JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
SICAIET
2024

Research Article
Collection: Artificial Intelligence and Emergence Technologies

Multi-Crops Leaves Diseases Classification Using Fuzzy Logic and Pre-trained CNN Methods

Hamid Ghous[1], Mubasher H. Malik[2*], Sumera Munawar[3], Syed Ali Nawaz[4], and Tanveer Aslam[4]

[1]Department of Computer Science, Institute of Southern Punjab, Multan, Pakistan.
[2]Vision, Linguistics and Machine Intelligence Research Lab, Multan, Pakistan.
[3]Department of Information Technology, Institute of Southern Punjab, Multan, Pakistan.
[4]Department of Information Technology, The Islamia University of Bahawalpur (IUB), Bahawalpur 63100, Pakistan.
[*]Corresponding Author: Mubasher H. Malik. Email: mubasher@isp.edu.pk

Academic Editor: Salman Qadri **Published:** February 01, 2024

Abstract: A nation's economy depends on the foundation of its agricultural sector, and the vitality of this sector is essential for the economy's steady growth. However, the frequency of plant leaf diseases threatens the quantity and quality of agricultural yields. It is important to classify these diseases effectively to identify and treat affected areas in plant images. Even though there are a lot of research publications on how to classify plant leaf diseases, automated detection models still need to be made more accurate; in this research, two crops widely grown in agricultural fields worldwide—cotton and tomatoes—will be further classified. Our approach entails creating a novel framework focusing on Artificial Intelligence (AI) techniques, particularly Deep Learning (DL) methods. Fuzzy logic edge detection rules were adopted to generate reliable datasets. After that, we employ deep learning models including AlexNet and GoogleNet, for classification purposes. In our experiments, we build datasets with varied parameter tuning values, using 70/30 or 80/20 ratios for training and testing. The results show that the AlexNet method works better than others. It is 99% accurate, and the error rate is as low as 0.01%. These findings highlight the DL Methods revolutionize the classification of plant leaf diseases. This presents an opportunity for enhancing agricultural outcomes and ensuring economic stability.

Keywords: Multi-crops; Plant Disease; Alexnet; GoogleNet; Fuzzy Logic; Edge Detection.

1. Introduction

About 70% of the world's gross domestic product is derived from agriculture, making it a significant economic force (Giller, 2021). Plant diseases tend to reduce the quality of agriculture. (Strange, 2005) The primary goals are identifying and recognizing plant diseases to enhance economic growth. When a disease first presents itself, the plant leaves are most susceptible. (Amjad, (2021)). Plants were initially observed with the unaided eye to identify diseases, which required a lengthy procedure. Plants are now monitored for diseases using automatic and partially automated techniques, replacing the manual method of disease identification. Compared to manual monitoring, these techniques were cheaper and produced accurate results. As a result, this motivates scientists to create increasingly sophisticated technologies that yield highly accurate results and gradually lessen human needs. The two main crops we examined in this paper were tomato and cotton. (Ganatra, 2018).

Globally speaking, cotton is the most critical crop that supplies raw materials to the cotton textile sector. ((Patki, 2016). The primary root cause of the lower yields was diseases of the cotton plant. Many issues that impede cotton crop growth and obscure the nature of the disease from the naked eye are caused by diseases. Most diseased plant tissue, accounting for 80–90% of cases, is found in the leaves. Thus, rather than the whole cotton crop, we are most concerned about the leaves of the crop. (Tripathy, (2021, November).). The tomato crop is precious commercially on the global market and is produced in large quantities. Diseases damage a plant's health and interfere with its ability to grow. It is vital to examine the growth of cultivated crops by ensuring their minor losses. This paper's primary goal is to identify simple methods for leaf disease detection that require the least amount of computer power and yield accurate results when used with modern-day techniques.

Previous research on plant-to-leaf diseases of tomatoes and cotton has extensively used image processing, machine learning, and deep learning techniques (nnabel, 2019). Real-time disease detection of tomato and cotton leaves is one of the most critical agricultural issues (Hossain, 2023). The main goal of this study is to propose a novel framework knowledge-based system that combines DLand AI models. Fuzzy logic is one of the best AI approaches where we can easily define the logical rules according to our problem. In this paper, we used a multi-crop leaf disease dataset from the internet. There are many ways to apply FL rules, but in this study, we used FL as a pre-processing approach, as discussed in sections 3 and 4. We defined FL rules to detect edges from images. After preparing the dataset, we used DL-based pre-trained CNN methods to classify the crop leaf disease. The term DL was introduced in 2000 by Igor Aizenberg. DL handles vast structured or unstructured datasets (Gupta, 2021). It can quickly solve complex operations or problems within a minute. Many DL-based pre-trained models can train any data (nnabel, 2019). This paper uses two types of pre-trained models: AlexNet (Arya, 2019) and GoogLeNet (Ballester, 2016)as discussed in section 3 for disease classification.

Section 2, namely Literature Review, describes the contributions of different researchers related to the current research problem.

2. Literature Review

Recognizing multiple crop diseases is a crucial first step toward high production in the agricultural sector. Multi-crop leaf disease identification and classification is a critical area of agriculture that attracts a lot of research interest (Gong, 2023). Automatic leaf disease detection systems are necessary to raise the standard of agricultural output. This review of the literature focuses on the identification of disease frameworks in tomato and cotton leaves. This literature review is organized using supervised, unsupervised, and hybrid methods.

