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Original Article

Disease Detection in Plant Leaf using LNet Based on Deep Learning

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Abstract - *Deep Learning is a kind of artificial intelligence that uses fake brain organizations to learn how to learn. One of the most promising but difficult problems in leaf disease detection is the efficient and precise identification of diseases in Plant leaves. However, examining the leaves and determining the type of disease takes hours throughout the pasture. As a result, applying deep learning techniques and algorithms to identify fruit leaf disease has a lot of potential in modern agriculture. The research employs cutting-edge algorithms such as Xception, Inception V3 and ResNet-50, which produce good accuracy. The proposed architecture called Leaf Network (LNet) produces improved efficiency than the above listed Convolutional Neural Networks. It allows for the effective design of early plant leaf detection to reduce disease induced in crops during growth, harvest, and post-harvest processing, as well as to assure advanced disease diagnosis and prevention in crops. As a result, Leaf Network (LNet) has an accuracy of 98.68% compared with all four Algorithms.*

Keywords - *CNN, Xception, Inception V3, ResNet-50 and Leaf disease classification.*

1. Introduction

In this field, examination and investigation into plant picture investigation, for example, elevated phenotyping and leaf fingerprinting, have started. Notwithstanding, because these techniques depend vigorously on costly gadgets or complex atomic innovations, they are difficult for the mainstream. Some researchers have recently used DL methods to recognize plant diseases. However, most of them extract deep options from illness representations while not considering task characteristics. Furthermore, these researches are limited to a few datasets with lesser classes and simple visual backgrounds.

1.1. Deep Learning

Artificial neural networks created the foremost roaring achievements within image recognition and organization. The majority of DL techniques are built on top of these networks. DL may be an assortment of Machine Learning (ML) techniques that use many layers of non-linear process units. Every unit improves its capability to remodel its computer file into many abstract and composite illustrations. Deep neural networks have outperformed other ML methods. They also achieved the first superhuman pattern recognition in some areas. DL is considered an important step in achieving sturdy computing, supporting this claim. Deep neural networks, notably Convolutional Neural Networks (CNN), are demonstrated to realize wonderful leads to image recognition.

1.2. Plant disease

Agriculture is a crucial industry for the world's growing population to meet their basic food demands. Disease detection in plants seems to be a crucial work that would have to be performed in agriculture. Given how frequently illnesses affect plants, finding infections in them is an important task in the agriculture industry. Monitoring and controlling the process of the plants is necessary to detect diseases in leaves. This ongoing inspection of the plants requires a huge amount of human labour and consumes a lot of effort. Digital farming techniques might be an intriguing way to swiftly and readily identify plant diseases.

2. Related Work

Since the foremost goal of image processing is to distinguish the symptom findings acquired from the environment, the most important task in this complicated environment is to figure out how to process the photos while localizing and detecting unhealthy fruit tree leaves. Fruit tree leaf disease feature extraction has a lot of issues when it comes to diagnosing leaf disease. Textures, shape, colour, and motion-related attributes are all distinct image features required for disease feature extraction. Numerous techniques have been developed and tested for precise identification to obtain accurate results. The identification model developed a perfectly alright image categorization system by applying class labels to training images.

Alex Krizhevsky et al. [1] proposed the ImageNet Neural Network algorithm and obtained an error rate below 15.3% while classifying. The neural Network (NN) has a huge amount of parameters, neurons and a total of five CL, three fully-connected layers and a maximum-pooling layer consisting of 1000-way softmax and GPU implementation of functions. The dropout method cuts down on overfitting in fully connected layers. X. Zhang et al., [2-4] greatly improved the quality of computer-aided supporting systems. The system's state-of-the-art technique examines current practices, preprocessing images, segmentation, feature extraction, selection, and classification problems of maize diseased pictures. According to recent informatics research, to achieve the best results, ML algorithms must be joined with enough diseased maize images. Different forms relying on expert domain information and semantically characterized them inside a layered structure model were summarised towards choice-making. They increased the precision of our algorithm, which attained a result of 87.25 percent accuracy in the test dataset of 1067 images.

Esteva A. [5] recommended Convolution Layers (CL) and max-pooling layers with some fully connected layers. Convolutional networks are the current state of the art in the field of ML; object detection from small images was re-evaluated, and the necessity of various pipeline components was questioned. On several image recognition benchmarks, it is discovered that max-pooling layers can be substituted with a CL augmented stride deprived of sacrificing correctness. A new deconvolution approach variant for visualizing structures learned by CNNs was introduced and practical to a wider range of network structures to analyze the performance. Hu et al. [6] proposed the anticipated evidence theory of Dempster–Shafer (D-S) and multi-featured mixture for pull-out features, improving D-S evidence theory and introducing variance decision rules processed. Turkoglu also demonstrated an enhanced version method of Local Binary Patterns (LBP) that employs the original LBP's original local quadratic value for converting the image to grayscale and procedures the R and G channels while accounting for overall and region.

Alehegn E and K. Q. In this article, Weinberger looks at even the most meaningful interpretation learning theories for medical image analysis [7-8]. It goes through the most significant DL topics for medical picture analysis. Convolutional networks, in particular, had also rapidly become the ideal method for analyzing medical images using deep learning algorithms. They summarise there have been completed 300 contributions to the arena and reviews the major DL basis relevant to medical data image analysis.

The authors [9] investigate how DL is applied to image categorization, segmentation, finding an object, registration and further assignments. G. Huang et al. [10] studied Convolutional networks that have been discovered to have shorter connections. Merging layers near the input and those close to the output leads to deeper, extra accurate, and more efficient training. This research tightly compacted Convolutional Network is a feed-forward network connecting each layer to the next. Four highly competitive object recognition experiments were used to evaluate the architecture, such as CIFAR-10, CIFAR-100, SVHN, and ImageNet. Oo, YM et al. [11] utilized advanced image processing techniques to identify and order the leaf plant disease. The plant's leaves determine the type of disease that infects the crops. Agriculturists can analyze the leaf plant infection and make early decisions. Advanced image processing might be a good, consistent, and precise method for leaf disease detection. It looks at how image processing can identify and categorize various leaf diseases to assist agriculturists in agriculture.

Beyene et al. [12-13] used ML and image processing techniques to discuss mechanisms for the initial detection of plant leaf diseases in the agricultural field for product safety, both quantitatively and qualitatively. As a result, various ML practices were used in this survey, including Artificial Neural Networks (ANN), CNN, Support Vector Machines (SVM), K-nearest Neighbor (KNN) and others. Eghbali and Hajihosseini [14] proposed a model of a large and deep complex neural network that has been trained to classify ImageNet LSVRC-2010 contains 1.2 million high-resolution photos for 1,000 distinct categories. According to experimental data, the highest TOP 1 and 5 error rates have been 37.5 percent and 17.0 percent, respectively. Also, 60 million constraints, 650 thousand neurons, five CL, and three fully connected layers make up the neural network in question. W A Ezat1 et al. [15] projected an algorithm for Multi-class Image classification with a 90.9 percent average accuracy. A pre-trained CNN model stands used to order images from the data. The deep learning CNN model's performance is improved using the transfer learning approach, which performs reasonably with less computation time. The attained results are related to the test results obtained for the local image descriptors super-vector coding, SVM.

