Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Diagnosis of Plant's Illness in Agriculture by CNN Technique in Deep Learning: An Analytical Review

Nilesh Kumar Dokania[1], SCSE
Sudeept Singh Yadav[2], SCSE
Galgotias University Greater Noida, India

Abstract :- Multiple diseases have the potential to drastically impair crop productivity, seriously a threat for food security. After recognizing diseases by different symptoms, taking action is made much easier by automatic systems for classifying plant illnesses. Therefore, it is critical and vital to accurately detect plant illnesses. In cultivation, early illness identification becomes crucial ensuring a successful harvest production. Traditional categorization techniques like visual analysis have lot of drawbacks, including the need for a lot of time and accuracy. Currently, classifying numerous plant diseases has proven to be very successful when using Deep learning (DL), machine learning (ML), and convolutional neural networks (CNN). CNN based on DL techniques, in particular, have found considerable use during classifying different plant illness or diseases. We demonstrated that (NN) Neural Networks, when used for diagnosis, can capture the hues, saturation, texture of contusion particular to a given disease, simulating human judgment. They represent cutting-edge technology in this area and have partially overcome the issues with conventional categorization methods. In this study, we analyzed the most recent CNN networks techniques and algorithms relevant to classifying plant leaf diseases and reviewed CNN models for automatic feature extraction and classifying technique. Additionally, we outlined CNN's primary issues and their associated fixes for classifying plant diseases. We also talked about the classification of plant diseases' future development. The findings encourage the end users for betterment in the diagnosis procedure, which will result in an even more effective application of DL for identifying plant illness.

Keywords*: ML, DL, CNN, NN, Leaf Disease Classification, Automatic Feature Extraction*.

1. Introduction

Many techniques in machine learning which includes Naïve-Bayes Classifier algorithm, Artificial neural networks (ANN), K-Means clustering, and support vector machines (SVM), decision trees, and random forests are frequently employed in research. Collection of data, preparation of dataset, preprocessing, feature extraction, picking and using machine learning algorithms, and performance evaluation are common steps in the machine learning process. ML techniques have primarily been utilized in molecular biology and plant disease-related agriculture up to now.

1.1. Feature extraction

A feature descriptor represents a picture or a section of it that keeps only the information that is essential and ignores everything else. The majorities of its uses are for object and image detection. Each has been discussed in this section. SURF, LBP, and HOG are a few of the feature descriptors that are used to find and identify objects. These feature descriptors are also briefly covered here. Fruits and vegetables' major and most important external visual traits are their color, size, shape, and texture.

1.1.1. Color features extraction

The bulk of the methods in use today compare a fruit's color to a set of predetermined reference colors to identify its maturity. A few examples of the several color models are HSV, RGB, GALDA, HIS, JPG, CMY, L*a*b* and sRGB. The comprehensive lists of these color models are presented in [15, 14]. Agricultural applications commonly make use of techniques for extracting color characteristics. The following two categories can be used to classify methods for obtaining color features: global strategies 1. Local approaches (local color histogram and color difference histogram) 2. Global color histogram (image bitmap).

1.1.2. Size features extraction

Several size measures, which are most frequently employed for size feature extraction, include area of object, perimeter of object, weight of object, height of object (length), breadth of object, and volume of object. Many different metrics for size features extraction include the radius, the equatorial diameter, and the major and minor axes. The most crucial factor in determining a fruit's quality is its size; the bigger the fruit, the better. More money is spent on larger fruits. Fruit's inherent imperfections make measuring it challenging.

1.1.3. Texture feature extraction

In order to measure the visual texture of a photograph, a collection of 2D arrays is known as texture of an image. It gives information on how colors or intensities are arranged spatially within a picture. For traditional algorithms to accurately portray the textures of fruit images, texture information is either ignored or not used enough. Fruit identification using color and texture cues has been studied. There are two methods for analyzing: the statistical method and the structured method.

1.1.4. Shape features extraction

The goal of the shape's description is to make the form so that objects belonging to various categories have quite varied values for it. The "uniqueness condition" is used to describe this situation. Any shape description approach should also be non-ambiguous or comprehensive, in addition to being distinct and invariant to affine geometric transformations. Fruit is graded and classified according to shape, which is highly desired while purchasing fruit. [37] Sapan Naik, Bankim Patel

2. Objectives

1. To research different plant diseases and evaluate the literature on them.
2. To enhance current CNN feature extraction techniques, compare them to relevant studies, and further develop a rigorous CNN feature extraction approach for deep learning.

3. Motivation and Literature Review

3.1. Motivation

India has historically been a farming nation. Ancient India's wealth was based on agriculture. In Rigveda, the world's oldest scripture, agriculture is laudably mentioned. Akshairma Divya:

कृषिमित कृष्व भिण्टे रामस्व बहुमान्यमाण। Rigveda- 34-13 means don't gamble, do agriculture and get money with respect. Krishirdhanya Krishirmedhya Jantunam Jeevan Krishi. (Krishi Parashar-Shlok-8) That is, agriculture provides wealth and intelligence and agriculture is the basis of human life. Asian Agro History Foundation translated and republished a Sanskrit book. In this book, about two thousand years ago, an agricultural scientist named Parashar had written the book Krishi Parashar and informed the farmers of that time how to get good yield by adopting the process of planting seeds, irrigation, fertilization etc. in the appropriate manner and moment. Apart from this book, a research paper of the University of Massachusetts also mentions Krishikandam composed by Parashara Rishi. The same institution had earlier also published a Sanskrit book named Vrikshayurveda, its author was Surpal. However, long before this, Varahamihira had also written Vrikshayurveda in his Brihat-Samhita. Surely this tradition must have been going on even before them. In these texts, the details of how to treat the diseases of trees and plants are found. Similarly, some other texts on agricultural science are as follows- Kashyapiya Krishisukti: (Kashyap), Vishwavallabh: (Chakrapani Mishra), Krishishasasanam (Dasaratha Shastri) etc. Apart from these texts, the important information of Indian agriculture is also found in Prakirna Vrikshayurveda, which has been obtained from Puranas as well. Modern agriculture faces a number of difficulties, such as the rising demand for food brought on by the world's population boom, climate change, and the depletion of natural resources, changes in dietary preferences, and safety and health concerns. Agriculture is becoming less profitable due to a number of problems that farmers face, including smaller land holdings, a lack of labor, climate change, severe weather, a loss in soil fertility, etc. Since a few years ago, climate change and other environmental issues have posed a constant threat to agriculture, making it extremely difficult to increase productivity. Increasing land use and practicing farming over a larger region or implementing the use of technology and best practices to boost productivity are two potential solutions to the food shortfall. In densely populated developing countries, expanding land area is simply not an option; the only solution is to use modern technologies including IOT along with associated fields like machine learning and AI to become smarter. The Sustainable Development Goal, which aims to "End starvation, accomplish adequate supply of food and better nutrition, and promote sustainable agriculture" (SDG-2) acknowledges the connections between promoting environmentally friendly farming, empowering small farmers, advancing gender parity, ending poverty in rural areas, ensuring healthy lifestyles, combating global warming, and other problems addressed within the set of 17 SDGs in the Post-2015 Development Era. In order to satisfy society's current food and textile demands, sustainable agriculture must be practiced. This is done without sacrificing the potential of generations to come to satisfy their own needs. Principle 1 states that "Improving effectiveness in the use of natural assets is crucial to achieving sustainable agriculture" and is one of the five main principles for directing the tactical advancement of innovative techniques and the shift to sustainability. This paper uses CNN and ML as the important resources to enhance the quality and mass reduction of plant in agriculture.