(Bedi, 2021) proposed a convolutional autoencoder network-based hybrid model to detect leaf diseases from peach plants. The Plant Village dataset was used for experiments. The proposed model produced 99.35% accuracy. On the other hand, (Agarwal, 2020) employs CNN-based architectures to create a framework for the real-time detection and classification of tomato leaf diseases. VGG16, Inception V3, and GoogLeNet were introduced as a training or testing model. The proposed model's average was 91.2% for the dataset of tomato plant leaves.

In contrast, the detection and classification of tomato leaf diseases are handled by (Llorca, 2018) using CNN-based transfer-learning frameworks like GoogLeNet and Inception-V3. The accuracy of identifying tomato leaf diseases was found to be 88.9%. On the other hand (De Luna, 2018)presented a novel pre-trained CNN system, similar to AlexNet and FRCNN, that is applied to transfer learning and anomaly detection training., which is used to recognize diseases with an average accuracy of 91.67%. Identification and the Transfer Learning method achieved an average accuracy of 91.67% for disease recognition.

Likewise, (Durmuş, 2017) suggested SqueezeNet and AlexNet frameworks, based on CNN, were used to detect tomato leaf disease from plant village datasets collected and segmented beforehand. In contrast to the SqueezeNet approach, the AlexNet approach achieves higher accuracy. On the other hand, (Gharghory, 2020)works with CNN-based pre-trained architectures like SqueezeNet, VGG-16, and AlexNet that are used to classify leaf diseases on plant village datasets. The suggested model for classification attains 99% accuracy. Conversely, (Tsironis, (2020).) examined two distinct Deep learning-based frameworks, AlexNet and SqueezeNet, which were employed to recognize ten special tomato leaf disease classes, including images of healthy leaves, from the Village plants dataset. These frameworks achieve the highest of 0.97% on the average village plants dataset. These frameworks achieve 0.97% accuracy on average.

(Prashar, (2019, April)) constructed an expert system to handle issues about agriculture more effectively and precisely. Diseases of cotton leaves are identified using a KNN classifier. MLP classifies diseases affecting infected leaves by using overlapping pooling with distinct layers. Overall, more than 96% of diseases were classified correctly. (D.Kokane, 2016)is developing a system for pattern-based recognition to identify leaf diseases. Hus moments extract features after image-based segmentation using the Active Contour technique. An adaptive neuro-fuzzy system was employed to train the disease dataset. The system's overall accuracy in pattern recognition is 85%.

In contrast, (Shah, (2019, February)) uses an artificial neural network framework to detect and classify diseases in cotton leaves. The suggested method extracts shape features and a set of significant textures from pre-processed images after using image pre-processing techniques for image segmentation. The proposed solution offers up to 90% accuracy.

On the other hand, (Udawant, 2019) discussed a new method based on the CNN technique used for classifying the diseased part of images of cotton plants. Dataset images are pre-processed using image-processing techniques like object detection, color transformation, and image enhancement. The overall precision of the suggested model for each image disease detection was 97%. To extract valuable features from images of cotton leaf spot diseases (Revathi, 2012) presented an innovative framework that uses edge detector segmentation based on homogeneity. They used pictures from multiple digital cameras to identify cotton leaf diseases and classified them using a neural network technique. The Sobel and Canny Edge detection technique was used to detect edges in the collected grayscale images. The novel framework that (Batmavady, 2019) proposed to identify cotton leaf diseases from the plant village Neural network and image processing techniques form the basis of this dataset—applying the fuzzy C-Means clustering approach to image-based segmentation. The Radial-Basis-Function (RBF) NN approach was then used to extract significant features from segmented images. Pre-processed datasets with many samples were trained and tested using SVM and neural network techniques. The average accuracy of the proposed classification methods was 85.44% and 90%, respectively. (Amjad, (2021)) have recently reviewed literature related to the research problem of cotton and tomato leaves disease. Moreover, they have suggested there is a need to implement an intelligent system.

The following section, Materials, and Methods, provides the proposed model showing the complete process of detection of leaf diseases.

3. Materials and Methods

Section 2 reviewed different models related to our research question, as discussed in section 1. It covers all the aspects of the proposed model, i.e., basics, workflow, dataset, algorithm, and the proposed model as discussed in the section.

3.1. Dataset

The dataset consists of an assortment of information gathered from different sources. This research will use three other datasets downloaded from the Kaggle website (www.kaggle.com). Two datasets were used for cotton leaf disease, and one dataset was used for tomato leaf disease. Table 1 displays information about these three datasets

Table 1. Dataset Description

Name of Dataset	Classes	Total Images
Cotton Disease Dataset	2	715
Cotton Leaf Disease Dataset	4	1703
Tomato Disease Dataset	10	10000

The multi-crop leaf disease classification model diagram is shown below in Figure 1.

3.2. Pre-processing

Image pre-processing is the name for image operations at the lowest level of abstraction, intended to improve image data that removes unwanted distortions or improves those image characteristics that are necessary for further processing. It doesn't improve the content of image details. In the data pre-processing phase, we perform different methods or functions on images to get the best quality images (Tabik, 2017).

In this paper, we performed the basic pre-processing operations on an image dataset. First, we labeled each dataset image in numbers, i.e., 1,2,3,4 or so on, and also changed the image type. After this process, we prepared our image dataset using the fuzzy logic edge detection technique. The basic concept of FIS is discussed in section 3. We used the FL edge detection technique as a pre-processing that helps to get the edges of images.

