressed that need to be enhanced to improve results. Image enhancement is the technique of quality improvement of the images. Histogram equalization, contrast adjustment, morphological operators, and filtering are commonly used image enhancement techniques. As output images have low contrast values after grayscale conversion, we need to stretch the contrast to differentiate between the region of interest and boundaries [26, 27]. Intensity transformation is usually used to overcome this problem. Intensity transformation can achieve the desired goal using different techniques such as gamma transformation, log transformation, negative of the image, and contrast stretching. The enhanced images of the three classes are shown in Figure 4.

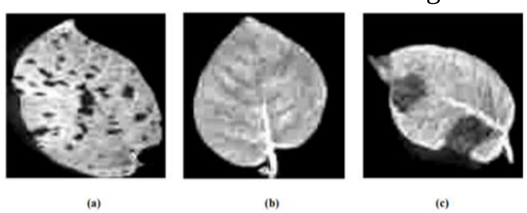

Figure 4: Enhanced Images of Leaves of Potato (a) Early Blight, (b) Healthy and (c) Late Blight

3.4. Fuzzy C-Means Clustering

One popular technique for clustering is Fuzzy C-means. In this method, each data point is assigned a probability of belonging to a cluster [28, 29]. Figure. 5 shows the fuzzy C-mean clustering of images of the three classes. The algorithm works as follows:

- Initialize the number of clusters.
- Initialize the partition matrix.
- Calculating the centroid of clusters.
- Update the matrix.
- Repeat the steps until the convergence is achieved.

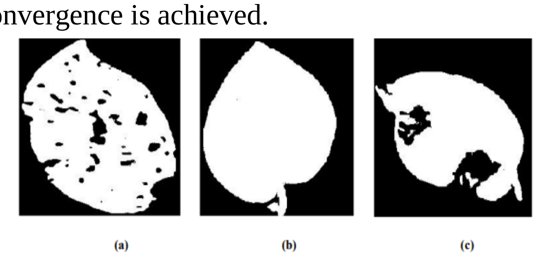

Figure 5: Fuzzy C-Means clustering of Leaves of Potato (a) Early Blight, (b) Healthy and (c) Late Blight

3.5. Morphological Dilation

Erosion and dilation are the two operators used 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 smaller. In dilation, two data inputs are taken: one is the image to be dilated, and another is the kernel, also known as the structuring element. The image 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 coincides. In the second case, all pixels in the background overlap, so the pixel values are left for the background [30, 31]. Fig. 6 shows the morphological dilation results on images of the three classes.

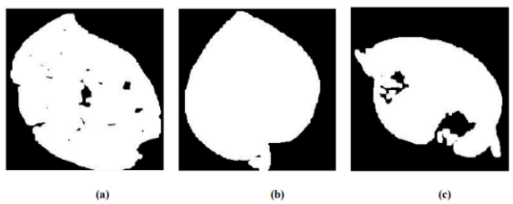

Figure 6: Morphological Dilation of Leaves of Potato (a) Early Blight, (b) Healthy and (c) Late Blight

3.6. Flood Fill Operation

Flood fill operation is useful in eliminating irrelevant objects in an image. In this method, specific areas of the image are filled with specified colors by putting lower and upper limits on the difference between negative and positive connected pixels [32, 33]. After morphological dilation, some black spots in the region of interest still need to be eliminated. The flood fill method is used to achieve this elimination. Fig. 7 shows the flood fill operation of images of the three classes, whereas Fig. 8 shows the segmented images.

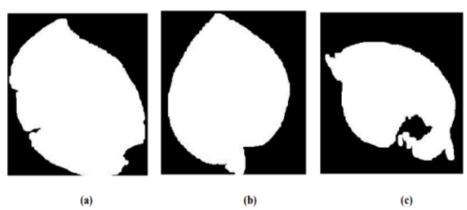

Figure 7: Flood Fill Operation of Potato leave images with (a) Early Blight, (b) Healthy and (c) Late Blight

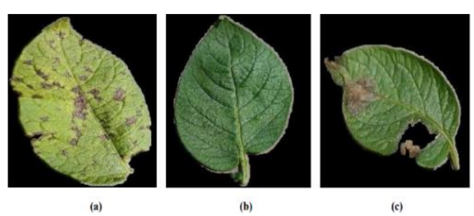

Figure 8: Segmented Potato Leave Images with (a) Early Blight, (b) Healthy and (c) Late Blight

3.7. Classification

Deep learning techniques integrate normalization, fully connected, convolutional, and pooling layers. Convolution, a process involving the application of a kernel to an image, is employed to alter the image. The classical convolutional neural network (CNN) is computationally expensive for images with high resolution. Therefore, there was a need for a network that could optimize GPU utilization, reduce training time, and improve performance. Acknowledging that AlexNet falls within the CNN category, it's important to note that the efficiency of AlexNet lies in its specific architecture and design choices. Unlike some generic CNNs, AlexNet incorporates innovations such as local response normalization and a carefully crafted architecture that enhances computational efficiency. AlexNet has unique architecture and consists of eight layers [34, 35]. Convolutional layers consist of kernels or filters for 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. The neurons in one layer are connected to all neurons in an adjacent layer by a fully connected layer [36, 37]. Fig. 9 presents typical layers in an AlexNet.

