IEC
Institute of Electronics
and Computer

Journal of Artificial Intelligence and Systems, 2022, 4, 1-21
https://iecscience.org/journals/AIS
ISSN Online: 2642-2859

An Overview of Deep Learning Models for Foliar Disease Detection in Maize Crop

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How to cite this paper: Jagrati Paliwal, Sunil Joshi (2022). An Overview of Deep Learning Models for Foliar Disease Detection in Maize Crop. Journal of Artificial Intelligence and Systems, 4, 1–21. https://doi.org/10.33969/AIS.2022040101.

Received: July 19, 2022
Accepted: October 4, 2022
Published: October 12, 2022

Abstract

Agriculture is an important sector of Indian economy and India is among the top three global producers of agricultural products. Protecting the crops and producing healthy yields is a prime goal of the agriculture industries. The agricultural crops are susceptible to diseases and demands proactive early diagnosis and treatment. Studies and research are in progress to find smart methods and techniques for accurate diagnosis of crop diseases to prevent major yield losses and financial losses. The present study outlines the role of deep learning in the crop disease detection and discusses the future advancements in maize disease detection. The paper focuses on the role of deep learning in identification of diseases on maize plant leaf and describes about some common maize diseases and its classification methods. The paper shall help readers to gain insight on deep learning techniques to solve classification problems and encourage them to proceed for future work in the concerned domain.

Keywords

Agriculture, Deep Learning, Maize, CNN

1. Introduction

Plant disease is a global threat to agricultural products and serves as source to economic losses as well [1]. Disease in plants is mostly caused by fungi and bacterial infestation. The diseases primarily affects leaf area and the diseased leaf starts developing symptoms in form of leaf spots, leaf blight, rusts etc [2]. The diseases producing noticeable symptoms on leaf belongs to foliar group of diseases. All such diseases may vary in texture, size, color, shape etc depending upon the type of disease. Plant diseases are a common factor hampering the plant growth and its productivity. Continuous plant health check is a prime factor of concern in agriculture. Many smart farming solutions have been developed to monitor plant conditions using IOT based sensors, microcontrollers etc [3]. Such solutions are capable in monitoring plant maturity levels, but also require technology advancement to further diagnose diseases present in them. Lack of proper monitoring causes serious effects on plants, due to which respective product quality and productivity is affected [4]. This marks an important action to detect plant disease at an early stage and take timely actions. If diseases are detected timely, an appropriate remedial action can be taken and major crop yield loss can be prevented. Manual identification of diseases in plants is a time consuming process and demands dependency on pathological knowledge and expertise. Farmers with less experience and knowledge face challenges in diagnosing plant diseases accurately. Such problems put forward the need of advanced and automated plant disease detection systems. In present times, image processing and machine learning techniques are being used to solve classification problems and to develop disease detection systems having very good accuracy rate. Deep learning techniques are special class of machine learning which has shown very high performance in field of image classification [5]. Convolution Neural Network (CNN) has become the trendiest deep learning technique to identify plant disease detection. There exist many neural network models such as AlexNet, GoogleNet, ResNet50, DenseNet, VggNet, Inception-V2 etc which can be used for feature extraction disease classification in plants. Deep learning techniques are more powerful in scanning large amount of data; develop learning and performing correlation to give faster classification results than the existing techniques. Therefore, using deep learning could help making disease detection process more easy and advanced [6]. The study aims to explore how advanced approaches can be helpful in identifying plant diseases and solve classification problems efficiently.

2. Foliar Diseases

Foliar disease is used to term the class of diseases that affects leaves of plants. Such diseases are generally caused by fungal organisms and impacts leaf texture, color and other leaf characteristics [7]. A foliar disease also affects photosynthesis activity in plant and is responsible for the visible symptoms like spots and lesions on leaf [8]. The most common foliar diseases of maize crop include Gray Leaf Spot, Northern Leaf Blight, and Common Rust etc. Under moist conditions, spores are produced by fungi that get onto maize leaves through multiple mediums and causes serious damage to the plant. This leads to development of lesions on leaf and produce more spores that spreads to cause infection to leaves [9]. Most common foliar diseases are:

2.1. Northern Leaf Blight

Northern Corn Leaf Blight is one of the most common maize leaf diseases and accounTable for most of the yield losses. Infection due to this disease is serious and it is important to continuously monitor the leaves for any signs of the disease [9]. As shown in fig 1, the diseased area of leaf starts discoloration and long broad brown lesions are observed on leaf surface.