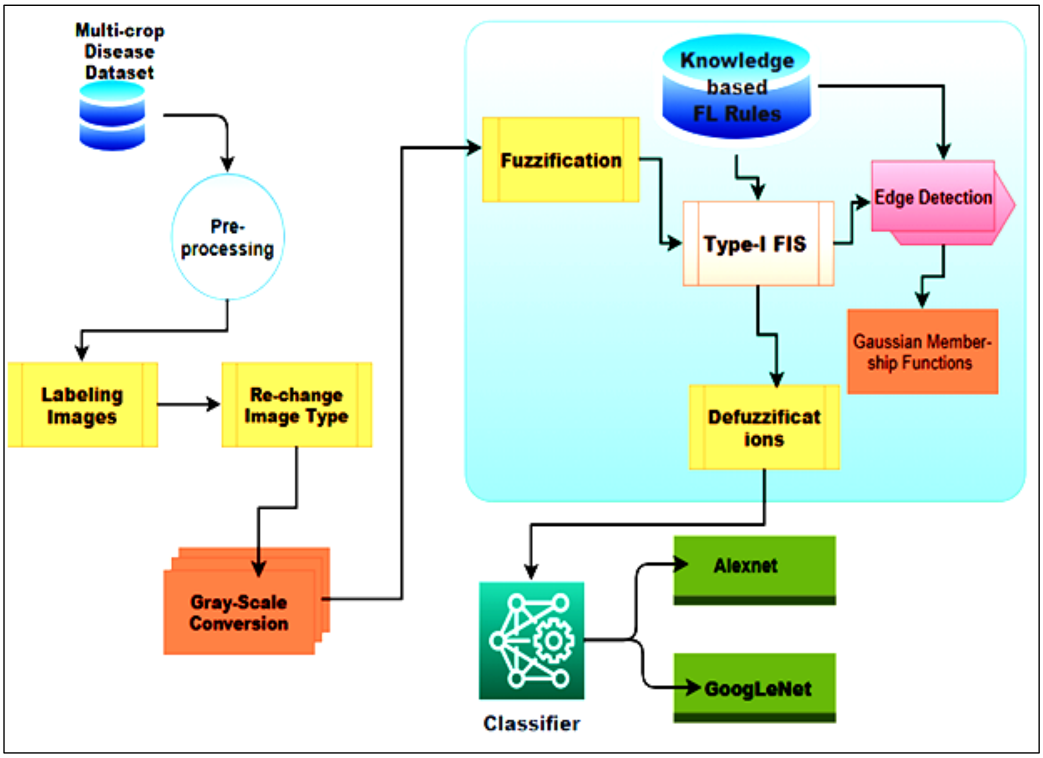

Figure 1. Multi-Crop Leave Disease Classification Model.

3.3. Fuzzy Logic

The fuzzy-logic (FL) approach was introduced with fuzzy set theory in 1965 by Lotfi Zadeh (Makkar, 2018). In traditional logic, A thing can be represented by one of two values: false, or zero, or accurate, or one. Fuzzy logic offers functional flexibility and reasoning. Because it shares many similarities with human reasoning, we can consider the accuracy and uncertainties of any given situation. Fuzzy logic does not require a deep understanding of the system.

We can create the Fuzzy Inference System (FIS) using fuzzy logic. An Artificial Intelligence System (FIS) is a type of AI that enables computers to simulate human problem-solving processes (Sabri, 2013). FIS is a function that maps several inputs to outputs using human interpretable rules. Experience-based knowledge can be encoded as logical rules using FIS. Therefore, a rule base or an inference mechanism has to be employed to design a fuzzy system. Fig. 2 illustrates the basic architecture of FIS (Artificial Intelligence)

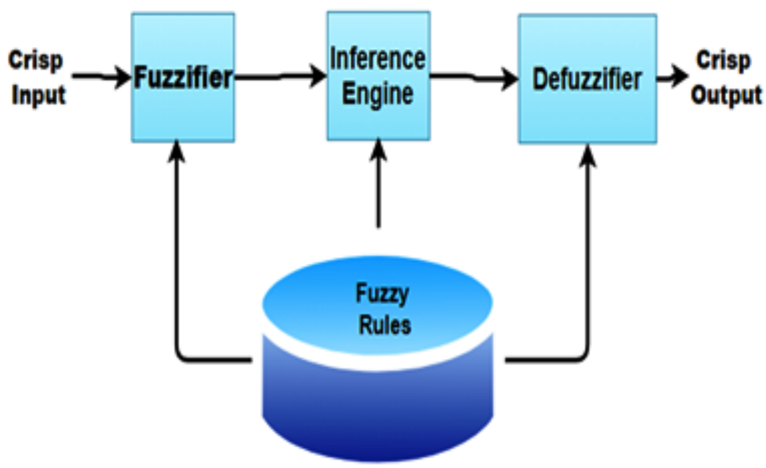

Figure 2. Basic Architecture of FIS (Hentout, 2023)

3.3.1. Fuzzy Image Processing

Different techniques are collected to understand and process input images into fuzzy sets using segmentation. Many fuzzy approaches are available to pre-process images, such as noise reduction, contrast enhancement, segmentation, and edge detection (Singh, 2017).

3.3.2. Fuzzy Edge Detection

Set of all the linked pixels that always lie in the region. Edge detection is an essential step in recovering information from images. FL approach can use membership functions to define the degree of pixels (Paika, 2013). In this paper, FIS is used for edge detection purposes, as discussed in Section 4

3.4. Deep Learning

The term Deep Learning was introduced in 2000 by Igor Aizenberg. DL is part of machine learning, and interns are part of artificial intelligence. DL is used to handle vast amounts of structured or unstructured datasets. DL can quickly solve complex operations or problems within a minute (Tripathi, 2020). In the DL model, there is no need to enter object features manually. It can automatically generate high-order features related to that respective object. DL is a robust set of techniques for learning using NN. It can be applied in medical fields, robotics fields, disease recognition, and many other fields (nnabel, 2019).