3.2. Literature Review

1) S. Poornima - This study's main objective is to evaluate and categorize plant diseases using ML. The symptoms of plant diseases are identified and classified using color-based image processing and edge-based algorithms. The segmented diseased leaf section is queried for relevant attributes using (SVM) multi class Support Vector Machine. This study examines plant diseases brought on by several pathogens, including bacteria, fungi, and viruses, in order to detect plant diseases early and frequently.

2) Yosuke Toda, Fumio Okura- In this study, a dataset of images which is available in public domain are trained with CNN, depicting plant diseases was used to apply a number of layered neuron based visualization techniques. Various parameters were declined by approximately 75% without compromising the classification of accuracy by identifying number of non contributing layers to inference through the interpretation of the generated attention maps.

3) Jinzhu Lu, Lijuan Tan and Huanyu Jiang- They viewed at the most of recent CNN techniques that were justified according the categorization of plant leaves illness in this work. They outlined the DL concepts used to categorise plant diseases. They also outlined CNN's primary issues and their associated fixes for classifying plant illness. They have also examined the classification of plant illness.

4) M. Sardogan- CNN modelling and (LVQ) learning vector quantization technique are used to examine the various classifications and detection of tomato plants' leaves illness. For automated feature extraction and categorization, they created a CNN model. Information on color is commonly utilized to study plant leaf diseases. Using RGB components in this model, the applications of filters to three channels. The experimentation outcomes show how the suggested technique can successfully identify different diseases of tomato leaf.

5) P. Sharma - CNN models are trained using segmented picture data, this work explores a potential solution to this issue. Furthermore, they demonstrated how the S-CNN model performs significantly better than F-CNN system in terms of self-classification confidence using an example involving tomato plants and the target spot disease kind.

6) X. Yang - Viruses and bacteria that cause illnesses and fungi are constantly present in plants' environments. Pathogen-caused plant diseases significantly reduce food yields across the globe. In an effort to strengthen plants' resistance to infections, some researchers looked at the genes that confer resistance in plants. This review's objective is to demonstrate how machine learning is being used to identify plant resistance genes and categorize plant illnesses.

7) M. Brahimi- In this study, they investigated multiple state-of-the-art CNN designs for classifying plant

diseases using three different learning methodologies. These innovative structures outperform existing best practices for diagnosing plant ailments with a success rate of 99.76%. In order to understand and analyze the CNN categorization mechanism, saliency maps have been proposed as a visualization tool. This visualization technique delivers additional insight into the signs of plant illnesses and boosts the openness of deep learning models.

8) K.Panda - This study focuses on various supervised machine learning methods for identifying plant diseases in maize using plant pictures. To choose the most accurate model for predicting plant diseases examines and compares the aforementioned classification techniques. RF algorithm against other classification techniques, it achieves the best accuracy of 79.23%.

9) Zhang C L.- This research article states that a method for identifying apple leaf disease was proposed using methods involving digital image processing and pattern recognition technologies. The RGB (Red, Green, and Blue) model first underwent modification to the HSI, YUV, & grey models after which a color transformation structure was applied to the RGB (Red, Green, and Blue) input image. After the background was eliminated using a predefined threshold value, the region-growing algorithm (RGA) was used to segment the image of the disease site. The most important traits were selected using a combination of correlation-based feature selection (CFS) and genetic algorithms (GA), which reduced the degree of complexity of the space of features and improved dependability. Finally, an SVM classifier identified the disorders.

10) S. Kumar - Identifying the plant illnesses and minimizing economic losses are the main goals of this research. They have suggested using deep learning to recognize images. The three primary architectures of neural networks (NN) have been studied. Faster fully CNN, one shot multi-book detector, and region-based convolution NN. The precision of 94.6% in the validation result illustrates the viability of the convolution neural network.

11) Y. Guo - This study recommends a mathematical framework for identifying and diagnosing plant diseases that is based on deep learning in order to boost efficiency and accuracy. First, using RPN, the leaves in complex situations are located and identified. On the basis of the result obtained from the RPN method, which contains the feature of symptoms, images are segmented using the Chan-Vese (CV) algorithm. The transferable learning model has been developed with a dataset of ill leaflets on a simple background. Finally, the separated leaflets are transmitted into the model. The model is tested using the rust, black rot, and bacterial plaque illnesses. The findings indicate that the approach's accuracy is 83.57%, that is higher than the old way. This lowers the impact of illness on crop production and is good for the industry's sustainable growth.

12) S. Sladojevic - Through the use of convolutional neural networks with deep layers and leaf image categorization, a novel approach for recognizing plant illnesses will be created in this study. The created model can recognize 13 different forms of plant ailments from healthy leaves by being able to distinguish between the leaves of plants and their surroundings. Caffe, a framework for deep learning, was used to do the deep CNN training. The experimental results employing the created model had a mean precision of 96.3% and ranged from 91% to 98% for independent class testing.

13) S. Singh Chouhan - This work uses a method known as Bacterial foraging optimization-based BRBFNN to automatically identify and categorize plant leaf diseases. The optimal weight was assigned to an RBFNN using bacterial foraging optimization (BFO), which enhances the network's rate and precision in recognizing and categorizing areas of plant leaves afflicted by different diseases. By finding and gathering seed locations with comparable properties for the procedure of extracting features, the region-expanding approach enhances the network's performance.