Maeda-Gutierrez, V. et al. [16] proposed that different CNN architectures were compared to classify tomato plant diseases. Here results show the necessary value obtained using the GoogleNet technique, an AUC of 99.72 percent and a sensitivity of 99.12 percent. It is reasonable to conclude that protecting tomatoes from the diseases mentioned due to their high success rate. Shao et al. [17] rebuilt three aspects of the model from UAV images to integrate the finding result of the similar target to avoid counting multiple times in images. Using optimal input resolution with F-Measure 0.952 improves detection performance, and cattle movement is relatively stationary compared to UAV movement. Two modules make up the proposed strategy by Karlekar, A. and Seal, A. [29]. The first module subtracts the complex background from the entire image to extract the leaf part. The other introduces Soy Net, a disease recognition in soybean plants using segmented leaf images. The experiment is carried out on a 16-category "Image Database of Plant Disease Symptoms." The anticipated model achieved a 98.14 percent identification accuracy. The Three state-of-the-art approaches based on hand-crafted features and six widely used deep learning CNN models, including VGG19, GoogleLeNet, Dense121, XceptionNet, LeNet, and ResNet50, are also compared. According to the findings, the proposed method outperforms other current methods/models.

Agarwal et al. [19] proposed for illness identification and categorization, a neural network-based technique is utilized. Two fully connected layers track three CL and three pooling layers in this model. The results determine the anticipated model's superiority over pre-trained models. The classification accuracy varies from 76% to 100% based on many classes, and the proposed model's accuracy is 91.2 percent. Liu, J. et al. [20] proposed an Efficient Net-based method for fine-tuning model parameters that can improve network recognition accuracy. In the test dataset, the test verification was carried out using VGG16, Inceptionv3, and Resnet50, respectively, to confirm the robustness and accuracy of the system. The result illustrates that the proposed model's training speed was meaningfully upgraded, and its acknowledgement accuracy is far superior to supplementary networks with an extreme acknowledgement accuracy of 98.52 percent. Agrawal [21-22] in this Plant disease detection necessitates significant effort, knowledge, and processing time. The cucurbitaceous family includes the most widely used and edible vegetables on the planet. Inside the food industry, the plants in just this family have great economic importance and thus are usually produced. This family contains 965 species. The returns from such a field will be drastically reduced if these plants contract a disease. As a result, the key to avoiding such losses is to treat them early on. As a result, plant diseases can be detected using DL Model like CNN. Because the plants' leaves are so large, they'd be seen as the main source for disease detection because the disease would be more recognizable on the leaves.

Hassan et al. [23] employed the models that were accomplished on the dataset that comprised fourteen species of plants, 38 definite classes of disease, and healthy leaves. Different restrictions, such as batch size, dropout, and the varying number of epochs, were used to evaluate the model's performance. Inception-V3, InceptionResNet-V2, MobileNet-V2, and EfficientNetB0 were used to attain accuracy rates of 98.4 percent, 99.1 percent, 97.0 percent, and 99.5 per cent percent, respectively. Furthermore, MobileNetV2 architecture is well-suited to mobile devices using the optimized parameter. The deep CNN model performed other models in terms of disease detection accuracy. Tripathy, S. [24] gives the accurate finding of disease signs in various plants using image processing techniques is a major concern. This result aims to develop a framework for plant disease diagnosis based on cotton plant leaves. Cotton leaves are photographed digitally and subjected to various image processing techniques. The region of interest (ROI) is removed from the enhanced images using threshold-based segmentation techniques. As a result, diseases are detected using a precise set of visual texture features in the region of interest. Finally, cure actions are taken to monitor the illness discovered in the plants. This research will assist the farmer's society in taking real disease-prevention measures.

Ramacharan [28] designed a method that can automatically detect diseases. Cotton leaf disease detection is critical in preventing a serious outbreak as soon as the disease is recognized. This research determines to distribute plans for the growth of a yarn leaf disease recognition application. To use this, the user must first upload an image of a cotton leaf and then use image processing to obtain a digitized leaf, which can then be further processed. Harakannanavar et al. [26] focused on the border of a leaf, which is extracted via contour tracing samples. To cite the informative structures of the leaf samples, multiple descriptors. Finally, the extracted features are classified with SVM and K-Nearest Neighbor (K-NN) ML techniques. The approaches listed above have low precision. In this project, a DL-based architecture is suggested for detecting and classifying plant leaf disease to improve further. This technique concentrates on categorizing the several diseases of plant leaves through learning both local and global features to increase the accuracy of detecting diseases. LNet architecture is used to identify plant leaf disease.

Many models based on CNN algorithm and architecture are used for detecting and classifying Images. But they are all not more accurate and efficient. The LNet architecture is built based on Xception architecture, which makes our model more accurate and Efficient.

3. Comparing the Existing Model

3.1. RESNET-50

There is one major difference between the Resnet50 architecture and the other model; due to apprehension of the time essential to train the layers, the constructing block was modified into a bottleneck strategy in this case. It used a three-layer stack in place of the earlier two layers. As a result, each of Resnet 34's 2-layer blocks was replaced with a 3-layer bottleneck block, resulting in the Resnet 50 architecture. The accuracy of the 34-layer ResNet model is 94.58 percent. The 50-layer ResNet achieves 3.8 billion FLOPS of performance.

3.2. INCEPTION V3

To reduce computational costs, convolutional neural networks (CNNs) are enhanced with Inception V3 Modules. A neural network should be designed fitly. As a result, it deals with an outsized range of pictures with a large variety of featured image content, additionally referred to as the salient components. Convolution is performed on Associate in Nursing input with not one; however, 3 different sizes of filters within the most elementary version of Associate in Nursing beginning V3 module (1x1, 3x3, 5x5), most pooling is additionally done. The outputs are concatenated and sent to the subsequent layer. The network gets wider, not deeper, by constantly structuring the CNN to perform its convolutions. The neural network may be designed to feature an additional 1x1 convolution before the 3x3 and 5x5 layers to create the method even less computationally big-ticket. The amount of input channels is restricted, and 1x1 convolutions are much less costly than 5x5 convolutions. This model achieves an accuracy of 92.02%.