Most DL techniques used NN models, so DL architectures were called DNN. Traditionally used to train a vast amount of data at a time, NN architecture automatically learns features from the dataset. DLNN has multiple types of interconnected node layers used to categorize or optimize object-related prediction. DLNN has two visible layers: the input or output layers and the remaining ones are hidden. The initial framework of NN is shown in Figure. 3

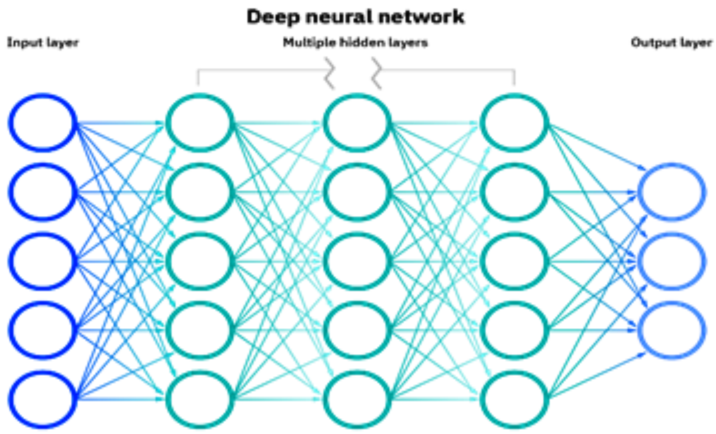

Figure 3. Basic Deep Learning Layers structure (Al-Nasiri, 2022)

3.5. Pre-trained Deep Neural Network Models

There are many DL-based pre-trained models available that can be used to train any data. It can quickly prepare many datasets, i.e., ImageNet, where we have about 14 million images. It can also classify the images into thousands of object categories (like coffee, pencil, animals, flowers, and much more). DL pre-trained models can quickly solve complex operations or problems within a minute. In the DL pre-trained model, there is no need to enter object features manually. It can automatically generate high-order features related to that respective object—pre-trained models' fundamental architecture for transfer learning. (Durmuş, 2017).

In this study, two types of pre-trained models were used for experiments. These models are as follows

- AlexNet
- GoogleNet

3.5.1. AlexNet

The AlexNet architecture was introduced by ALEX Krizhevsky in 2012. It is a CNN-based pre-trained eight layers deeper, as shown in Figure 4. AlexNet has multiple convolution layers, and it might look similar to LeNet but is much more profound. This architecture was developed based on the ImageNet dataset. AlexNet trains millions of images at a time and can also classify them into thousands of object categories (like coffee, pencil, animals, flowers, and much more). Figure 4 illustrates the use of five convolutional layers of AlexNet, A softmax layer, and two fully connected layers. Convolutional filters are the primary step in each convolutional layer, and then comes the nonlinear activation function (ReLU). According to (Gharghory, 2020), this network has an input size of 277x277x3.

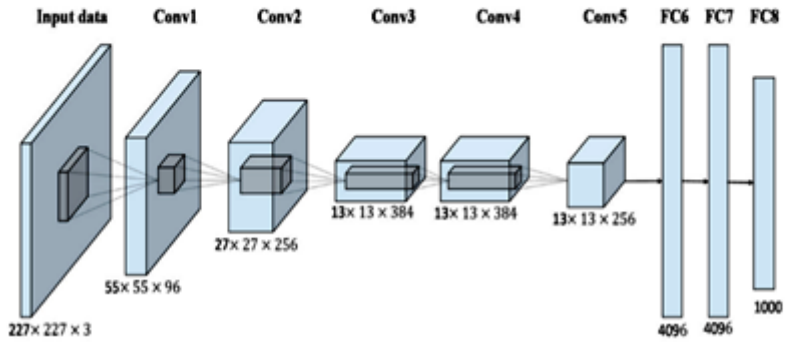

Figure 4. Basic Architecture of AlexNet ({Han, 2017)

Our experiments used one input layer and the last three fully connected layers for disease classification. The input layer is used for the input dataset into the model. In transfer learning using AlexNet, the previous three layers of AlexNet are configured for a thousand classes.

3.5.2. GoogleNet

The GoogLeNet architecture was introduced by Szegedy in 2014. It is a CNN-based pre-trained that is twenty-two layers deeper, as shown in Figure 5. GoogLeNet doesn't have fully connected layers because whether we want to use it is optional. Google's model used an inception module rather than thoroughly combined layers. Inception modules perform simple convolution operations. It defines three convolution layers (1x1, 3x3, and 5x5) or one max pooling layer (3x3) and padding applied on each operation/layer. GoogLeNet is employed to increase accuracy and decrease errors. The input size of the network is 244x244x3. In our experiments, we used one input layer; the last classification was used for disease classification (Zilvan, 2022).