14) M. Attique Khan - An innovative technique is used in this study to identify and recognize apple illnesses. There are three pipeline steps that are used: step1-the preprocessing phase spot segmentation technique and step4extraction of features, and classification. The evolutionary algorithm is used to optimize the retrieved

characteristics, and the One-vs-All M-SVM is used to classify them. The Plant Village dataset is used to generate the experimental results. Four apple disease classes, are assessed using the suggested methods.

15) L. LI- This research article details current development when examining crop leaves disease identification with the use of deep learning. Using the aid of deep learning and cutting-edge imaging techniques, they discussed the problems and current developments in plant leaf disease identification in this research. For academics looking to learn more about plant diseases' detection and insect pests, this work will be an invaluable resource.

16) F. Marzougui - In this research, they employed a computer technique in deep learning. This area makes use of CNNs using some of the most well-known architectures, including the "ResNet" architecture, to enable the early diagnosis of plant diseases. They employed an enhanced dataset with appropriate accuracy rates in the research environment, which included pictures of both healthy and sick leaves that were manually cut out and placed on a consistent background. With regard to a variety of object detection issues, our Deep Learning approach has demonstrated very strong performance. The model performs its function by categorizing photos into two groups: (diseased). The created system produces greater detection performances than those suggested in the according to the results, state-of-the-art.

17) Malusi Sibiya and Mbuyu Sumbwanyambe- CNN's enabling principles were used in this study to mimic networks for recognizing images and disease categorization. CNN network trained with "Neuroph" to recognize and categorize photos of maize diseased leaves captured on a smartphone. A revolutionary training method was used to quicken the system's quick and easy application in practise. Out of healthy leaves, the proposed model already showed its ability to distinguish between different variants of maize leaf diseases.

18) Halil Durmus, Ece Olcay Günes, Mürvet Krc- In this study, RGB cameras were utilized to identify physical alterations on leaves of tomato plants. In order to identify ailments, DL techniques were used in this study. The selection of the appropriate deep learning architecture presented the biggest implementation issue. To achieve this, the two different DL network designs, AlexNet and SqueezeNet, were examined one after the other. On the Nvidia Jetson TX1, all of these DL networks completed training and validation. The training used images of leaves from tomatoes from the Plants dataset. In ten separate classes, health-related images are used. Additionally, photos downloaded and used to assess training networks.

19) W. Albattah - They have created a categorization system for plant illnesses using a Customized Center-Net design with the goal to manage the stressed vegetation. There are three phases to the suggested strategy. Annotations are made in the beginning to identify the region of interest. Second, a more advanced version of Center-Net is presented, with DenseNet-77 being suggested for the extraction of deep key points. Eventually, a number of plant illnesses are identified and categorized using the one-stage detector Center Net. They used the standard dataset from Plant Village Kaggle to carry out the performance study.

20) Kamilaris A - In this study, a review of research projects using CNN was carried out. The pros and cons of employing CNNs in agriculture are discussed, and they are contrasted with other methods now in use. The overall results show that CNN is a promising technique that outperforms currently popular image-processing methods shows classification accurately.

4. Comparative analysis and Findings

Table 1. Different Methods used to identify plant diseases

Referred Literature in concerned area	Technologies and Algorithms used	Advantages	Limitations
Plant diseases can be quickly and precisely identified and classified. Ref. 21	ANN, Method of Otsu and K Mean	Method of color occurring	Analysis are challenging in prediction

Crop disease evaluation technique based on Digital image processing. Ref. 22	Vector-Median type filter	Using a median filter, strong edges are discovered.	There is a median filter applied to each pixel.
Using image processing to find and classify pests in greenhouses. Ref. 23	SVM	Static image deficiencies are also readily seen.	All pixel median operations are challenging.
Using image processing methods, automatically calculate the infection level of live coffee leaves. Ref. 24	Fuzzy C Means type Segmentation and Lookup-Table	Affected leaf tissue enhances the color comparison.	effective only on coffee plants leaves.
Using the k means method and correspondence filters, automatically identify plant pests. Ref. 25	K-Means	Accurately identified shapes, sizes, and orientations of various sizes.	problem arose with K means values for unique clusters.
Statistical techniques for quantitatively identifying fungus from photos of fruits. Ref. 26	Nearest- Neighbor Classifier	The simplest nearest neighbor classifier	only detectable fungi illnesses.
Based on morphological alterations, illnesses of rice leaves are categorized. Ref. 27	SVM, Otsu's Thresholding and Bayes-Classifiers	Various techniques have been employed.	Aging leaves' color distortion causes misdiagnosis and the duration
Using image processing, cotton pests and pathogens are detected. Ref. 28	RGB, HIS and YCbCr Color type Models	The other two models can readily measure the, and YCbCr is the most effective for feature extraction. Extent of a pest's damage.	Interference from noise is a concern.
Utilising image analysis to gauge the severity of the cassava brown-colored leaf spot disease. Ref. 29	Otsu's-Method	Errors are removed, and manual time is cut down.	segmentation of sick leaves is less accurate.

Ref.1. S. Poornima, S. Kavitha, S. Mohanavalli, N. Sripriya

Table 2. Different Studies on plant leave illness based on various CNN techniques

Reffered Literature with Objective using CNN Technique	Different Sizes and Tyes of Dataset used	Technologies and Algorithms used	Accuracy Rate	Advantages & Limitations
List 26 illnesses and 14 crop species. Ref. 36	54,306 of Plant Images from rural areas.	GoogLeNet & AlexNet	99.35%	Not suitable for use in reality

Locate disease and pest sources utilizing tomato plants pictures taken on-site via means of cameras. Ref. 72	5000 Images from different types of areas	ResNet & VGGNet	83%	Due to a lack of samples, there would be less accuracy in the useful application
Describe rice and maize leaf ailments. Ref. 60	500 rice images also 466 images of maize	VGGNet & Inception	92%	The module's mobile device deployment and more practical applications will be the main goals of subsequent study.
Name the four common varieties of apple leaves illnesses (rust, mosaic, together with Alternaria leaf blotch) Ref. 83	13,689 of images of ill apple plant leaves	AlexNet	97.62%	CNN model's robustness can be increased by using the picture creation method suggested in this paper.
classify the nine tomato leaf ailments. Ref. 67	14,828 of images of ill tomato plant leaves	Alex-Net & Google-Net	99.18%	Less no. of samples used
Identify two corn leaves (rust, northern leaf blight) illness. Ref. 55	Some of Plant Images from rural areas.	DCNN	88.46%	There are just two detected and categorised corn illnesses, and the dataset is insufficient.
Identify three maize leaves illness. Ref. 56	15,408 images of diseased maize leaves from Kaggle data source	VGG-16 & 19	98.20%	The dataset lacks significant diversity.
Identification and treatment of plant diseases. Ref. 53	87,848 of Plant Images from rural areas.	AlexNet, OWTBn & VGG	99.53%	Achieving a very high success rate
Develop more durable deep CNN. Ref. 59	5,632 of images of diseased tea leaves	MCT, Alex-Net & Google-Net	Not clear	The two segmentation methods employed were rotation of forty and blurred having a kernel dimension of five.