3.3. XCEPTION

Xception could be a depth-wise divisible Convolutions-based deep CNN created by Google scientists. Beginning V3 modules in CNNs were understood by Google as associate degrees in-between consistent convolution and the depth-wise divisible convolution action. In this sense, a depth-wise divisible convolution is considered to associate degree beginning V3 module with the foremost towers doable. This surveillance leads them to suggest a replacement deep CNN-supported beginning, with depth-wise divisible convolutions rather than beginning V3 modules. This model achieves an accuracy of 96.34%.

4. Problem Statement

In the agricultural industry all over the world, plant diseases create important production and economic losses. Plant health monitoring and disease detection are essential for long-term agriculture. Apple Scab, Cherry Powdery Mildew, Grape Black Rot, and Tomato Leaf Mold are the most common diseases that affect plant leaves. When diseases are detected by looking at the plant with the naked eye, the results are inaccurate. It leads to improper pesticide application, which bases harmful chronic diseases in humans because of bio magnification and a reduction in yield quality and quantity. As a result, detecting plant leaf diseases is critical for protecting high-quality and high-yield crops. There is currently no commercially available sensor for assessing the health of leaves in real-time. Scouting, an expensive, labour-intensive, and time-consuming process, is currently the most widely used mechanism for monitoring stress in leaves. This project aims to develop and test a framework for detecting plant leaf diseases. According to studies, relying solely on expert observation with the naked eye to detect such diseases can be prohibitively expensive, particularly in developing countries.

5. Proposed Method-LEAF NETWORK (LNet)

The proposed system usually represents the image's pixel matrix in a neural network for image processing. From each pixel, the mean RGB value is subtracted. The plant leaf dataset contains 14 different classes. The dataset split consists of Training with 78%, Validation with 20% and Testing with 2%. The proposed Leaf Network (LNet) model contains layers including seven convolutional layers, three maximum pooling layers, and fully connected layers in this study. It classifies the images as different leaf diseases. After training and validating the model, the input test image is given. The output is predicted with the disease name of the particular plant. The Leaf Network (LNet) appears to be the most promising for detecting and classifying plant leaf disease.

The preprocessing expands image data by removing adverse imbalances or magnifying some significant image features for succeeding analysis and computing. So we used preprocessing images to enhance image features. It includes, but is not limited to, resizing, orienting, and colour corrections. Here data of the images are converted into a form that allows ML algorithms to solve it. Preprocessing of images includes the following steps: Examine the image files, Translate the JPEG information into RGB pixel matrices with channels, Convert these to floating-point tensors for neural network input and Rescale the pixel values to the [0, 1] interval (between 0 and 255).

The demonstration of the effectiveness of this method is based on Xception. The existing architecture of Xception is the basis for the newly designed convolutional network of LNet. All the layers of LNet are shown below in Fig 1 and Fig. 2. Each CNN layer has several filters, such as 32, 64, 128, 256, 512, etc., which is equivalent to the total number of channels in the output of a CL. Max pooling is a pooling operation that picks up the greatest element from the area of pixel values of the feature map enclosed by the filter. Then need to classify the data into various classes after feature extraction. It can be done using a fully connected neural network. In addition to a fully connected layer, the final layer uses the softmax activation function to obtain probabilities of an input being in a specific class. The input layer contains all of CNN's data. It usually represents the image's pixel matrix in a neural network for image processing. Deepness, width, and resolution are categorized into three types of scaling dimensions of a CNN.

In a network, the depth is equal to the number of layers. The width of the network is referred to as its size. In a CL, the width measurement is many layers, while a resolution is referred to as image firmness passed to a CNN. For our model called LNet, this research used Xception architecture as the base functional model. It can use a few layers in the LNet and Replace them with a few other layers for classification. The final layers of our model are Flatten layer with 512 neurons, the dense layer with 1024 neurons, the Dropout layer with 1024 neurons s and the dense layer with 14 neurons.