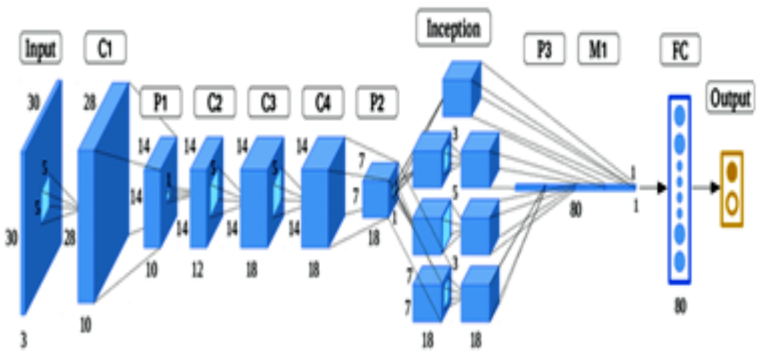

Figure 5. Basic Architecture of GoogLeNet (Kumar, 2023)

4. Results

DL Using the chosen AlexNet & and GoogleNet layers, as explained in Section 3, a pre-trained method was applied to the prepared cotton diseases dataset to classify the diseases. 30% to 20% of the image dataset was used to test the model in the experiments, with 70% to 80% of the images used for training. We only experimented with the Sdgm optimizer, whose learning rate was set to 1e-4 for all experiments. We performed the three experiments by tuning various parameters on the dataset, which aids in determining the optimal accuracy outcomes. The specifics of these trials are given in Table 2.

Table 2. Hyper-parameter for training Cotton Disease Dataset-I

AlexNet		GoogLeNet	
70% /30%	80% /20%	70% /30%	80% /20%

Batch Size	10	10	10	10	10	10	10	15	15	10	15
Epoch Size	6	10	15	6	10	15	15	25	25	15	25
Validation Frequency	3	3	3	3	3	3	6	3	9	6	6
Accuracy	0.89%	0.92%	0.94%	0.92%	0.90%	0.93%	0.85%	0.81%	0.89%	0.84%	0.90%
Loss Rate	0.10%	0.07%	0.05%	0.07%	0.09%	0.06%	0.14%	0.18%	0.10%	0.15%	0.09%

After performing different parameters on cotton dataset one, we found the best accuracy results at a 70/30 ratio using the AlexNet model, as shown in Fig. 8. Fig. 9 illustrates the con-fusion matrix used to evaluate each class performance of our proposed classifier. In this paper, we check the outcome of our suggested classifier for cotton disease classification by calculating some testing techniques such as validation accuracy, recall, precision, F1_Score, and loss rate, as discussed in section 3. The details of these evaluation measures are shown in the following Fig. 10 according to training parameter values.

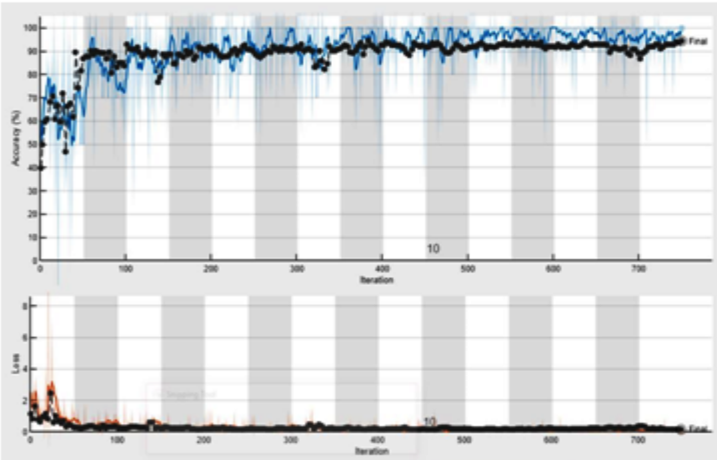

Figure 6. Visual Representation of Training at Ratio 70:30.

Figure 7 shows the Confusion Matrix of Classification Prediction of each class.

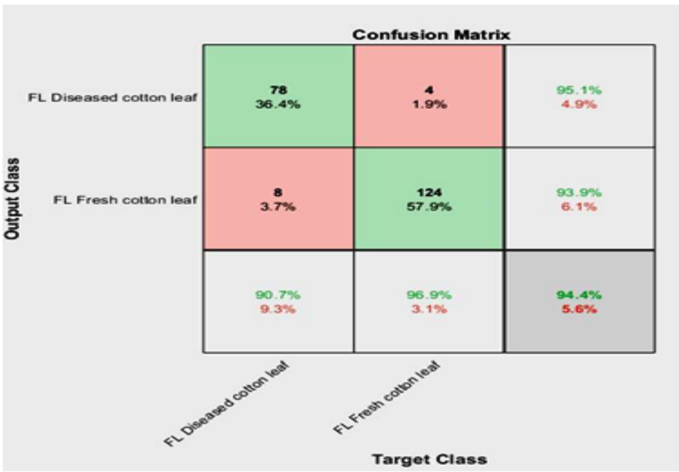

Figure 7. Confusion Matrix of Classification Prediction of Each Class

Figure 8 shows the graphical representation of Results produced using AlexNet using Dataset-1.

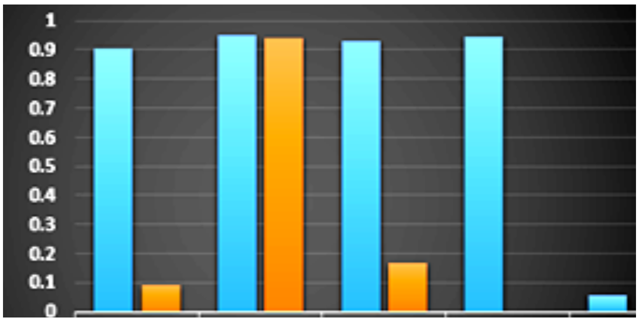

Figure 8. Evaluation Results of AlexNet using Dataset-1

The DL-tested CNN method was employed on the ready cotton diseases dataset two to differentiate the diseases using specified AlexNet & GoogLeNet layers, as explained in section 3. In the experiment, 70% or 80% of the image dataset was used to train the model, and the remaining 30% or 20% was used to validate the model. We only experimented with the Sdgm optimizer, whose learning rate was 1e-4 for all experiments. We performed the three tests on the dataset by adjusting various parameters, which aids in determining the optimal accuracy outcomes. Table 3 provides the specifics of these experiments.