[3] Jinzhu Lu, Lijuan Tan and Huanyu Jiang

AI, ML and Image Processing have a lot of potential in agriculture. However, a shortage of funding prevents agriculture-specific development. What I outlined and discovered through various literature reviews is presented below. By analyzing various research papers' CNN and other techniques we can outline that still there is a large scope of improvement over existing methods for feature extraction using CNN based on large dataset, upgrade performance, real time analysis, overcome the over fitting issues, scalability, cost effectiveness with accuracy etc.

5. Machine Learning Methods and Algorithms Interpretation Methods

At the very end of the process of classifying fruits and vegetables as well as the grading process, which involves supervision and non-supervision learning, machine learning algorithms are critical as classifiers and decision makers. Different types of technologies based on classifiers are as follows.

5.1. K- Nearest neighbor (KNN)

A statistical classifier called K, or closest neighbor (KNN), concentrates by a distance metric. Its duty is assigning of data to the closest category of its k neighbors. We first select K neighbors then select the Euclidean distance-based list of the new point's k nearest neighbors, and last we tally the various data points in every group category before selecting a new position where there are more points

5.2. SVM (Support- Vector- Machine)

One of the most significant classification methods is SVM. Kernel functions are used by SVM to convert data nonlinearly into a high-dimensional space. SVM was initially solely designed to be utilized for 2-class problems. In an effort to maximize the separation between support vectors, the SVM attempts to construct a hyper plane that exists between the two classes. The distinctiveness of SVM is provided by its support vectors, which are nothing more than the extremes of both classes. In order to minimize dimensionality, PCA is used in conjunction with the 92% accurate SVM classifier.

5.3. ANN

ANNs, are computer programs modeled after biological systems and designed to process information similarly to how the human brain does. ANNs are just like computer-based complex programs that have been designed to work similarly to our brains. ANNs are adept at handling ambiguous data as well as the kinds of issues that call for the interpolation of enormous volumes of data. There are three layers that make up an ANN: the data input layer, the layer that is hidden & the output layer. Nodes exist in each stratum, also referred to as neurons. All the layer that is hidden and the result layer have activation procedures. Depending on the application at hand, a particular set of activation methods may be used.

5.4. DL and CNN

CNN & DL improvements have been beneficial for applications involving the challenging task of fruit recognition, such as categorization and recognition of images. Deep learning quickly recognizes the features of an image. It collects contextual information and global features, which significantly lowers picture identification errors. Deep learning has acquired more popularity recently than machine learning algorithms. [37] Sapan Naik, Bankim Patel

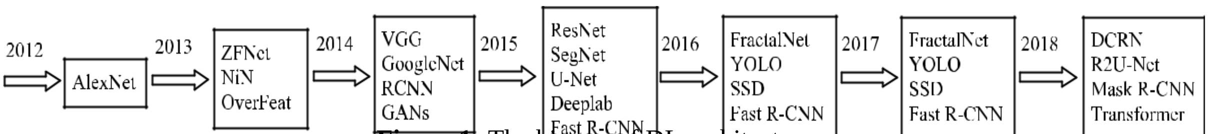

Figure 1: The history of DL architectures.

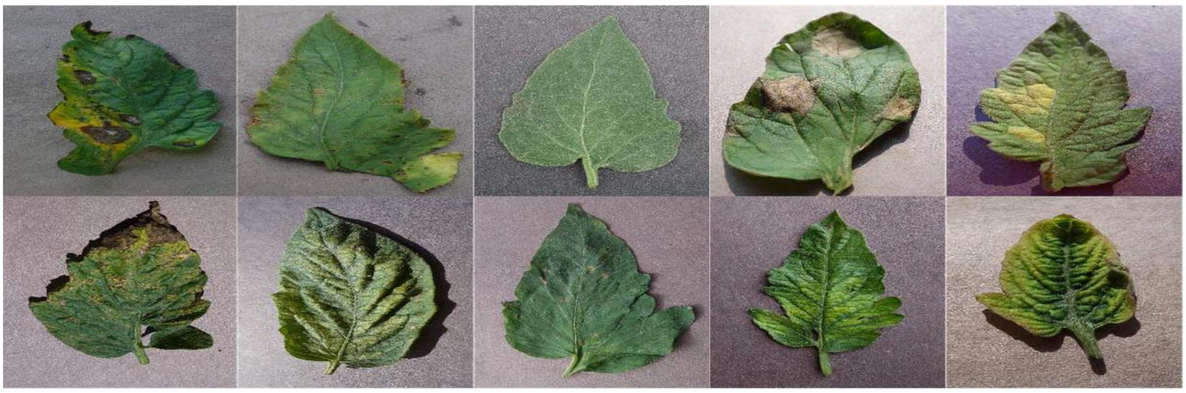

Figure 2: Different types of leaf with bad patches shows different diseases

6. Analysis And Discussions

Table 3. Comparison of the available methods

Ref.	Technique	Accuracy (%)	Advantage	Limitations
[38]	Deep-Learning Method	91.4%	The approach requires less training data	Result s for a tiny dataset
[39]	CNN Method	91.2%	The technique is computationally efficient	Over-fitting over a small classes
[40]	Deep-Learning Method	99%	The model has better further improvement required	Generalization power
[41]	CNN Method	97.18%	The work is strong. Some samples had noise and aberrations present	Economically inefficient
[42]	Deep-Learning Method	76.1%	The project can pinpoint the impacted area from photos with low resolution	Time-consuming
[43]	Deep-Learning (KNN) Method	96%	The method has improved the accuracy of categorization for samples with complicated backgrounds	Over-fitting for a large-size dataset
[44]	CNN Method	98%	The work is rigid for noisy samples	High Computation cost

[19] Ref. W. Albattah

7. Future Proposed Work

The proposed work focuses on plant disease identification using to accomplish a few goals, including: I Find the limits of the infected region, quantify the afflicted area by disease, ascertain construct a model of illness type prediction based on the color and shape of the affected area. categorization are all steps in the disease detection process. As input, there are pictures of several plants, including some with ailments. To locate the sick region and segment it independently, edge-based (sobel and morphological) and color-based techniques are applied. Multiclass SVM is used to group diseases according to their type.