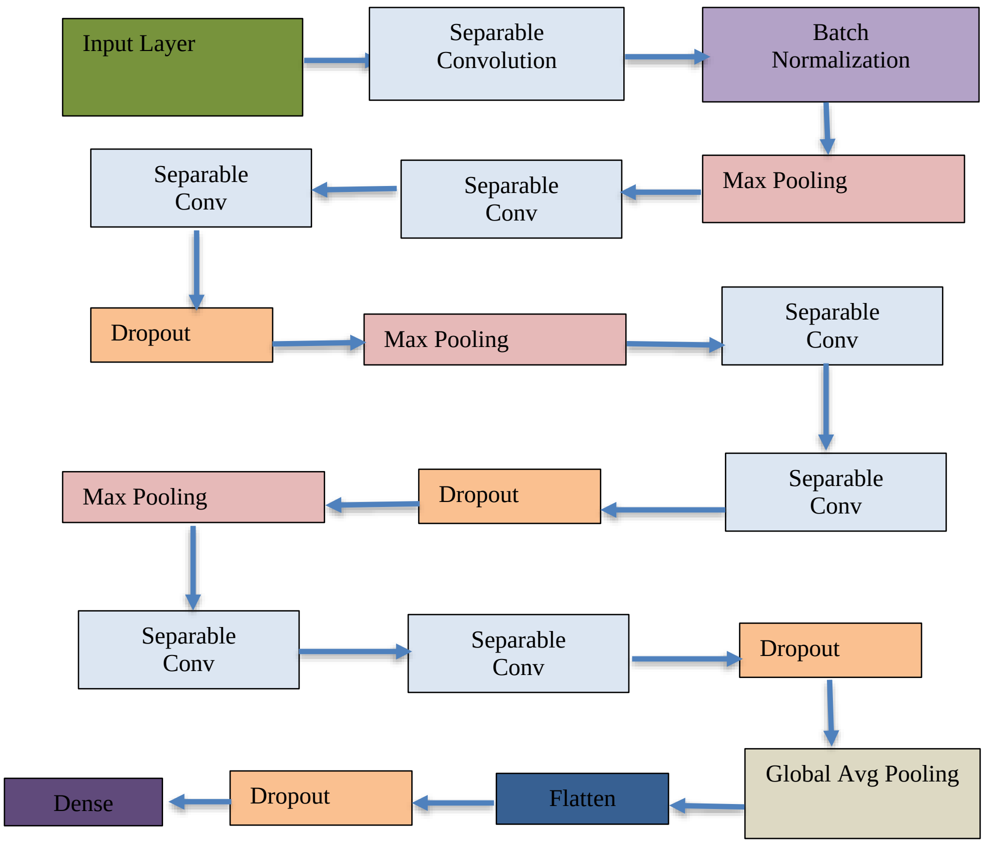


Fig. 1 LNet Architecture

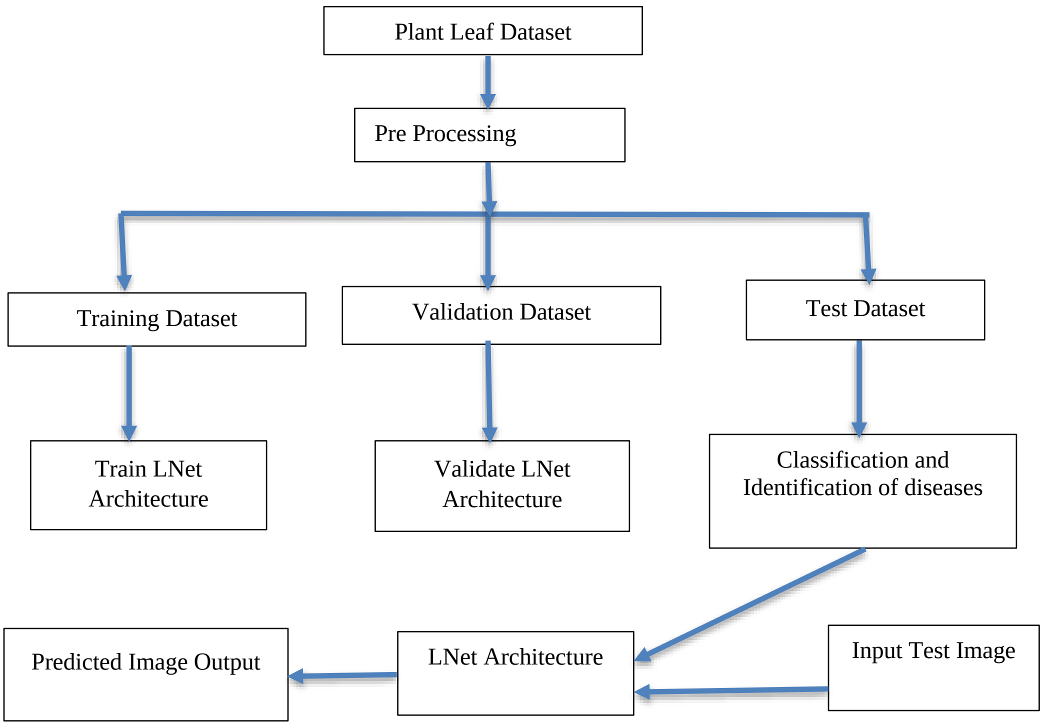
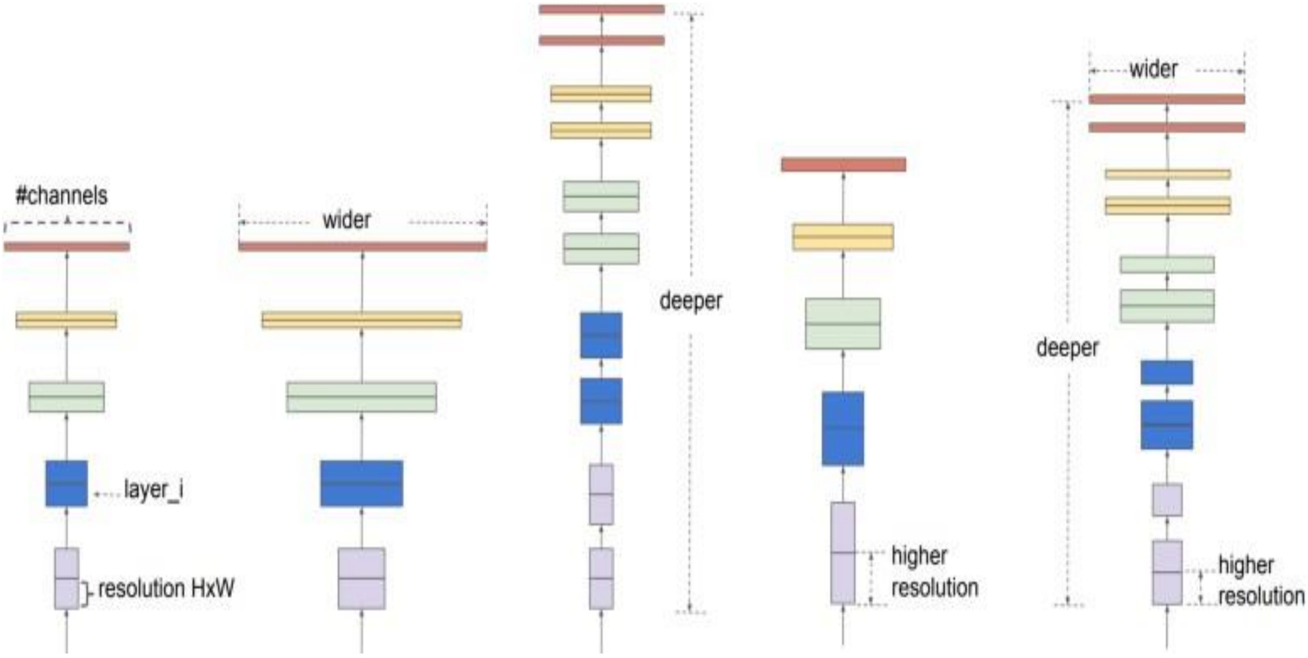


Fig. 2 Flow of the Proposed Leaf Network

5.1. Proposed CNN

The input layer is where the entire CNN gets its information. It usually represents the image's pixel matrix in a neural network for image processing.

Rescaling: The three scaling dimensions of a CNN are its depth, width, and resolution. The network's depth, equivalent to its total of layers, is simply called depth. The term "width" merely refers to the size of the network. One width measure is the number of straits in a CL, even though resolution merely refers to the image resolution passed to a CNN. The comparison of the scaling method is given in Fig. 3.



1)baseline 2)width 3)depth 4)resolution 5)compound

Fig 3. Comparison of Scaling Methods.

5.1.1. Normalization

Batch normalization means a network layer which enables every layer to understand more independently from the others. It's being used to brand the earlier layers' output more normal. The activations in the normalization scale are the input layer. When batch normalization is used, learning becomes more efficient and can also be used as a regularisation to avoid overfitting the method. The layer is applied to the linked list to standardize the inputs or outputs. They are used in a variety of locations between the node's layers.

5.1.2. Separable Conv2D

The separable convolution deals with the image of width and height. Simply put, a separable spatial convolution divides a kernel into two smaller kernels. Many filters make up each convolution layer. In practice, it was a quantity such as 32, 64, 128, 256, 512, etc. It relates to the number of streams in the output of a CL.

5.1.3. Max Pooling

Max pooling is a type of pooling which selects the highest component from the area of an attribute space protected by the filter. As a result, the max-pooling layer's output will be a feature map that includes the significant characteristics from earlier.