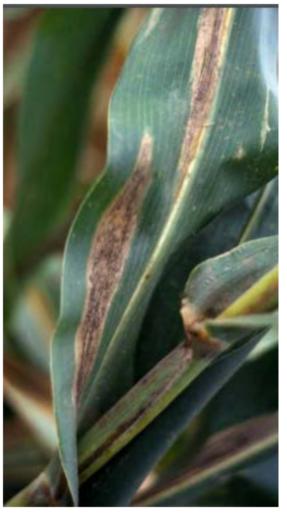

Figure 1 Lesions caused by Northern Leaf Blight [9]

NCLB disease growth can be seen at moderate temperatures (18 - 27 °C), under high humid conditions or heavy dews. The symptoms can be identified by dark-grayish spores present on leaf surface, which are transferred among plants due to rain splashes or wind, causing infection. Once infection has occurred, the pathogen will grow in the plant tissue causing blights. – Lesions of grey-green color are seen developed on leaf surface that adopts a brown color in later stage. These Lesions grow gradually and merge together to form a large area of dead leaf tissue, producing cigar shaped long lesion structures [9].

2.2. Gray Leaf Spot

Gray Leaf Spot disease, also known as cercospora leaf spot, occurs in subtropical, temperate and humid areas. The disease results in small, elongated lesions like the brown-gray necrotic spots. Leaf wetness and cloudy conditions are the main reason for the development of gray leaf spot disease on maize leaves. [10]. As shown in Figure 2, early Symptoms in Gray leaf spot disease comes out as lesions as small necrotic pinpoints with chlorotic halos, being more visible when leaves are backlit. Lesion color ranges from tan to brown before sporulation begins.

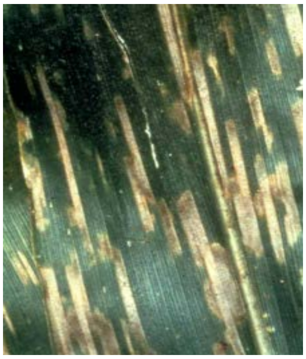

Figure 2 Gray Leaf Spot [10]

Early lesions are ambiguous and have chances to be confused with the other foliar diseases. As the infection grows, lesions become gray in color, and starts developing diverse shape and structure. Gray leaf spot lesions impacts the photosynthesis process of plant leaf, which further reduces carbohydrates allocated towards grain fill. [10].

2.3. Common Rust

The disease is recognized by small, elongate, powdery pustules over both surfaces of the leaves. As shown in Figure 3, during early stage of the infection, pustules are seen dark brown in color which turns black as the plant matures which is the clear sign of epidermis rupture [11].

Figure 3 Common Rust disease on maize leaf [11]

Common rust starts out as small flecks on the leaves, which later turns into small tan spots, further becoming brick-red to cinnamon-brown color pustules. Pustules tend to have an elongated, uneven appearance. Rust diseases are very common and can cause substantial yield losses [11], [9].