The steps in recognizing and classifying images are image acquisition, preprocessing, feature extraction, and classification.

A. Acquisition of Images - The many commercial crop kinds, food grain, fruit, and cereal samples, along with healthy and unaffected farming/horticulture, are collected using a digital camera for the present assignment.

B. Pre-processing Operation of Images – Usually, factors such as noise, varying lighting, climatic conditions, low image resolutions, unpleasant backgrounds, etc. prevent the use of the images obtained during image capture for successful identification and classification.

C. Image Segmentation- Image segmentation is defined as dividing an image into parts that are distinct and meaningful based on a set of criteria. In many pattern recognition applications, image segmentation is typically seen as an intermediary step. Threshold, edge, and region-based techniques are the three types of image-segmentation techniques. Threshold-based image-segmentation algorithms typically employ the histogram of the input image to identify one or more thresholds. Edge-based image segmentation techniques are made to identify the edges in an input image.

D. Feature Extraction- Common cereals or fruits in bulk samples demonstrate that each crop has a unique surface pattern. In these circumstances, the texture or color becomes the best option for identification. Because of the color and texture characteristics of the image samples, we will be able to distinguish between usual agriculture production and production that has been affected.

E. Classification Based Classifier- We can use BPNN to categorize different products and carry out autonomous disease detection. In the input as well as the output layers, respectively, the quantity of neurons reflects both the number of categories of output and the intensity of input information. A classifier is trained, verified, and evaluated using images of different horticultural and agricultural goods.

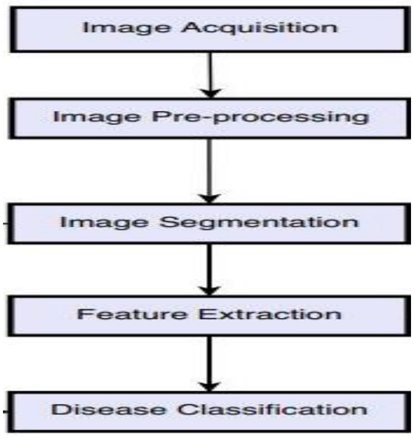

Figure 3: Process Flow

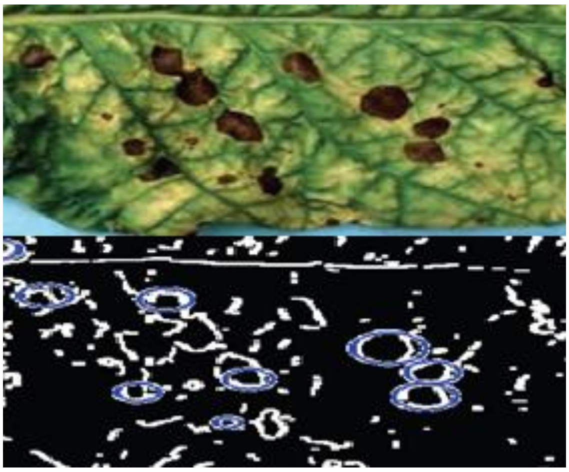

Figure 4: An example of a leaf's disease spot detection output

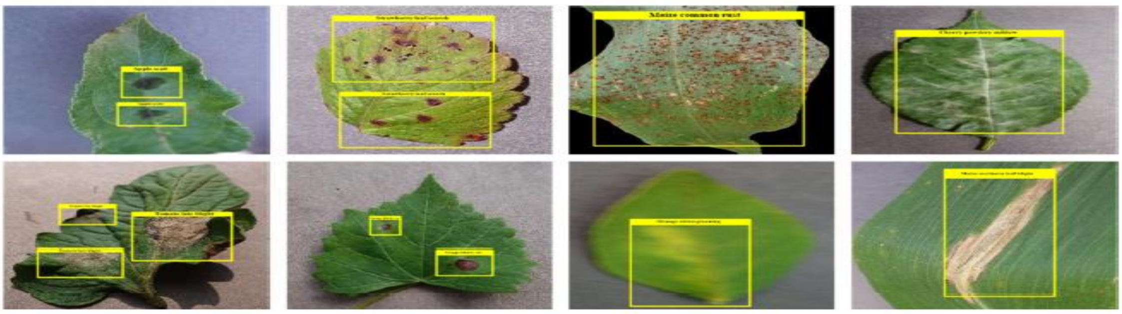

Figure 5: Different Feature Classifiers on sample leaves

8. Conclusion

The fundamentals of deep learning were reviewed in this paper, along with a thorough analysis of recent research on its use in identifying plant leaf diseases. Deep learning algorithms can accurately identify illnesses in plant leaves because of the training data. As a way to increase accuracy, it has also been emphasized how crucial it is to collect huge datasets with lots of variation, augment existing data, learn transfer learning, and display CNN activation maps. However, there are some drawbacks as well. Nowadays, the classification and detection of plant diseases make extensive use of deep learning techniques. It has partially or fully fixed the problems that existed with traditional machine learning methods. Image classification & target recognition, are some of the key uses of the machine learning field known as "Deep Learning”. We examined the bulk of the current CNN networks for this study that have anything to do with categorizing plant leaf diseases. We provide the CNN methodologies employed in this procedure as well as the Deep Learning concepts involved in the categorization of plant diseases. We also discuss some problems and their associated Deep Learning solutions for categorizing plant diseases using both external and internal criteria, such as insufficient datasets, no optimal reliability, compressed model, unsupervised machine learning and train; symptomatic variations, gathering the complete range of variance, and gradually increasing the diversity of the dataset; and future plant disease taxonomy was another topic we covered. The early detection of plant leaf diseases requires the use of various Deep Learning frameworks, despite the fact that some study uses hyper spectral photographs of the diseased leaves. Real-time identification of plant illnesses using Deep Learning methods is advantageous. When used with the datasets they were intended for the vast majority of Deep Learning systems reported in the literature performs well in terms of detection; but, when used with different datasets, they perform badly, demonstrating the model's lack of robustness. In order to accommodate the various disease datasets, resilience needs to be improved in models for deep learning.