5.1.4. Global Average Pooling

Global Average Pooling is a technique that replaces fully connected layers in outmoded CNNs. The goal is to build one feature map for each classification task's categories in the last layer.

5.1.5. Activation

The perceptron is just a node in a Neural Network located at the end or even in the middle. They play a role in determining whether or not a neuron will fire. This research used the ReLU activation and Softmax functions in this example.

5.2. Training the model

For our model called LNet, we use Xception architecture as the base functional model. Few layers are used in the LNet and Replaced with a few other layers for classification. The final layers of our model are Flatten layer with 512 neurons, the dense layer with 1024 neurons, the Dropout layer with 1024 neurons and the dense layer with 14 neurons. Table1 and Table 2 show the model's layers and quantity of parameters.

Table 1. Layers of the model

Layers	Dimension	Parameters
Separable Conv2d	218 x 218 x 32	155
Batch Normalization	218 x 218 x 32	128
Max Pooling	109 x 109 x 32	
Separable Conv2d	107 x 107 x 64	2400
Separable Conv2d	105 x 105 x 128	8896
Dropout	105 x 105 x 128	
Max Pooling	52 x 52 x 128	
Dropout	48 x 48 x 256	
Max Pooling	24 x 24 x 256	
Separable Conv2d	22 x 22 x 256	68096
Separable Conv2d	20 x 20 x 512	133888
Dropout	20 x 20 x 512	
Global Average Pooling	512	
Flatten	512	
Dense	1024	525312
Dropout	1024	
Dense	14	14350
	Total params:	**805,065**
	Trainable params:	**805,001**
	Non-trainable params:	**64**

Table 2. Number of parameters in the model

Layers	Dimension	Parameters
Separable Conv2d	50 x 50 x 128	17664
Separable Conv2d	48 x 48 x 256	34176

5.3. Classify the images

The softmax function is a multi-dimensional comprehensive form of the logistic function, also known as softargmax and normalized exponential function. It can be used in regression models and is frequently used with the last original signal of such a neural network to standardize the network's outcome to something like a probability distribution placed above-predicted output classes, relying on Luce's choice axiom. The softmax function takes a coordinates z of K actual values as input. It converts it to a likelihood function to K probabilities comparative to the exponentials of the input numbers. It is the before actually softmax, some few vector elements could be negative as well as higher than just one, so they possibly not add up to just one; nevertheless, after softmax, every element are the period [0,1], and the elements will add up with 1, enabling them just to be viewed as probabilities. Furthermore, higher probabilities will result from input data components.

$$\sigma(\vec{z})^{i} = \frac{\sum_{j=1}^{K} e^{zj}}{e^{zi}} \qquad (1)$$

σ = softmax

$\vec{z}$ = input vector

e^{zi} = standard exponential function for an input vector

K = number of classes in the multi-class classifier

e^{zj} = standard exponential function for output vector

6. Result and Analysis

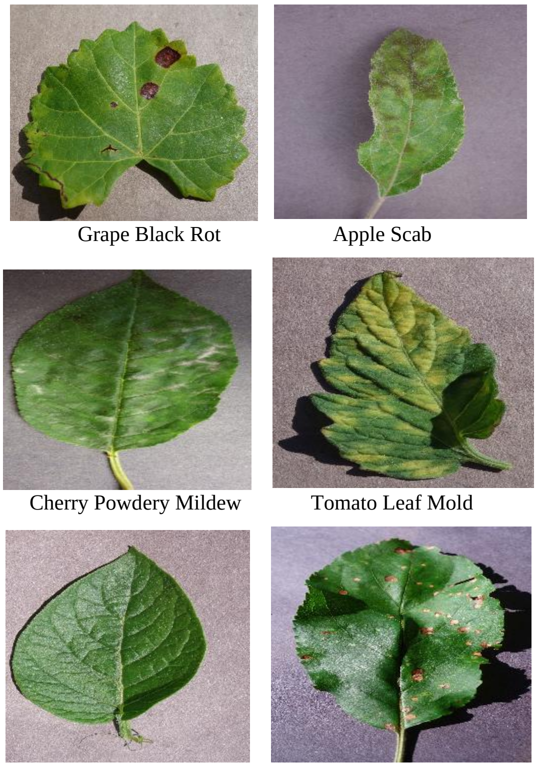
Leaf Network (LNet), though, has greater accuracy and gives better prediction results most suitable for the plant leaf dataset.

6.1. Dataset Description

An appropriate dataset was obtained from the plant leaf disease dataset originally hosted at Kaggle. 12854 images are included in the dataset and are all coloured images. Images are divided into 14 different categories, namely, Apple black rot, Apple scab, Apple Cedar apple rust, Apple healthy, Cherry healthy Grape Black Rot, Cherry Powdery mildew, Grape healthy, Grape Esca (Black Measles), Grape Leaf Blight, Potato Early Blight, Potato healthy, Tomato Leaf Mold, Tomato healthy. The parameter of batch_size= 32 and epochs= 15 are used in this research. Figure 5.2 represents the sample images of the six different types of leaf disease

Table 3. Dataset description

Class	No. of train images	No. of validation images	No. Of test images
Apple Scab	504	126	11
Apple Black Rot	496	125	10
Apple Cedar Apple Rust	220	55	11
Apple Healthy	1316	329	10
Cherry Powdery Mildew	841	211	10
Cherry Healthy	683	171	11
Grape Black Rot	944	236	10
Grape Esca (Black Measles)	974	277	10
Grape Leaf Blight (Isariopsis Leaf spot)	860	216	11
Grape Healthy	338	85	10
Potato Early Blight	800	200	12
Potato Healthy	121	31	12
Tomato Leaf Mold	761	191	12
Tomato Healthy	1272	319	12



Grape Black Rot   Apple Scab

Cherry Powdery Mildew   Tomato Leaf Mold

Potato Healthy   Apple Black Rot

Fig. 4 Dataset Sample Images

6.2. Experiment result discussion

The proposed method can identify and classify Plant Leaf Disease based on features in the feature extractor of CNN. To enhance the precision and efficiency of the Plant Leaf Disease detection and grouping system, we use LNet, Xception, ResNet and Inception V3 Algorithms. This algorithm is utilized in large-scale leaf disease detection. Compared to all the architectures, Leaf Network (LNet) gives higher accuracy of 98.68 % with a loss function value of 0.0320. The accuracy in Plant Leaf Disease Detection and Classification is shown below in Table 4, and the Comparison graph for all models with accuracy and loss function is below in fig.5.