3. Review of Plant Disease Detection and Related Work

Liu and Wang (2021) researched over plant disease detection and pest detection methods based on deep learning. The deep learning technique was compared with traditional image processing methods. Deep learning methods reduces the long chain steps into end to end feature extraction providing broad prospects and great potential [12]. Hassan et al. (2021) proposed DCNN models, to analyze leaf structures and identify diseases in them. As the CNN models possess large number of parameters and have higher computation cost, authors chose to replace standard convolution of CNN model with depth separable convolution, which reduces the computation cost and large number of parameters [13]. Atila et al. (2020) proposed EfficientNet deep learning architecture for disease detection in plants and compared the achieved results with the other state of the art deep learning models. The plant village dataset comprising of 55,448 original images and 61,486 augmented images was used to train models. Transfer learning approach was used to train the EfficientNet architecture and other deep learning models, where all layers were set to be trainable. Proposed architecture achieved 99% of accuracy and 98% of precision results [14]. Guo et al. (2020) proposed a recognition model which uses combination of three different types of algorithms i.e. RPN algorithm, CV algorithm, and TL algorithm to solve disease identification problem in complex environment. Images were first segmented and then applied as input to the proposed model architecture. The results showed accuracy of 83.57%, which were better than the traditional used methods [15]. Saleem et al. (2020) in their research attempted the localization and classification of the disease in plant leaves. Three deep learning meta-architectures including the Faster Region-based Convolutional Neural Network (RCNN), Single Shot Multi Box Detector (SSD), and Region-based Fully Convolutional Networks (RFCN) were applied by using the Tensor Flow object detection framework. An improvement in the mean average precision of the proposed deep learning technique was attempted through deep learning optimizers. The highest mean average precision (mAP) of 73.07% was achieved by SSD model trained with Adam optimizer [16]. Bansal and Kumar (2020) presented a detailed review of the deep learning frameworks for maize disease detection. Author discussed about the common maize diseases and their visual symptoms at different stages of plant growth. The research encourages the readers to learn about future research work ideas of the maize disease detection using deep learning [17]. Bedi and Gole (2020) proposed a novel hybrid model based on Convolutional Auto

Encoder (CAE) network and Convolutional Neural Network (CNN) for automatic plant disease detection. In this work, the proposed hybrid model was applied to detect Bacterial Spot disease present in peach plants using their leaf images. Peach Plant images were taken from plant village library dataset. The proposed system achieved training accuracy of 99.35% and testing accuracy 98.38% and used only 9,914 training parameters [18]. Jana et al. (2020) proposed an automated framework model to classify the pepper plant disease. The framework included four major steps i.e. image acquisition pre-processing extraction and classification. The classifier had been designed to classify between a healthy leaf and a diseased pepper leaf using Deep Belief Network [19]. Mounika et al. (2020) presented the paper describing the detection of different types of diseases occurring for the crops and an algorithm which classified the different types of diseases by using the image processing techniques. Image segmentation is one of the image techniques which detects the disease automatically and classify the diseases [20]. Itamar et al. (2019) proposed a new method to segment diseased areas of leaf automatically. The Simple Linear Iterative Clustering (SLIC) algorithm was used to group color pixel with similar features together to form super pixels. Artificial neural networks (ANNs) were trained to classify super pixels as healthy or unhealthy using the color characteristics of super pixel clusters. By contrasting the classifier's automatic segmentations with a manual database, performance was evaluated. The mean error of the area obtained was below 11%, and the average F-score was 0.67, which is higher than existing old techniques [21]. Jiang et al. (2019) proposed a deep learning approach that was based on improved Convolutional Neural Networks (CNNs) for the real-time detection of apple leaf diseases. The dataset for apple leaf disease was prepared by the author using data augmentation and picture annotation techniques. A model for detecting apple leaf disease was put out utilising the GoogLeNet Inception and Rainbow concatenation structures. Experimental results showed that the model had a detection performance of 78.80 percent mAP on the selected dataset and a high-detection speed of 23.13 FPS using 26,377 images of diseased apple leaves [22]. Karol et al. (2019) proposed system which helps in identification of plant disease and provides respective remedial action to treat the detected disease. The input dataset was segregated where different plant species were renamed to form a proper database. Training data was used to train the classifier and then output was predicted with best accuracy. CNN model was used for prediction. A prototype drone model with an attached high resolution camera was also designed to monitor large agricultural fields that could capture images of the plants. The images were further used as an input for the software deciding health status of the plant image [23]. Sladojevic et al. (2016) proposed a new approach where leaf image classification techniques and deep convolutional networks were used together to identify disease in plants. The developed model could recognize 13 different types of plant diseases, with the ability to distinguish plant leaves from their surroundings [24]. Mohanty et al. (2016) used deep learning approach of AlexNet and GoogleNet over plant village data set of healthy and diseased leaf images to perform image based plant disease detection [25].