Table 3. Hyper-parameter for training Cotton Disease Dataset-II

	AlexNet				**GoogLeNet**	
	70% /30%		**80% /20%**		**70% /30%**	**80% /20%**
Batch Size	10	20	10	10	20	20
Epoch Size	6	25	6	10	25	25
Validation Frequency	5	12	3	3	12	12
Accuracy	0.79%	0.99%	0.89%	0.99%	0.98%	0.96%
Loss Rate	0.20%	0.001%	0.10%	0.001%	0.01%	0.03%

After performing different parameters on cotton dataset one, we found the best accuracy results at a 70/30 or 80/20 ratio using the AlexNet model, as shown in Figure 9. Figure 10 illustrates the confusion matrix used to evaluate each class outcome of our proposed classifier. We determined the performance of the proposed classifier for cotton diseases classification by calculating some assessment metrics such as validation accuracy, recall, precision, F1_Score, and loss rate, as discussed in section 3. The details of these evaluation measures are shown in Figure 11 below according to training parameter values.

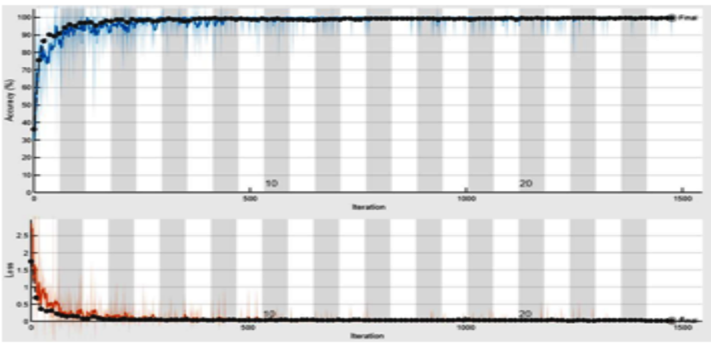

Figure 9. Visual Representation of Training at Ratio 70:30.

Confusion Matrix of classification of prediction of each class is shown in Figure 10.

Figure 10. Confusion Matrix of Classification Prediction of Each Class

Figure 11 shows the results of AlexNet using Dataset-II.

Figure 11. Evaluation Results of AlexNet using Dataset-II

The DL pre-trained CNN method was used to prepare the tomato diseases dataset to classify the diseases using selected AlexNet & GoogLeNet layers, as detailed in section 3. In the experiment, 70% or 80% of the image datasets were used to train the model, and the remaining 30% or 20% was used to validate the model. We only experimented with the Sdgm optimizer, whose learning rate was 1e-4 for all experiments. The outcomes of these experiments are given in Table 4

Table 4. Hyper-parameter for training Tomato Disease Dataset-III

	AlexNet		**GoogLeNet**	
	70% /30%	**80% /20%**	**70% /30%**	**80% /20%**
Batch Size	128	128	128	128
Epoch Size	40	40	40	40
Validation Frequency	64	64	64	64

Accuracy	0.96%	0.97%	0.85%	0.85%
Loss Rate	0.04%	0.03%	0.14%	0.14%

After performing different parameters on cotton dataset one, we found the best accuracy results at an 80/20 ratio using the AlexNet model as shown in Figure 12.. Figure 13 illustrates the confusion matrix used to deliver each class performance of our proposed classifier. We computed several evaluation metrics, including validation accuracy, recall, precision, F1Score, and loss rate, as covered in section 3, to assess the effectiveness of our suggested classifier for the classification of cotton illnesses. Referencing training parameter values, the details of the evaluation measures are displayed in Figure 14.

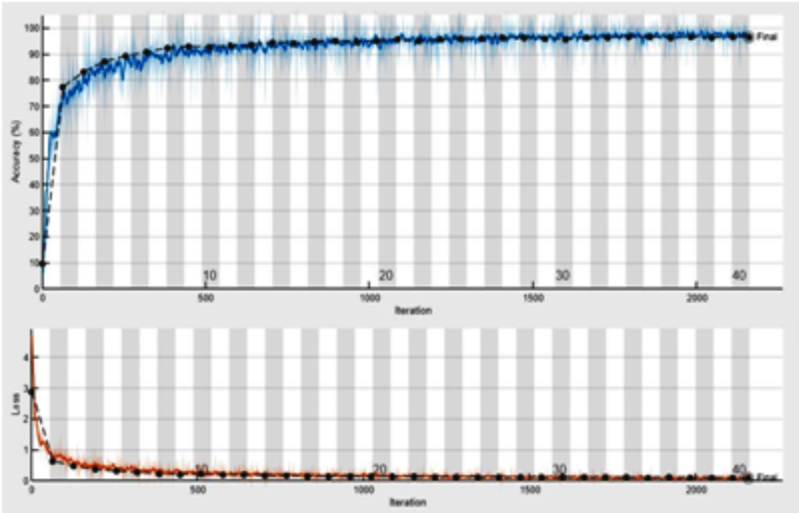

Figure 12. Visual Representation of Training at Ratio 70:30

.

Figure 13 shows the confusion matrix of classification prediction of each class.