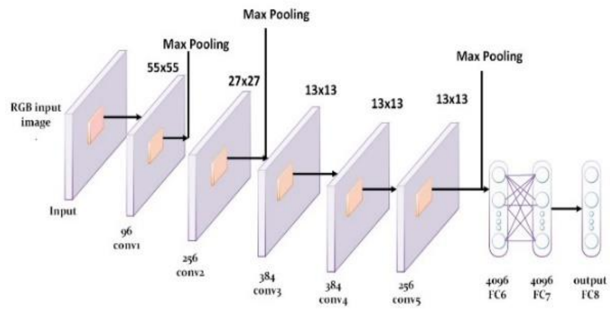

Figure 9: Detailed Architecture of Alexnet

4. Results and Discussion

We used grayscale segmented images and the AlexNet network to identify potato early and late blight. For this purpose, the dataset was split into two parts. We trained our model using 70% of the images in the dataset, while the remaining 30% were kept aside for testing. The AlexNet is trained for the training data of the leaf images using a learning rate of 0.0001 and a single CPU for 26 epochs because from this, we meet our validation criteria. The validation accuracy of 97.35% has been achieved with a maximum of 416 iterations in 30 minutes and 58 seconds. After that, the trained network is tested using a test set. Our results show a 97.57% accuracy for potato disease identification. Fig. 10 shows the classification results for three classes in a confusion matrix. It is to be observed that the early blight and healthy potato classes are classified with 100% accuracy. Only two images of late blight are misclassified as the wrong classes. In addition to accuracy, we also measured precision, recall, and F1 score.

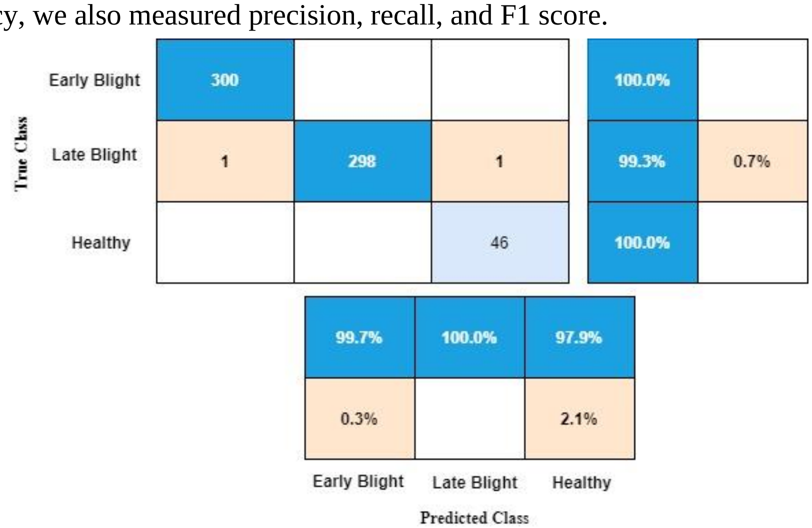

Figure 10: Confusion Matrix for Validation Data

Figure 11 shows the performance measure for each class. The early blight class achieved the highest accuracy (98.3%). The early and late blight classes achieved 98% precision. The highest recall (99%) was achieved by the healthy class. For the F1 score, early blight and healthy classes score the best, with 98%. The overall accuracy, precision, recall, and F1 scores were measured to be 97.57%, 97.67%, 96.67%, and 97.33%, respectively.