Table 4. Accuracy of LNet compared with different architectures

S.No	Architectures	Accuracy (in percentage)	Epochs
1	LNet (Proposed System)	98.68	15
2	Xception	96.34	15
3	ResNet-50	94.58	15
4	Inception V3	92.02	15

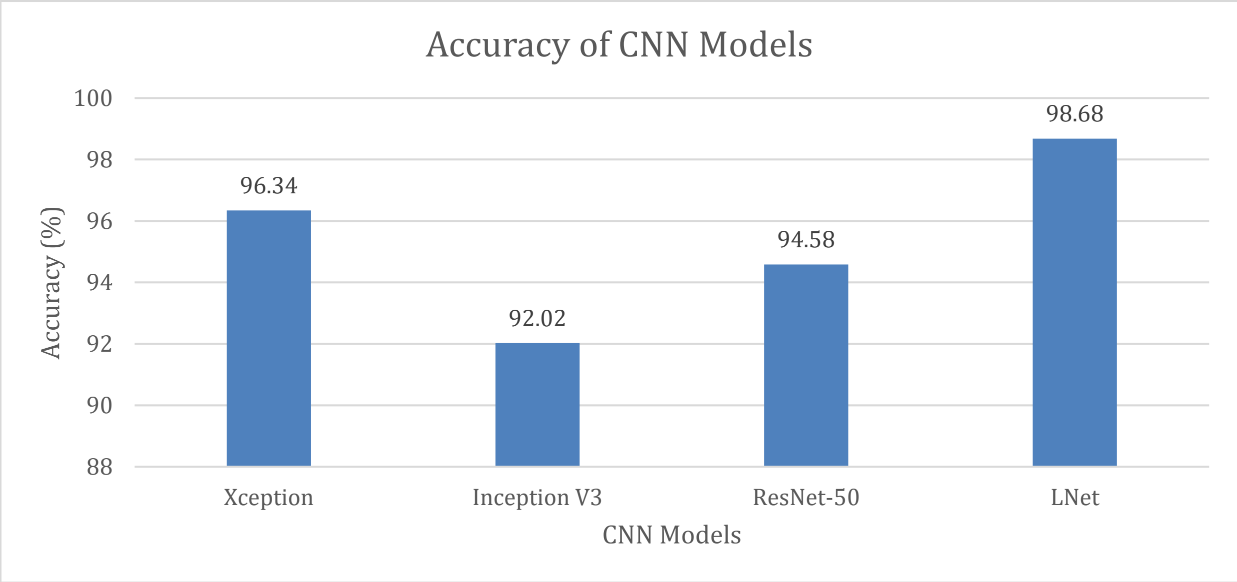


Fig. 5 LNet Accuracy graph compares with different architectures

Table 5 and Fig.6 show the loss function value compared with different architectures. LNet shows 0.0320. Xception, ResNet-50, Inception V3 contains 0.1066, 1.1376 and 0.5003 respectively. Hence proposed LNet architecture produces a very low error. Fig.7 shows the confusion matrix of the LNet Model.

Table 5. Loss Function Value of proposed LNet compared with different architectures

S.no	Architectures	Loss Function Value	Epochs
1	LNET	0.0320	15
2	Xception	0.1066	15
3	ResNet-50	1.1376	15
4	Inception V3	0.5003	15