Refrences

[1] S. Poornima, S. Kavitha, S. Mohanavalli, N. Sripriya, Detection and Classification of Diseases in Plants using Image Processing and Machine Learning Techniques, AIP Conference Proceedings 2095, 030018 (2019); https://doi.org/10.1063/1.5097529, 09 April 2019

[2] Yosuke Toda, Fumio Okura, How Convolutional Neural Networks Diagnose Plant Disease, AAAS Plant Phenomics, A Science Partner Journal, Volume 2019, Article ID 9237136, 14 pages, https://doi.org/10.34133/2019/9237136, 26 March 2019

[3] Jinzhu Lu, Lijuan Tan and Huanyu Jiang, Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification, Agriculture 2021, 11, 707. https:// doi.org/10.3390/agriculture11080707, https://www.mdpi.com/journal/agriculture, 27 July 2021

[4] Melike Sardogan, Adem Tuncer and Yunus Ozen, Plant Leaf Disease Detection and Classification based on CNN with LVQ Algorithm, UBMK’ 18, 3rd International Conference on Computer Science and Engineering, 978-1-5386-7893-0/18/$13.00, 2018 IEEE

[5] Parul Sharma, Yash Paul Singh Berwal, Wiqas Ghai, Performance analysis of deep learning CNN models for disease detection in plants using image segmentation, https://doi.org/10.1016/j.inpa.2019.11.001, www.sciencedi rect.com, INFORMATION PROCESSING IN AGRICULTURE 7 (2020) 566– 574, journal homepage: www.elsevier.com/locate/inpa, 18 Nov. 2019

[6] Xin Yang, Tingwei Guo, Machine learning in plant disease research, Bio Medical Research Journal, Volume 34, 2019

[7] Mohammed Brahimi, Marko Arsenovic, Sohaib Laraba, Srdjan Sladojevic, Kamel Boukhalfa and Abdelouhab Moussaoui, Deep Learning for Plant Diseases:Detection and Saliency Map Visualisation, Springer International Publishing AG, part of Springer Nature 2018, J. Zhou and F. Chen (eds.), Human and Machine Learning, Human–Computer, Interaction Series, https://doi.org/10.1007/978-3-319-90403-0_6, 2018

[8] Kshyanaprava Panda Panigrahi, Himansu Das, Abhaya Kumar Sahoo and Suresh Chandra Moharana, Maize Leaf Disease Detection and Classification Using Machine Learning Algorithms, Springer Nature Singapore Pte Ltd. 2020, H. Das et al. (eds.), Progress in Computing, Analytics and Networking, Advances in Intelligent Systems and Computing 1119, https://doi.org/10.1007/978-981-15-2414-1_66, 2020

[9] Zhang C L, Zhang S W, Yang J C, Shi Y C, Chen J. Apple leaf disease identification using genetic algorithm and correlation based feature selection method. https://www.ijabe.org, Int J Agric & Biol Eng, 2017; 10(2): 74–83, DOI: 10.3965/j.ijabe.20171002.2166, March, 2017, Vol. 10 No.2

[10] Sumit Kumar, Veerendra Chaudhary, Ms. Supriya Khaitan Chandra, Plant Disease Detection Using CNN, Turkish Journal of Computer and Mathematics Education Vol.12 No.12 (2021), 2106-2112, 23 May 2021

[11] Yan Guo, Jin Zhang, Chengxin Yin, Xiaonan Hu, Yu Zou, Zhipeng Xue and Wei Wang, Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming, Hindawi, Discrete Dynamics in Nature and Society, Volume 2020, Article ID 2479172, 11 pages, https://doi.org/10.1155/2020/2479172, 18 August 2020

[12] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk and Darko Stefanovic, Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification, Hindawi Publishing Corporation, Computational Intelligence and Neuroscience, Volume 2016, Article ID 3289801, 11 pages, http://dx.doi.org/10.1155/2016/3289801, 29 May 2016

[13] Siddharth Singh Chouhan, Ajay Kaul, Uday Pratap Singh and Sanjeev Jain, Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards Plant Pathology, DOI 10.1109/ACCESS.2018.2800685, IEEE Access, February 2017

[14] Muhammad Attique Khan, M Ikramullah Lali, Muhammad Sharif, Kashif Javed, Khursheed Aurangzeb, Syed Irtaza Haider, Abdulaziz Saud Altamrah, And Talha Akram, An Optimized Method for Segmentation and Classification of Apple Diseases based on Strong Correlation and Genetic Algorithm based Feature Selection, DOI 10.1109/ACCESS.2019.2908040, IEEE Access, http://www.ieee.org/publications_standards/publications/rights/index.html, 2018

[15] LILI LI, SHUJUAN ZHANG, AND BIN WANG, Plant Disease Detection and Classification by Deep Learning-A Review, Digital Object Identifier 10.1109/ACCESS.2021.3069646, IEEE Access, VOLUME 9,, https://creativecommons.org/licenses/by/4.0, April 19, 2021

[16] Fatma MARZOUGUI, Mohamed ELLEUCH and Monji KHERALLAH, A Deep CNN Approach for Plant Disease Detection, 978-1-7281-8855-3/20/$31.00, IEEE Xplore, 21st International Arab Conference of Technology, 2020

[17] Malusi Sibiya and Mbuyu Sumbwanyambe, A Computational Procedure for the Recognition and Classification of Maize Leaf Diseases Out of Healthy Leaves Using Convolutional Neural Networks, Agri Engineering 2019,1,119–131;doi:10.3390/agriengineerig1010000 www.mdpi.com/journal/agriengineering, 13 March 2019

[18] Halil Durmus, Ece Olcay Günes, Mürvet Krc, Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning, T.R: Ministry of Food, Agriculture and Livestock, and ITU TARBIL Environmental Agriculture Informatics Applied Research Center

[19] Waleed Albattah, Marriam Nawaz, Ali Javed, Momina Masood and Saleh Albahli, A novel deep learning method for detection and classification of plant Diseases, Complex & Intelligent Systems (2022) 8:507–524, https://doi.org/10.1007/s40747-021-00536-1, 28 September 2021

[20] Kamilaris A, Prenafeta-Boldú F X (2018). A review of the use of convolutional neural networks in agriculture. The Journal of Agricultural Science 156, 312–322. https://doi.org/10.1017/S0021859618000436, 25 June 2018

[21] H.Al-Hiary, S. Bani-Ahmad, M.Reyalat, M.Braik and Z.AlRahamneh, Computer Applications. 17, 31-38 (2011).