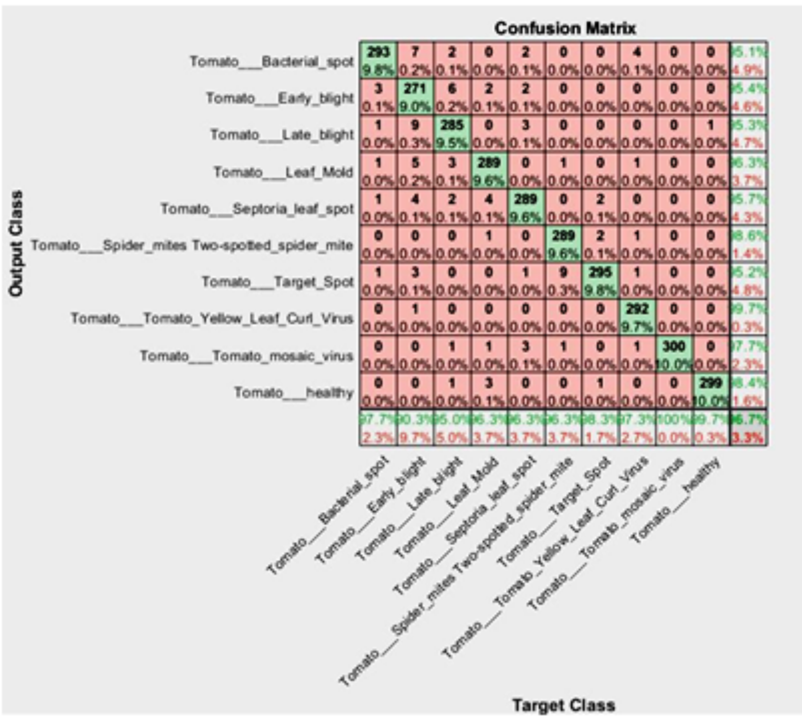

Figure 13. Confusion Matrix of Classification Prediction of Each Class

Figure 14 shows the graphical representation of the evaluation results of AlexNet using Dataset-II.

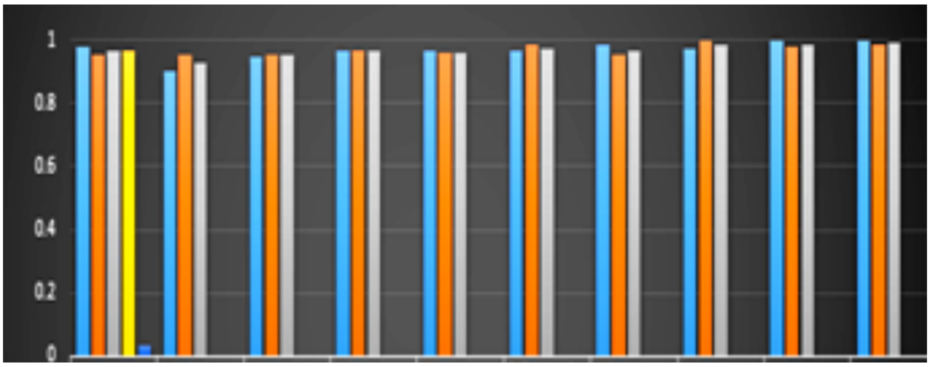

Figure 14. Evaluation Results of AlexNet using Dataset-II

5. Discussion

The experiment performed on tomato and cotton leaves found the best rules using FL, and later, AlexNet and GoogleNet were implemented for classification. In experiments, split each dataset into two ratios: 70/30 or 80/20. The DL model has been trained using different parameter tuning values. After performing experiments, we found the best accuracy results at an 80/20 ratio using the AlexNet model. We achieved 99% accurate results; in the future, we can develop our application or tool-based expert system where we define fuzzy-based rules. Using this tool, we can apply any pre-processing with classification on any dataset. Multi-crop disease detection is a challenging domain for AI methods. Still, we have found that using fuzzy logic for feature selection can improve understanding of multi-crop disease detection.

6. Conclusions

Agriculture is the foundation of about 70% of the world economy, indicating its importance in the contemporary world. The diseases of plants lower the quality of agriculture. Various methods have been proposed in the agricultural industry for detecting leaf disease in multi-crop environments. Several researchers have recently employed image processing, ML, and DL techniques to identify leaf disease in multi-crop crops, such as cotton and tomatoes. After examining the literature, we created a unique framework using AI and DL techniques. We use an AI-based FL approach to pre-process a multi-crop disease dataset to select the optimal DL architecture for disease classification. Online resources provided us with a multi-crops disease dataset. We use DL or AI techniques to experiment with the collected dataset after creating a novel framework or gathering datasets. In experiments, split each dataset into two ratios: 70/30 or 80/20. The DL model has been trained using different parameter tuning values. After performing experiments, we found the best accuracy results at an 80/20 ratio using the AlexNet model. We achieved 99% accurate results; in the future, we can develop our application or tool-based expert system where we define fuzzy-based rules. Using this tool, we can apply any type of pre-processing with classification on any dataset.