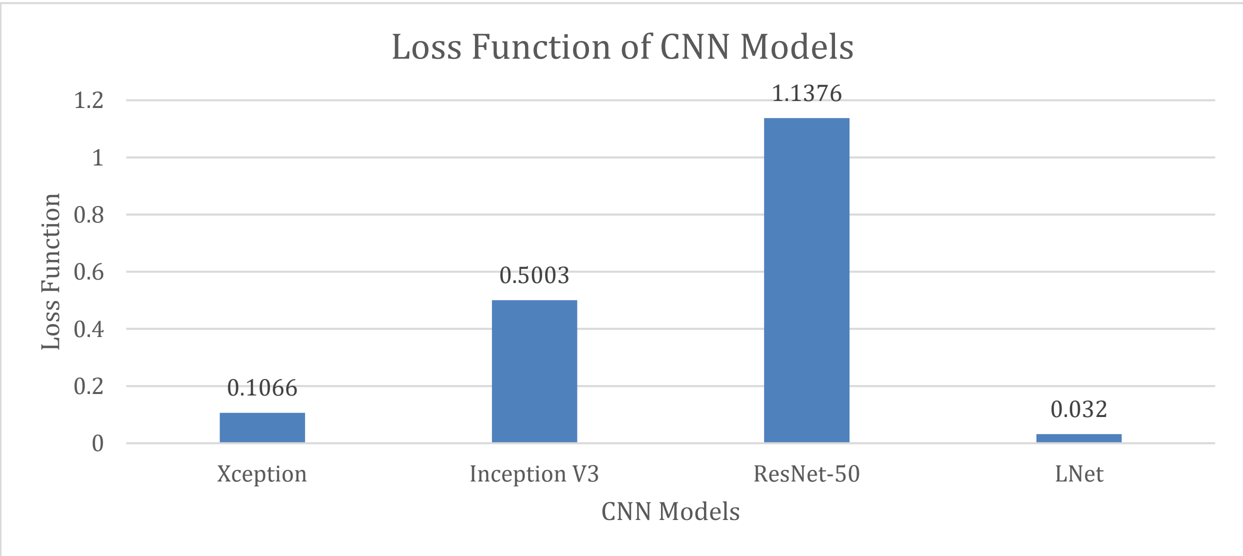


Fig. 6 LNet Error value graph compared with different architectures

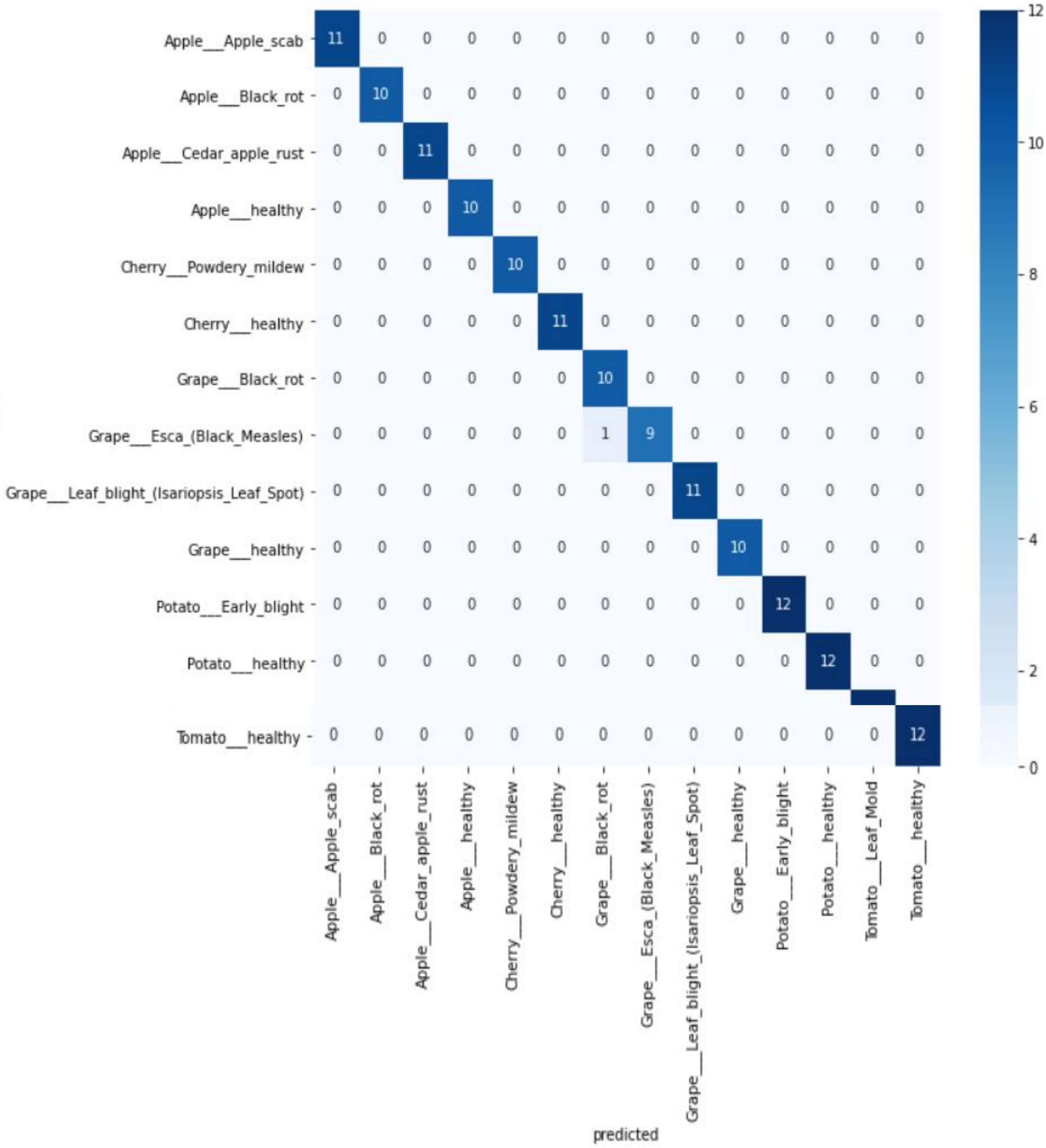


Fig. 7 Confusion Matrix Of LNet

Fig.8 represents the Result of Loss Values and Accuracy Using LNet Architecture with epoch. During LNet training, the accuracy of the training and validation datasets increases quickly from the 1st to 3rd epochs, increases further from the 4th to 15th epochs and ultimately approaches the Model accuracy graph's threshold point at the 15th epoch. During LNet training, the loss values of the training and validation datasets slowly decline from the 1st to 4th epochs, progressively decrease from the 5th to 15th epochs and finally approach the threshold point at the 15th epoch in the Model Loss Function graph.

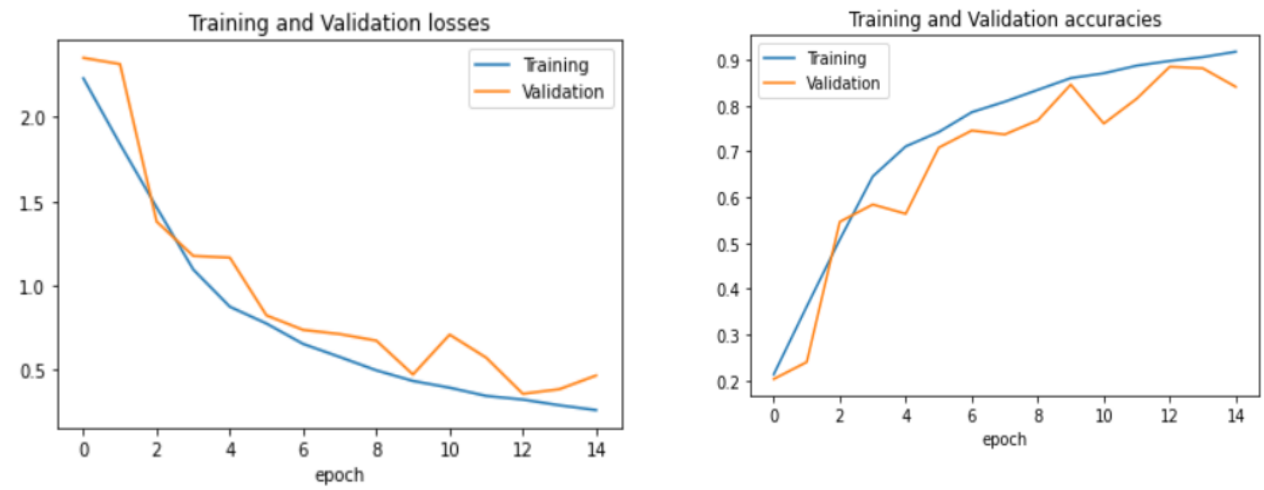


Fig. 8 Result of Loss Values and Accuracy Using LNet Architecture with epoch.

7. Conclusion and Future direction

Finally, the Plant leaf Diseases are detected, and the execution of the projected system is measured by accuracy, which is comparatively better than the current system. However, it should be noted that it is not a real-time project. This system has increased the accuracy of plant leaf disease detection, and the performance of the classifying system is faster by using the LNet algorithm. The proposed method considers all the grid cells of the frame to detect multiple objects in each frame, improving the accuracy of disease detection and classification. It just detects apples, potatoes, grapes, tomatoes and cherries. This system can be trained and enhanced to detect and classify other Plant diseases. It needs a large dataset. The system's accuracy decreases in certain situations, like when the background for each image Changes; as of now, there is a common background for all. In future work, its performance can be improved by addressing it. It may be extended for vegetables and field crops in future.

References

[1] Krizhevsky, A., IlyaSutskever, and Geoffrey E. Hinton.(2012) " Imagenet classification with deep convolutional neural networks." *In Advances in neural information processing systems*, Vol. pp.1097-1105.

[2] He, K., Zhang, X., Ren, S. and Sun, J. (2015). Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(9), pp.1904–1916. doi:10.1109/tpami.2015.2389824.

[3] Dosovitskiy, A., Fischer, P., Springenberg, J.T., Riedmiller, M. and Brox, T. (2016). Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38(9), pp.1734–1747. doi:10.1109/tpami.2015.2496141.

[4] Hu, M., Bu, X., Sun, X., Yu, Z. and Zheng, Y. (2017). Rape Plant Disease Recognition Method of Multi-Feature Fusion Based on D-S Evidence Theory. *Mathematical and Computational Applications*, 22(1), p.18. doi:10.3390/mca22010018.