4. Deep Learning Theory and Architecture

Deep learning is a subset of Machine Learning introduced in 1943 [26]. The technique is based upon Artificial Neural Network (ANN) algorithms, where input data is allowed to progress through multiple layers of network for processing the output results and attempts to learn from large amount of data. Neural Networks are integral part of deep learning models and comprises of three core layers i.e. an Input layer, Hidden layers and an output layer. Architecture of deep learning models depends on the number of hidden layers. The “deep” in deep learning refers to the depth of layers in a neural network. A neural network consisting of more than three layers, including both input and output layers can be considered a deep learning algorithm [27]. As shown in Figure 4, the network comprises of multiple layers of interconnected nodes, having different weight and bias, which works all together to recognize and classify input data. The circles shown in Figure 4 are called nodes of the network each possessing some part of input data, and lines connecting them are called weights.

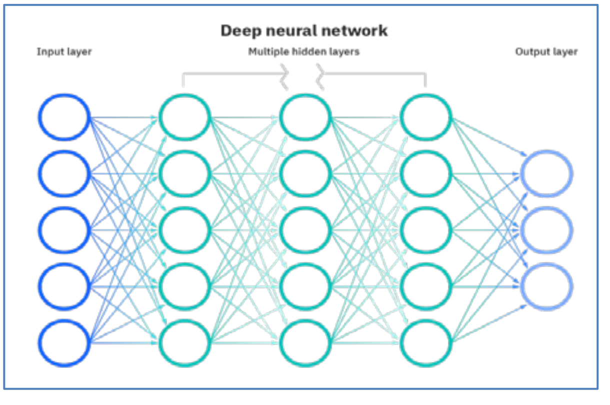

Figure 4 Deep Neural Network [28]

Multiple hidden layers that make up the network's strength contribute to its increased accuracy. Deep Learning solutions prove to be an impressive approach in agriculture and can be used for identification of plant diseases and other applications. Deep learning eliminates the requirement of well structured labeled data and methods of data pre processing, which is typically involved in machine learning. Deep learning algorithms can process unstructured data, like text and images, and it automates feature extraction. Deep learning neural networks performs actions by virtue of multiple layers of interconnected nodes, data inputs, weight and bias. These multiple layers are interconnected and take input from the previous layers to refine and optimize the prediction or categorization [29].

4.1. Deep Convolution Neural Network - Basic Principle

The strength of DCNN is in layering. The network comprises of different layers forming a 3 dimensional network to process the input image elements. The network uses the input images to train the classifier and applies "convolution" operation on image elements.

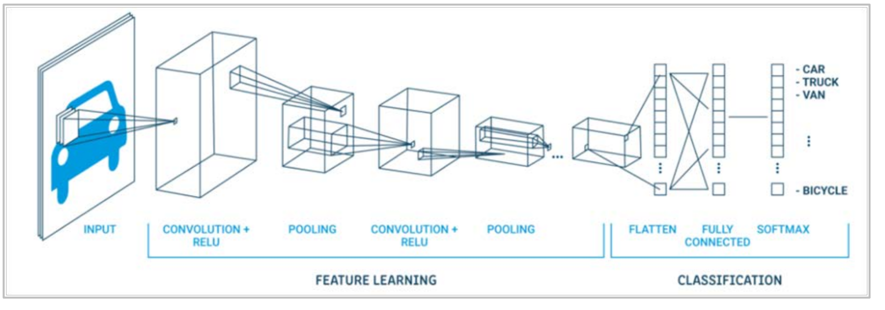

Figure 5 Deep Convolution Neural Network Architecture [30]