References

1. Han, X. a. (2017). Pre-trained alexnet architecture with pyramid pooling and supervision for high spatial resolution remote sensing image scene classification. Remote Sensing, 9(8), 848.
2. Agarwal, M. S. (2020). Tomato leaf disease detection using convolution neural network. Procedia Computer Science. 293-301.
3. Al-Nasiri, Y. A.-b.-H. (2022). Five-Component Load Forecast in Residential Sector Using Smart Methods. Iraqi Journal for Electrical And Electronic Engineering, 18(1).
4. Amjad, K. &. ((2021)). Critical review on multi-crops leaves disease detection using artificial intelligence methods. Int J Sci Eng Res, 12, 2.
5. Arya, S. a. (2019). A Comparative Study of CNN and AlexNet for Detection of Disease in Potato and Mango leaf. In 2019 International conference on issues and challenges in intelligent computing techniques (ICICT) (pp. 1-5). IEEE.
6. Ballester, P. a. (2016). On the performance of GoogLeNet and AlexNet applied to sketches. In Proceedings of the AAAI conference on artificial intelligence (p. 30).
7. Batmavady, S. &. (2019). Detection of cotton leaf diseases using image processing. Int J Rec Technol Eng (IJRTE), 8.
8. Bedi, P. a. (2021). Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. Artificial Intelligence in Agriculture, 5, 90--101.
9. Bhandari, R. a. (2021). Climatic change and its impact on tomato (Lycopersicum esculentum l.) production in plain area of Nepal. Environmental Challenges, 4, 100129.
10. D.Kokane, M. C. (2016). A Review: To Detect and Identify Cotton leaf disease based on pattern recognition technique. International Journal Of Engineering And Computer Science, 4,, 110–118.
11. De Luna, R. G. (2018). Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition. In TENCON 2018-2018 IEEE Region 10 Conference,IEEE, 1414-1419.
12. Durmuş, H. G. (2017). Disease detection on the leaves of the tomato plants by using deep learning. 6th International conference on agro-geoinformatics,IEEE, (pp. 1-5).
13. Ganatra, N. &. (2018). A survey on diseases detection and classification of agriculture products using image processing and machine learning. International Journal of Computer Applications,, 1-13.
14. Gharghory, S. M. (2020). Performance Analysis of Efficient Pre-trained Networks based on Transfer Learning for Tomato Leaf Diseases Classification. International Journal of Advanced Computer Science and Applications., 11(8).
15. Giller, K. E. (2021). The future of farming: Who will produce our food? Food Security, 13(5), 1073-1099.
16. Gong, X. a. (2023). An analysis of plant diseases identification based on deep learning methods. The plant pathology journal, 39(4), 319.
17. Gupta, R. a. (2021). Artificial intelligence to deep learning: machine intelligence approach for drug discovery. Molecular diversity, 25, 1315--1360.
18. Hentout, A. a. (2023). A review of the literature on fuzzy-logic approaches for collision-free path planning of manipulator robots. Artificial Intelligence Review, 56(4), 3369--3444.
19. Hossain, M. I. (2023). Detecting tomato leaf diseases by image processing through deep convolutional neural networks. Smart Agricultural Technology, 5, 100301.
20. Kumar, L. a. (2023). mproving Sustainability with Deep Learning Models for Inland Water Quality Monitoring Using Satellite Imagery. nternational Conference on Mining Intelligence and Knowledge Exploration, 387--395.
21. Llorca, C. Y. (2018). Image-based pest and disease recognition of tomato plants using a convolutional neural network. Proceedings of international conference technological challenges for better world.
22. Makkar, R. a. (2018). Application of fuzzy logic: A literature review. Int. J. Stat. Appl. Math, 3(1), 357--359.
23. nnabel, L. S. (2019). Machine learning for plant leaf disease detection and classification–a review. International conference on communication and signal processing (ICCSP),IEEE, 0538-0542).

24. Paika, E. V. (2013). Edge detection-fuzzy inference system. International journal of management \& Information Technology, 4(1), 148--155.
25. Patki, S. S. (2016). A review: Cotton leaf disease detection. . IOSR Journal of VLSI and Signal Processing, 6(3), 78-81.
26. Prashar, K. T. ((2019, April)). CNN based on overlapping pooling method and multi-layered learning with SVM & KNN for American cotton leaf disease recognition. International Conference on Automation, Computational and Technology.
27. Revathi, P. &. (2012). Homogenous segmentation based edge detection techniques for proficient identification of the cotton leaf spot diseases. International Journal of Computer Applications, , 47(2), 875-888.
28. Sabri, N. a. (2013). Fuzzy inference system: Short review and design. Int. Rev. Autom. Control, 6(4), 441--449.
29. Shah, N. &.-4. ((2019, February)). Detection of disease in cotton leaf using artificial neural network. Amity International Conference on Artificial Intelligence (AICAI) IEEE, (pp. 473-476).
30. Singh, L. S. (2017). Image Enhancement Techniques On Fuzzy Domain: A Review. International Journal of Computer Engineering and Technology, 8(2), 80--99.
31. Strange, R. N. (2005). Plant disease: a threat to global food security. Annu. Rev. Phytopathol, 43, 83-116.
32. Tabik, S. a.-P. (2017). A snapshot of image pre-processing for convolutional neural networks: case study of MNIST. International Journal of Computational Intelligence Systems, 10(1), 555--568}.
33. Tripathi, A. N. (2020). A Depth of Deep Learning for Big Data and its Applications. International Journal of Engineering Research \& Technology (IJERT) ISSN, 2278--0181.
34. Tripathy, S. ((2021, November).). Detection of cotton leaf disease using image processing techniques. In Journal of Physics:. IOP Publishing., Conference Series (Vol. 2062, No. 1, p. 012009).
35. Tsironis, V. B. ((2020).). Tomatod: evaluation of object detection algorithms on a new real-world tomato dataset. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, , 43, 1077-1084.
36. Udawant, P. &. (2019). Diseased portion classification & recognition of cotton plants using convolution neural networks. International Journal of Engineering and Advanced Technology,, 8(6), 3492-3496.
37. Zilvan, V. R. (2022). Convolutional variational autoencoder-based feature learning for automatic tea clone recognition. Journal of King Saud University-Computer and Information Sciences, , 34(6), 3332-3342.