[5] Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M. and Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), pp.115–118. doi:10.1038/nature21056.

[6] Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., van der Laak, J.A.W.M., van Ginneken, B. and Sánchez, C.I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, [online] 42, pp.60–88. doi:10.1016/j.media.2017.07.005.

[7] Alehegn E (2017), Maise leaf diseases recognition and classification based on imaging and machine learning techniques, *International Journal Innovative Research in Computation and Communication Engineering*, 5(12):1–11.

[8] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger (2017). DA-U-Net: Densely Connected Convolutional Networks and Decoder with Attention Gate for Retinal Vessel Segmentation. *IOP Conference Series: Materials Science and Engineering*, 533, p.012053. doi:10.1088/1757-899x/533/1/012053.

[9] Zhang, X., Wang, S., Liu, J. and Tao, C. (2018). Towards improving diagnosis of skin diseases by combining deep neural network and human knowledge. *BMC Medical Informatics and Decision Making*, 18(S2). doi:10.1186/s12911-018-0631-9.

[10] Oo, YM and Htun, NC (2018). Plant Leaf Disease Detection and Classification using Image Processing. *International Journal of Research and Engineering*, 5(9), pp.516–523. doi:10.21276/ijre.2018.5.9.4.

[11] Beyene, H., Joshi, D.N.A. And Kotecha, DK (2018). Plant Diseases Prediction Using Image Processing And Machine Learning Techniques: Survey. *International Journal Of Computer Application*, 1(8). doi:10.26808/rs.ca.i8v1.23.

[12] Zhang, Z., Liu, H., Meng, Z. and Chen, J., (2019). "Deep learning-based automatic recognition network of agricultural machinery images". *Computers and Electronics in Agriculture*, Vol. 166, p.104978.

[13] Beyene, H. and A.Joshi, N. (2019). Classification of Healthy and Diseased Cactus plants using SVM. *International Journal of Computer Sciences and Engineering*, 7(5), pp.1412–1426. doi:10.26438/ijcse/v7i5.14121426.

[14] Eghbali, H. and Hajihosseini, N. (2019). Deep Convolutional Neural Network (CNN) for Large-Scale Images Classification. *SSRN Electronic Journal*. doi:10.2139/ssrn.3476258.

[15] Ezat, W.A., Dessouky, M.M. and Ismail, N.A. (2020). Multi-class Image Classification Using Deep Learning Algorithm. *Journal of Physics: Conference Series*, 1447, p.012021. doi:10.1088/1742-6596/1447/1/012021.

[16] Maeda-Gutiérrez, V., Galván-Tejada, C.E., Zanella-Calzada, L.A., Celaya-Padilla, J.M., Galván-Tejada, J.I., Gamboa-Rosales, H., Luna-García, H., Magallanes-Quintanar, R., Guerrero Méndez, C.A. and Olvera-Olvera, C.A. (2020). Comparison of Convolutional Neural Network Architectures for Classification of Tomato Plant Diseases. *Applied Sciences*, [online] 10(4), p.1245. doi:10.3390/app10041245.

[17] Shao, W., Kawakami, R., Yoshihashi, R., You, S., Kawase, H. and Naemura, T.,(2020) "Cattle detection and counting in UAV images based on convolutional neural networks". *International Journal of Remote Sensing*, Vol.41(1), pp.31-52.

[18] R. Surendiran, R. Aarthi, M. Thangamani, S. Sugavanam, R. Sarumathy, " A Systematic Review using Machine Learning Algorithms for Predicting Preterm Birth," *International Journal of Engineering Trends and Technology*, vol. 70, no. 5, pp.46-59, 2022. https://doi.org/10.14445/22315381/IJETT-V70I5P207.

[19] Agarwal, M., Singh, A., Arjaria, S., Sinha, A. and Gupta, S. (2020). ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network. *Procedia Computer Science*, 167, pp.293–301. doi:10.1016/j.procs.2020.03.225.

[20] Liu, J., Wang, M., Bao, L. and Li, X. (2020). EfficientNet based recognition of maize diseases by leaf image classification. *Journal of Physics: Conference Series*, 1693, p.012148. doi:10.1088/1742-6596/1693/1/012148.

[21] Liu, X., Min, W., Mei, S., Wang, L. and Jiang, S.,(2021)" Plant Disease Recognition: A Large-Scale Benchmark Dataset and a Visual Region and Loss Reweighting Approach" *IEEE Transactions on Image Processing*,Vol. 30, pp.2003-2015.

[22] Tripathy, S. (2021). Detection of Cotton Leaf Disease Using Image Processing Techniques. *Journal of Physics: Conference Series*, 2062(1), p.012009. doi:10.1088/1742-6596/2062/1/012009.

[23] Agrawal, I., Hegde, P., Shetty, P. and Shingane, P. (2021). LEAF DISEASE DETECTION OF CUCURBITS USING CNN. *ITM Web of Conferences*, 40, p.03043. doi:10.1051/itmconf/20214003043.

[24] Hassan, S.M., Maji, A.K., Jasiński, M., Leonowicz, Z. and Jasińska, E. (2021). Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach. *Electronics*, 10(12), p.1388. doi:10.3390/electronics10121388.

[25] R. Surendiran, K. Duraisamy, "An Approach in Semantic Web Information Retrieval," *SSRG International Journal of Electronics and Communication Engineering*, vol. 1, no. 1, pp.17-21, 2014. https://doi.org/10.14445/23488549/IJECE-V1I1P105.

[26] Harakannanavar, S.S., Rudagi, J.M., Puranikmath, V.I., Siddiqua, A. and Pramodhini, R. (2022). Plant Leaf Disease Detection using Computer Vision and Machine Learning Algorithms. *Global Transitions Proceedings*. doi:10.1016/j.gltp.2022.03.016.

[27] R. Surendiran, "Similarity Matrix Approach in Web Clustering". Journal of Applied Science and Computations, vol. 5, no. 1, pp.267-272, 2018.

[28] Ramacharan, Dr.S. (2021). A 3-Stage Method for Disease Detection of Cotton Plant Leaf using Deep Learning CNN Algorithm. *International Journal for Research in Applied Science and Engineering Technology*, 9(VII), pp.2503–2510. doi:10.22214/ijraset.2021.36913.

[29] Karlekar, A. and Seal, A. (2020). SoyNet: Soybean leaf diseases classification. *Computers and Electronics in Agriculture*, 172, p.105342.

[30] R. Surendiran, K.Alagarsamy, "Skin Detection Based Cryptography in Steganography (SDBCS)," *International Journal of Computer Science and Information Technologies*, vol. 1, no. 4, pp.221-225, 2010.