The network design is depicted in Figure 5 as having four layers: the convolution layer, the ReLu layer, the pooling layer, and the fully connected layer. Convolution layer is a key building component in deep learning networks that applies a convolution filter to the picture to identify features of the image. In order to extract visual information, the filter separates the image into tiny sections known as receptive fields. The filter multiplies its elements with receptive field elements and convolves with images using specific weights. Convolution is performed by [32]:

$$f_l^k(p,q) = \sum_c \sum_{x,y} i_c(x,y) \cdot e^k_l(u,v)$$

Where, ic(x,y) is an element of the input image tensor Ic , which is element wise multiplied by ekl(u,v) index of the kth convolution filter kl of the lth layer. Convolution operation have weight sharing ability, which helps it to extract image features by sliding filter with same set of weights on image [30],[31],[32]. Rectified linear unit layers (Relu), are activation functions applied to lower the over fitting challenges. The convolution maps are passed through Rectified Linear Unit (ReLu), which replaces negative numbers of the filtered images with zeros. Activation function which helps to accelerate learning is given by [32]:

$$T^{k}{}_{l} = g_a (F^{k}{}_{l})$$

Where, Fkl is the output of convolution, assigned to activation function ga (.), to add non linearity and returns the output Tkl for lth layer. Next to Relu is pooling layers which gradually reduces the size of the image, keeping only the most important information. It sums up nearby information of receptive field and gives the dominant response as output. The operation formula of pooling layer is given by [32]:

$$Z^{k}{}_{l} = g_p (F^{k}{}_{l})$$

The Zkl represents pooled featured map of lth layer of kth input feature map Fkl, and gp(.) defines the type of pooling operation which helps to extract features [32]. Once the feature extraction is done, image classification operation is performed using fully connected layers. A vector containing flattened picture pixels that have been reduced, filtered, and corrected by convolution and pooling layers is fed into the fully connected layers at the network's end. The outputs of the fully connected layers are then finalized by applying a softmax function, which yields the likelihood of the class to which the input picture belongs. [30], [31].

4.2. Deep Convolution Neural Network Architectures

DCNN architectures are categorized into 7 broad categories. Each category involves different network architectures with varied depth, connections, parameters and processing units. The taxonomy of DCNN architectures is represented in fig 6. The architectures have been extensively applied in many image classification algorithms and have given remarkable results [32].

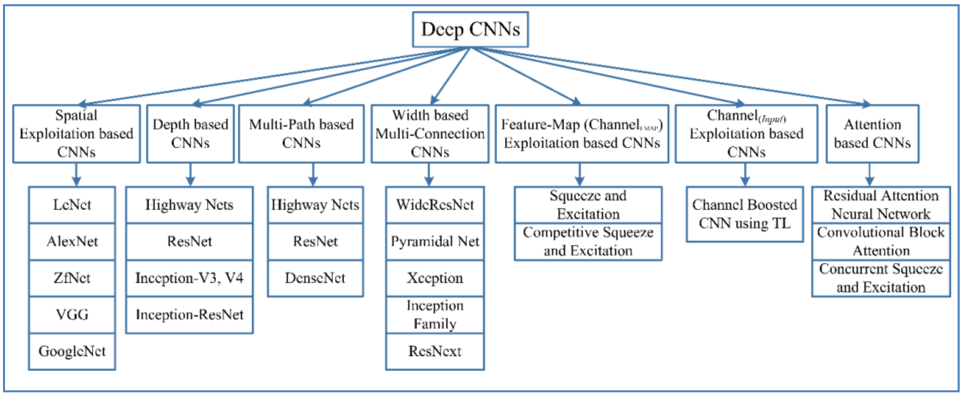

Figure 6 Taxonomy of deep CNN architectures showing seven different categories [32]

As seen in section 3 of the paper, DCNN models have been used extensively used in plant disease detection systems. The method involves a structured procedure from collection of input data images to the detection of diseased in leaf as output. Data Images are acquired and used as input to the deep learning model. These input images progress through the layers of the model one by one. Input data images can also be processed, resize, rotate etc as required to improve the predictions and achieve high accuracy [33]. The DCNN (Deep Learning Convolution Neural Network) models can run on Windows (any version above7), Linux or Ubuntu Operating Systems. Many open source libraries and frameworks such as Tensorflow, Pytorch, theano, caffe, keras etc are available to build and train the desired network model. All these frameworks support different API's to support and build deep learning models easily [34]. As depicted in Figure 7, the input dataset is applied to the detection system model and further hyper parameter tuning is done on the input dataset to select best suited batch size, no. of epochs, image size and other parameters by hit and trial to achieve high accuracy.