[22] Y. Tian, L. Wang and Q. Zhou, Computer and computing technologies in agriculture. 427-433 (2011).

[23] R.G. Mundada and V.V. Gohokar, IOSR - Electronics and Communication Engineering. 5, 57-63 (2013).

[24] E. Hitimana and O. Gwun, Proceedings of Second International Conference on Signal, Image Processing and Pattern Recognition, Sydney, Australia (2014), pp. 255–266.

[25] F. Fina, P. Birch, R. Young, J. Obu, B. Faithpraise and C. Chatwin, Advanced Biotechnology and Research. 4, 189-199 (2013).

[26] J. D.Pujari, R. Yakkundimath and A.S.Byadgi, Intelligent Systems & Applications in Engineering Advanced Technology & Science. 1, 60–67 (2013).

[27] S. Phadikar, J. Sil, and A. K. Das, Information and Electronics Engineering. 2, 460-463 (2012).

[28] Q. He, B. Ma, D. Qu, Q. Zhang, X. Hou and J. Zhao, TELKOMNIKA, Indonesian Journal of electrical engineering. 11, 3445 - 3450 (2013).
[29] K. Powbunthorn, W. Abudullakasim and J. Unartngam, Proceedings of the International conference of the Thai Society of Agricultural Engineering, Thailand (2012).
[30] Rabia Masood, S.A. Khan and M.N.A. Khan, Modern Education and Computer Science. 1, 24-32 (2016).
[31] Sindhuja, Sankaran, Ashish Mishra, Reza Ehsani and Cristina Davis, Computers and Electronics in Agriculture, 72, 1–13 (2010).
[32] Sonam Saluja, Aradhana Kumari Singh and Sonu Agrawal, Advanced Research in Computer and Communication Engineering. 2 (2013).
[33] J. Illingworth and J. Kittler, Computer Vision, Graphics, and Image Processing. 44, 87-116 (1988).
[34] Ferentinos, K. P., Computers and Electronics in Agriculture. 145, 311-318 (2018); Kamilaris, A. and Prenafeta-Boldú, F. X., ibid. 147, 70-90 (2018).
[35] Lee, S.H., Chan, C.S., Wilkin, P. and Remagnino, P., Proceedings of IEEE International Conference on Image Processing (ICIP 2015). Quebec city, Canada, pp. 452–456.
[36] Mohanty, S. P., Hughes, D. P. and Salathé, M., Frontiers in plant science. 7, 1419 (2016).
[37] Sapan Naik, Bankim Patel, Machine Vision based Fruit Classification and Grading - A Review, International Journal of Computer Applications (0975 – 8887), Volume 170 – No.9, July 2017, https://www.researchgate.net/publication/318486455
[38] Argüeso D et al (2020) Few-Shot Learning approach for plant dis-ease classification using images taken in the field. Comput Electron Agric 175:105542
[39] Agarwal M et al (2020) ToLeD: Tomato leaf disease detection using convolution neural network. Procedia Comput Sci 167:293–301
[40] Richey B et al (2020) Real-time detection of maize crop disease via a deep learning-based smartphone app. in Real-Time Image Pro-cessing and Deep Learning 2020. International Society for Optics and Photonics
[41] Zhang Y, Song C, Zhang D (2020) Deep learning-based object detection improvement for tomato disease. IEEE Access 8:56607–56614
[42] Batool A et al (2020) Classification and Identification of Tomato Leaf Disease Using Deep Neural Network. In: 2020 International Conference on Engineering and Emerging Technologies (ICEET). IEEE
[43] Goncharov P et al (2020) Deep Siamese Networks for Plant Disease Detection. In: EPJ Web of Conferences. 2020. EDP Sciences
[44] Karthik R et al (2020) Attention embedded residual CNN for dis-ease detection in tomato leaves. Appl Soft Comput 86:105933
[45] D. P. and Salathé, M., Frontiers in plant science. 7, 1419 (2016).
[46] Duan K et al (2019) Centernet: Keypoint triplets for object detection. In: Proceedings of the IEEE/CVF International Conference on Computer Vision
[47] Aceto G et al (2020) Toward effective mobile encrypted traffic classification through deep learning. Neuro computing 409:306–315
[48] Hinton GE, Osindero S, Teh Y-W (2006) A fast learning algorithm for deep belief nets. Neural Comput 18(7):1527–1554
[49] Aceto G et al (2019) MIMETIC: Mobile encrypted traffic classifi-cation using multimodal deep learning. Comput Netw 165:106944Wang Y et al (2019) Multi-Scale DenseNets-Based Aircraft Detec-tion from Remote Sensing Images. Sensors 19(23):5270
[50] Albahli S et al (2021) An improved faster-RCNN model for hand-written character recognition. Arab J Sci Eng 1–15
[51] Albahli S et al (2021) Recognition and Detection of Diabetic Retinopathy Using Densenet-65 Based Faster-RCNN. Comput Mater Contin 67:1333–1351
[52] Hughes D, Salathé M (2015) An open access repository of images on plant health to enable the development of mobile disease diag-nostics. arXiv preprint arXiv:.08060

[53] Ferentinos, K. Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric. 2018, 145, 311–318. [CrossRef]

[54] Brahimi, M.; Mahmoudi, S.; Boukhalfa, K.; Moussaoui, A. Deep interpretable architecture for plant diseases classification. In Proceedings of the 2019 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA), Poznan, Poland, 18–20 September 2019.

[55] Mishra, S.; Sachan, R.; Rajpal, D. Deep Convolutional Neural Network based Detection System for Real-time Corn Plant Disease Recognition. Procedia Comput. Ence 2020, 167, 2003–2010. [CrossRef]

[56] Darwish, A.; Ezzat, D.; Hassanien, A.E. An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis. Swarm Evol. Comput. 2019, 52, 100616. [CrossRef]

[57] Amanda, R.; Kelsee, B.; Peter, M.C.; Babuali, A.; James, L.; Hughes, D.P. Deep Learning for Image-Based Cassava Disease Detection. Front. Plant Sci. 2017, 8, 1852.