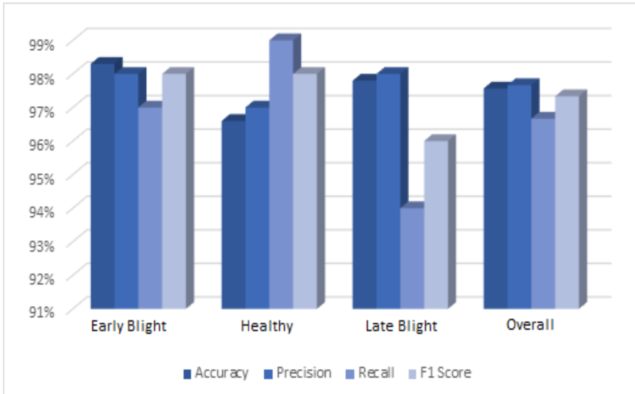

Figure 11: Performance Measures for Each Class

Table **1** presents a comparison of our techniques with previous works. The previous methods consisted of complex frameworks with a larger number of layers or a combination of pre-processing, segmentation feature extraction, and classifier, which increases the time complexity as in [33] VGG16 has 16 layers, but our proposed method uses only eight layers. Although the proposed models have less accuracy compared to the past papers, the proposed method is more efficient, accurate, and less time-consuming. Additionally, some works employed custom datasets, which are not available for use.

Table 1: Comparison of Accuracy of other Methods with the Proposed Method

Ref.	Year	Dataset	Methodology	Acc.
[17]	2020	PlantVillage	Image normalization and color space conversion, HSV-based masking, and Random Forest	97
[22]	2020	PlantVillage	Augmentation and image resizing, VGG16 and VGG19	91
[23]	2021	PlantVillage	K means algorithm, SVM, Gray level co-occurrence matrix	95.99
[38]	2021	AI Challenger	Gaussian filtering, adaptive SLIC algorithm, LBP, and SVM	97.4
[39]	2020	PlantVillage	CNN	99.6
[40]	2021	Custom	GoogleNet, VGGNet, and EfficientNet,	97
[41]	2017	PlantVillage, Custom	HSV color space, Fuzzy C-means clustering, texture features, and ANN	92
[42]	2021	PlantVillage, Custom	YOLOv5 and CNN	99.7

[43]	2020	Kaggle, Dataquest	AlexNet, VggNet, ResNet, LeNet, and sequential model	97
[44]	2020	PlantVillage	EfficientNet and MobileNet	98
Proposed	2022	PlantVillage	Grayscaled image, segmentation, AlexNet	97.57

5. Conclusion

We proposed a methodology to identify potato plant diseases using deep learning in less time and with higher accuracy. We target two classes of potato diseases, late and early blight. The proposed technique consists of image segmentation, including image enhancement, soft clustering, morphological dilation, flood fill operation, and AlexNet architecture for accurately classifying plant diseases. The RGB images of potato crop from the PlantVillage data set are used. Our model attained an accuracy of 97.57%, recall of 96.67%, precision of 97.67%, and F1 score of 97.33%. Our future work will focus on identifying all diseases in potato plants.

References

[1] Mitra, Sandip, and Abhirup Sarkar. "Relative profitability from production and trade: a study of selected potato markets in West Bengal." *Economic and Political Weekly* (2003): 4694-4699.

[2] Henfling, Jan W. *Late blight of potato*. Vol. 4. International Potato Center, 1987.

[3] Vibhute, Anup, and Shrikant K. Bodhe. "Applications of image processing in agriculture: a survey." *International Journal of Computer Applications* 52, no. 2 (2012): 34-40.

[4] Manavalan, R. "Automatic identification of diseases in grains crops through computational approaches: A review." *Computers and Electronics in Agriculture* 178 (2020): 105802.

[5] Ngugi, Lawrence C., Moataz Abelwahab, and Mohammed Abo-Zahhad. "Recent advances in image processing techniques for automated leaf pest and disease recognition–A review." *Information processing in agriculture* 8, no. 1 (2021): 27-51.

[6] Deng, Li, and Dong Yu. "Deep learning: methods and applications." *Foundations and trends® in signal processing* 7, no. 3–4 (2014): 197-387.

[7] Ilyas, Qazi Mudassar, and Muneer Ahmad. "Smart farming: An enhanced pursuit of sustainable remote livestock tracking and geofencing using IoT and GPRS." *Wireless communications and mobile computing* 2020 (2020): 1-12.

[8] Albarrak, Khalied, Yonis Gulzar, Yasir Hamid, Abid Mehmood, and Arjumand Bano Soomro. "A deep learning-based model for date fruit classification." *Sustainability* 14, no. 10 (2022): 6339.

[9] Ibrahim, Nehad M., Dalia Goda Ibrahim Gabr, Atta-ur Rahman, Sujata Dash, and Anand Nayyar. "A deep learning approach to intelligent fruit identification and family classification." *Multimedia Tools and Applications* 81, no. 19 (2022): 27783-27798.

[10] Sharma, Meenakshi, Prashant Kaushik, and Aakash Chawade. "Frontiers in the solicitation of machine learning approaches in vegetable science research." *Sustainability* 13, no. 15 (2021): 8600.