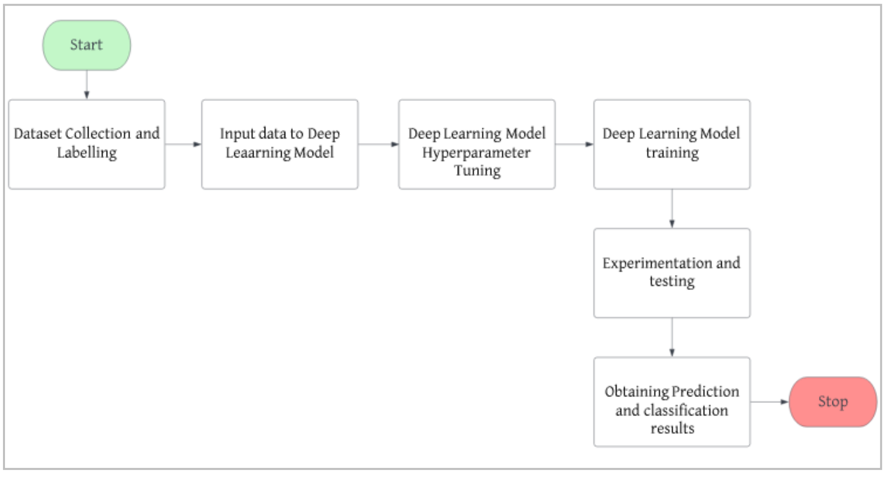

Figure 7 Block Diagram of Plant Disease Detection System Model

After tuning the parameters model is set to train. In Practice the input dataset is set to split into training and testing dataset. Generally, 80% of data is used for training and 20% is used for testing. Once the model training is completed, experiments are performed to predict classification accuracies.

4.3. Deep Learning in diagnosis of Plant Diseases

With the recent advancements in deep learning, DL models have been widely used for diagnosis of plant diseases and have shown outstandingly effective results in solving image classification problems. The approach is highly recommended for agriculture solutions. Table 1 provides summary of deep learning algorithms used in detection of diseases in fruits, vegetables and other crop plants.

Table 1 Summary of DL architectures

DL/ Architecture	Selected Plant/ Dataset	Performance Results	References
DCNN	Plant village dataset	Accuracy : 99%	[14]
GoogleNet and ALexNet	Plant village dataset	Accuracy : 99.95%	[25]
CNN	Maize	Accuracy : 92.85%	[35]
ResNet, GoogLeNet, AlexNet,	Tomato	Accuracy : 97.28%	[36]
LeNet	Banana	Accuracy : 98.61%	[37]
VGG ,AlexNet, GoogLeNet, Overfeat	Grape, cantaloupe, blueberry, apple, banana, cassava, eggplant, cherry, cucumber, corn, orange, cabbage, gourd, onion, celery	Accuracy :99.53%	[38]
ResNet50,AlexNet, VGG 19, SqueezeNet, VGG16, Inceptionv3, GoogLeNet, InceptionResNetv2, Resnet101	Peach, Apricot, Cherry, Walnut	Accuracy : 97.86	[39]
Inceptionv3	Cassava	Accuracy : 93%	[40]
CNN	Cucumber	Accuracy : 82.3%	[41]
CNN	Maize	Accuracy : 96.7%	[42]