[58] Lin, Z.; Mu, S.; Shi, A.; Pang, C.; Student, G.; Sun, X.; Student, G. A Novel Method of Maize Leaf Disease Image Identification Based on a Multichannel Convolutional Neural Network. Trans. ASABE 2018, 61, 1461–1474. [CrossRef]

[59] Yuwana, R.S.; Suryawati, E.; Zilvan, V.; Ramdan, A.; Fauziah, F. Multi-Condition Training on Deep Convolutional Neural Networks for Robust Plant Diseases Detection. In Proceedings of the 2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA), Tangerang, Indonesia, 23–24 October 2019.

[60] Chen, J.; Chen, J.; Zhang, D.; Sun, Y.; Nanehkaran, Y.A. Using deep transfer learning for image-based plant disease identification. Comput. Electron. Agric. 2020, 173, 105393. [CrossRef]

[61] Fujita, E.; Kawasaki, Y.; Uga, H.; Kagiwada, S.; Iyatomi, H. Basic investigation on a robust and practical plant diagnostic system. In Proceedings of the 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA), Anaheim, CA, USA, 18–20 December 2016.

[62] Ghazi, M.M.; Yanikoglu, B.; Aptoula, E. Plant identification using deep neural networks via optimization of transfer learning parameters. Neurocomputing 2017, 235, 228–235. [CrossRef]

[63] Hidayatuloh, A.; Nursalman, M.; Nugraha, E. Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model. In Proceedings of the 2018 International Conference on Information Technology Systems and Innovation (ICITSI), Bandung, Indonesia, 22–26 October 2018.

[64] Juncheng, M.; Keming, D.; Feixiang, Z.; Lingxian, Z.; Zhihong, G.; Zhongfu, S. A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Comput. Electron. Agric. 2018, 154, 18–24.

[65] Bollis, E.; Pedrini, H.; Avila, S. Weakly Supervised Learning Guided by Activation Mapping Applied to a Novel Citrus Pest Benchmark. In Proceedings of the 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Seattle, WA, USA, 14–19 June 2020.

[66] Ge, M.; Su, F.; Zhao, Z.; Su, D. Deep Learning Analysis on Microscopic Imaging in Materials Science. Mater. Today Nano 2020, 11, 100087. [CrossRef]

[67] Brahimi, M.; Boukhalfa, K.; Moussaoui, A. Deep Learning for Tomato Diseases: Classification and Symptoms Visualization. Appl. Artif. Intell. 2017, 31, 1–17. [CrossRef]

[68] Arsenovic, M.; Karanovic, M.; Sladojevic, S.; Anderla, A.; Stefanovic, D. Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection. Symmetry 2019, 11, 939. [CrossRef]

[69] Peng, Y.; Wang, Y. An industrial-grade solution for agricultural image classification tasks. Comput. Electron. Agric. 2021, 187, 106253. [CrossRef]

[70] Wang, Y.; Wang, J.; Zhang, W.; Zhan, Y.; Guo, S.; Zheng, Q.; Wang, X. A survey on deploying mobile deep learning applications: A systemic and technical perspective. Digit. Commun. Netw. 2021. [CrossRef]

[71] Gao, J.; Westergaard, J.C.; Sundmark, E.H.R.; Bagge, M.; Liljeroth, E.; Alexandersson, E. Automatic late blight lesion recognition and severity quantification based on field imagery of diverse potato genotypes by deep learning. Knowl. Based Syst. 2021, 214, 106723. [CrossRef]

[72] Fuentes, A.; Yoon, S.; Kim, S.C.; Park, D.S. A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition. Sensors 2017, 17, 2022. [CrossRef]

[73] Barbedo, J.G.A. Factors influencing the use of deep learning for plant disease recognition. Biosyst. Eng. 2018, 172, 84–91. [CrossRef]

[74] Coulibaly, S.; Kamsu-Foguem, B.; Kamissoko, D.; Traore, D. Deep neural networks with transfer learning in millet crop images. Comput. Ind. 2019, 108, 115–120. [CrossRef]

[75] Abdalla, A.; Cen, H.; Wan, L.; Rashid, R.; He, Y. Fine-tuning convolutional neural network with transfer learning for semantic segmentation of ground-level oilseed rape images in a field with high weed pressure. Comput. Electron. Agric. 2019, 167, 105091. [CrossRef]

[76] Thenmozhi, K.; Reddy, U.S. Crop pest classification based on deep convolutional neural network and transfer learning. Comput. Electron. Agric. 2019, 164, 104906. [CrossRef]

[77] Suh, H.K.; IJsselmuiden, J.; Hofstee, J.W.; van Henten, E.J. Transfer learning for the classification of sugar beet and volunteer potato under field conditions. Biosyst. Eng. 2018, 174, 50–65. [CrossRef]

[78] Hendrycks, D.; Mu, N.; Cubuk, E.D.; Zoph, B.; Gilmer, J.; Lakshminarayanan, B. AugMix: A Simple Data Processing Method to Improve Robustness and Uncertainty. arXiv 2019, arXiv:1912.02781.

[79] Ho, D.; Liang, E.; Stoica, I.; Abbeel, P.; Chen, X. Population Based Augmentation: Efficient Learning of Augmentation Policy Schedules. In Proceedings of the International Conference on Machine Learning, Long Beach, CA, USA, 9–15 June 2019; 2731–2741.

[80] Lim, S.; Kim, I.; Kim, T.; Kim, C.; Kim, S. Fast AutoAugment. Adv. Neural Inf. Process. Syst. 2019, 32, 6665–6675.

[81] Cubuk, E.D.; Zoph, B.; Shlens, J.; Le, Q.V. Randaugment: Practical automated data augmentation with a reduced search space. In Proceedings of the 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Seattle, WA, USA, 14–19 June 2020.

[82] Yun, S.; Han, D.; Chun, S.; Oh, S.J.; Yoo, Y.; Choe, J. CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features. In Proceedings of the IEEE/CVF International Conference on Computer Vision, Seoul, Korea, 27–28 October 2019;6023–6032. Available online: https://openaccess.thecvf.com/content_ICCV_2019/papers/Yun_CutMix_Regularization_ Strategy_to_Train_Strong_Classifiers_With_Localizable_Features_ICCV_2019_paper.pdf (accessed on 22 July 2021).

[83] Bin, L.; Yun, Z.; Dongjian, H.; Yuxiang, L. Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks. Symmetry 2017, 10, 11.