[11] Mukhiddinov, Mukhriddin, Azamjon Muminov, and Jinsoo Cho. "Improved classification approach for fruits and vegetables freshness based on deep learning." *Sensors* 22, no. 21 (2022): 8192.

[12] Dhiman, Poonam, Vinay Kukreja, Poongodi Manoharan, Amandeep Kaur, M. M. Kamruzzaman, Imed Ben Dhaou, and Celestine Iwendi. "A novel deep learning model for detection of severity level of the disease in citrus fruits." *Electronics* 11, no. 3 (2022): 495.

[13] Khan, Asif Iqbal, S. M. K. Quadri, Saba Banday, and Junaid Latief Shah. "Deep diagnosis: A real-time apple leaf disease detection system based on deep learning." *computers and Electronics in Agriculture* 198 (2022): 107093.

[14] Sinshaw, Natnael Tilahun, Beakal Gizachew Assefa, Sudhir Kumar Mohapatra, and Asrat Mulatu Beyene. "Applications of Computer Vision on Automatic Potato Plant Disease Detection: A Systematic Literature Review." *Computational Intelligence and Neuroscience* 2022 (2022).

[15] Poornima, S., S. Kavitha, S. Mohanavalli, and N. Sripriya. "Detection and classification of diseases in plants using image processing and machine learning techniques." In *AIP conference proceedings*, vol. 2095, no. 1. AIP Publishing, 2019.

[16] Too, Edna Chebet, Li Yujian, Sam Njuki, and Liu Yingchun. "A comparative study of fine-tuning deep learning models for plant disease identification." *Computers and Electronics in Agriculture* 161 (2019): 272-279.

[17] Iqbal, Md Asif, and Kamrul Hasan Talukder. "Detection of potato disease using image segmentation and machine learning." In *2020 international conference on wireless communications signal processing and networking (WiSPNET)*, pp. 43-47. IEEE, 2020.

[18] Mahum, Rabbia, Haris Munir, Zaib-Un-Nisa Mughal, Muhammad Awais, Falak Sher Khan, Muhammad Saqlain, Saipunidzam Mahamad, and Iskander Tlili. "A novel framework for potato leaf disease detection using an efficient deep learning model." *Human and Ecological Risk Assessment: An International Journal* 29, no. 2 (2023): 303-326.

[19] Lee, Trong-Yen, I-An Lin, Jui-Yuan Yu, Jing-min Yang, and Yu-Chun Chang. "High efficiency disease detection for potato leaf with convolutional neural network." *SN Computer Science* 2, no. 4 (2021): 297.

[20] Lee, Trong-Yen, Jui-Yuan Yu, Yu-Chun Chang, and Jing-Min Yang. "Health detection for potato leaf with convolutional neural network." In *2020 Indo–Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN)*, pp. 289-293. IEEE, 2020.

[21] Tiwari, Divyansh, Mritunjay Ashish, Nitish Gangwar, Abhishek Sharma, Suhanshu Patel, and Suyash Bhardwaj. "Potato leaf diseases detection using deep learning." In *2020 4th international conference on intelligent computing and control systems (ICICCS)*, pp. 461-466. IEEE, 2020.

[22] Sholihati, Rizqi Amaliatus, Indra Adji Sulistijono, Anhar Risnumawan, and Eny Kusumawati. "Potato leaf disease classification using deep learning approach." In *2020 international electronics symposium (IES)*, pp. 392-397. IEEE, 2020.

[23] Singh, Aditi, and Harjeet Kaur. "Potato plant leaves disease detection and classification using machine learning methodologies." In *IOP Conference Series: Materials Science and Engineering*, vol. 1022, no. 1, p. 012121. IOP Publishing, 2021.

[24] Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." *Frontiers in plant science* 7 (2016): 1419.

[25] Kekre, Hemant B., and Sudeep D. Thepade. "Color traits transfer to grayscale images." In *2008 first international conference on emerging trends in engineering and technology*, pp. 82-85. IEEE, 2008.

[26] Qi, Yunliang, Zhen Yang, Wenhao Sun, Meng Lou, Jing Lian, Wenwei Zhao, Xiangyu Deng, and Yide Ma. "A comprehensive overview of image enhancement techniques." *Archives of Computational Methods in Engineering* (2021): 1-25.

[27] Hong, Lin, Yifei Wan, and Anil Jain. "Fingerprint image enhancement: algorithm and performance evaluation." *IEEE transactions on pattern analysis and machine intelligence* 20, no. 8 (1998): 777-789.

[28] Katarya, Rahul, and Om Prakash Verma. "An effective web page recommender system with fuzzy c-mean clustering." *Multimedia Tools and Applications* 76 (2017): 21481-21496.

[29] Selvakumar, J., A. Lakshmi, and T. Arivoli. "Brain tumor segmentation and its area calculation in brain MR images using K-mean clustering and Fuzzy C-mean algorithm." In *IEEE-international conference on advances in engineering, science and management (ICAESM-2012)*, pp. 186-190. IEEE, 2012.

[30] Anishiya, P., and S. Mary Joans. "Number plate recognition for indian cars using morphological dilation and erosion with the aid of ocrs." In *International Conference on Information and Network Technology*, vol. 4. 2011.

[31] Khayyat, Muna, Louisa Lam, Ching Y. Suen, Fei Yin, and Cheng-Lin Liu. "Arabic handwritten text line extraction by applying an adaptive mask to morphological dilation." In *2012 10th IAPR International Workshop on Document Analysis Systems*, pp. 100-104. IEEE, 2012.

[32] Meem, Mahinul Islam, Pranab Kumar Dhar, Md Khaliluzzaman, and Tetsuya Shimamura. "Zebra-crossing detection and recognition based on flood fill operation and uniform local binary pattern." In *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, pp. 1-6. IEEE, 2019.

[33] Wayalun, Pichet, Phatthanaphong Chomphuwiset, Natthariya Laopracha, and Phatthanaphon Wanchanthuek. "Images Enhancement of G-band Chromosome Using histogram equalization, OTSU thresholding, morphological dilation and flood fill techniques." In *2012 8th International Conference on Computing and Networking Technology (INC, ICCIS and ICMIC)*, pp. 163-168. IEEE, 2012.

[34] Shanthi, T., and R. S. Sabeenian. "Modified Alexnet architecture for classification of diabetic retinopathy images." *Computers & Electrical Engineering* 76 (2019): 56-64.

[35] Zhu, Ling, Zhenbo Li, Chen Li, Jing Wu, and Jun Yue. "High performance vegetable classification from images based on alexnet deep learning model." *International Journal of Agricultural and Biological Engineering* 11, no. 4 (2018): 217-223.

[36] Hassan, Syed Al E., Shahzad Akbar, Sahar Gull, Amjad Rehman, and Hind Alaska. "Deep learning-based automatic detection of central serous retinopathy using optical coherence tomographic images." In *2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA)*, pp. 206-211. IEEE, 2021.

[37] Hosny, Khalid M., Mohamed A. Kassem, and Mohamed M. Foaud. "Classification of skin lesions using transfer learning and augmentation with Alex-net." *PloS one* 14, no. 5 (2019): e0217293.

[38] Hou, Chaojun, Jiajun Zhuang, Yu Tang, Yong He, Aimin Miao, Huasheng Huang, and Shaoming Luo. "Recognition of early blight and late blight diseases on potato leaves based on graph cut segmentation." *Journal of Agriculture and Food Research* 5 (2021): 100154.

[39] Barman, Utpal, Diganto Sahu, Golap Gunjan Barman, and Jayashree Das. "Comparative assessment of deep learning to detect the leaf diseases of potato based on data augmentation." In *2020 International Conference on Computational Performance Evaluation (ComPE)*, pp. 682-687. IEEE, 2020.

[40] Afzaal, Hassan, Aitazaz A. Farooque, Arnold W. Schumann, Nazar Hussain, Andrew McKenzie-Gopsill, Travis Esau, Farhat Abbas, and Bishnu Acharya. "Detection of a potato disease (early blight) using artificial intelligence." *Remote Sensing* 13, no. 3 (2021): 411.

[41] Patil, Priyadarshini, Nagaratna Yaligar, and S. M. Meena. "Comparision of performance of classifiers-svm, rf and ann in potato blight disease detection using leaf images." In *2017 IEEE international conference on computational intelligence and computing research (ICCIC)*, pp. 1-5. IEEE, 2017.

[42] Rashid, Javed, Imran Khan, Ghulam Ali, Sultan H. Almotiri, Mohammed A. AlGhamdi, and Khalid Masood. "Multi-level deep learning model for potato leaf disease recognition." *Electronics* 10, no. 17 (2021): 2064.

[43] Asif, Md Khalid Rayhan, Md Asfaqur Rahman, and Most Hasna Hena. "CNN based disease detection approach on potato leaves." In *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, pp. 428-432. IEEE, 2020.

[44] Tilahun, Natnael, and Bekel Gizachew. "Artificial Intelligence Assisted Early Blight and Late Blight Potato Disease Detection Using Convolutional Neural Networks." *Ethiopian Journal of Crop Science* 8, no. 2 (2020).