DCNN	Rice	Accuracy : 95.48%	[43]
GoogLeNet and AlexNet	Tomato	Accuracy: 99 %	[44]
VGG-FCN-S , VGG-FCN-VD16	Wheat	Accuracy: 97.95%	[45]
VGG-A, CNN	Radish	Accuracy : 93.3%	[46]
AlexNet	Soybean	Accuracy : 94.13%	[47]
AlexNet , SqueezeNet v1.1	Tomato	Accuracy : 95.65%	[48]
Support Vector Machine , AlexNet DCNN, Random forest	Cucumber	Accuracy : 93.4%	[49]
Improved GoogLeNet	Maize	Accuracy : 98.9%	[50]
MobileNet, Reduced MobileNet, Modified MobileNet	24 types of plant	Accuracy : 98.34%	[51]
VGG-16, ResNet 101, Inception-V4 ,ResNet 152, DenseNets-121, ResNet-50	Soybean, tomato, strawberry, blueberry, bell pepper, squash, orange, corn, grape, cherry, potato, peach, raspberry, apple	Accuracy : 99.75%	[52]
AlexNet, VGG-16, GoogLeNet, ResNet-20 , SVM, User defined CNN	Apple	Accuracy : 97.62%	[53]
MLP ,LeafNet, SVM	Tea leaf	Accuracy : 90.16%	[54]

OR-AC-GAN	Tomato	Accuracy 96.25%	[55]
3D CNN	Soybean	Accuracy : 95.73%	[56]
DCNN	Wheat	Accuracy 85%	[57]
ResNet-50	Wheat	Accuracy : 87%	[58]
AlexNet , VGG-16	Apple, banana	Accuracy : 98.6%	[59]
LeNet	Grapes	Accuracy : 95.8%	[60]
LeNet	Soybean	Accuracy : 99.32%	[33]
VGG-Inception	Apple	Accuracy : 78.8%	[22]

Various DCNN architectures such as Alex Net, GoogleNet, ResNet, VGG, LeNEt etc have been used for disease classification. Figure 8 shows the graphical representation of the accuracies achieved by DCNN model in plant disease detection. The average classification accuracy achieved using the deep learning models is more than 90%.

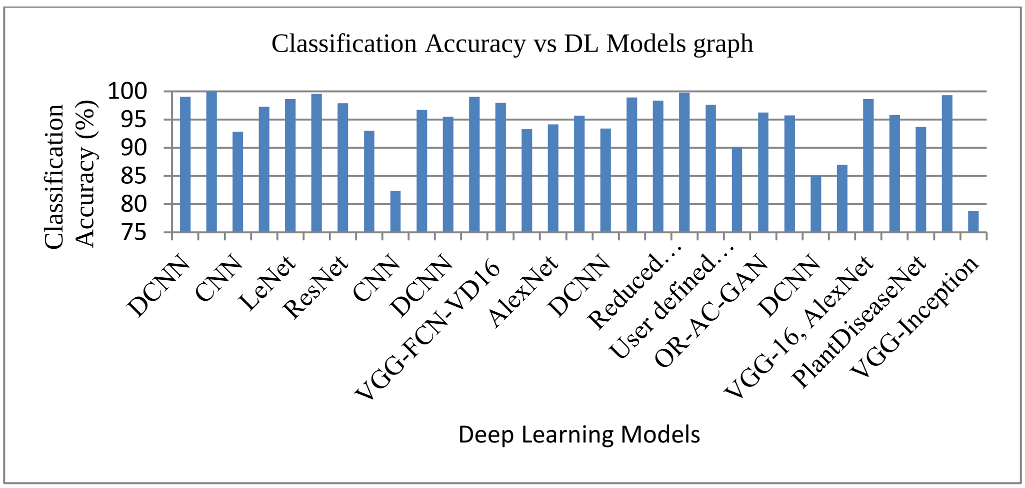

Figure 8 Classification accuracy graph of different DL Models

The details presented in Table 1 are analyzed further to identify the best suited models for disease detection in fruits, vegetables and crops respectively. Fruit plants used for analysis included image datasets for common fruits like apple, grapes, banana, strawberry etc. Figure 9 shows that LeNet, ResNet, DenseNet, VGG networks performs better than hybrid model like VGG –Inception, and achieves classification accuracy of more than 95% to detect diseases in fruit plants.

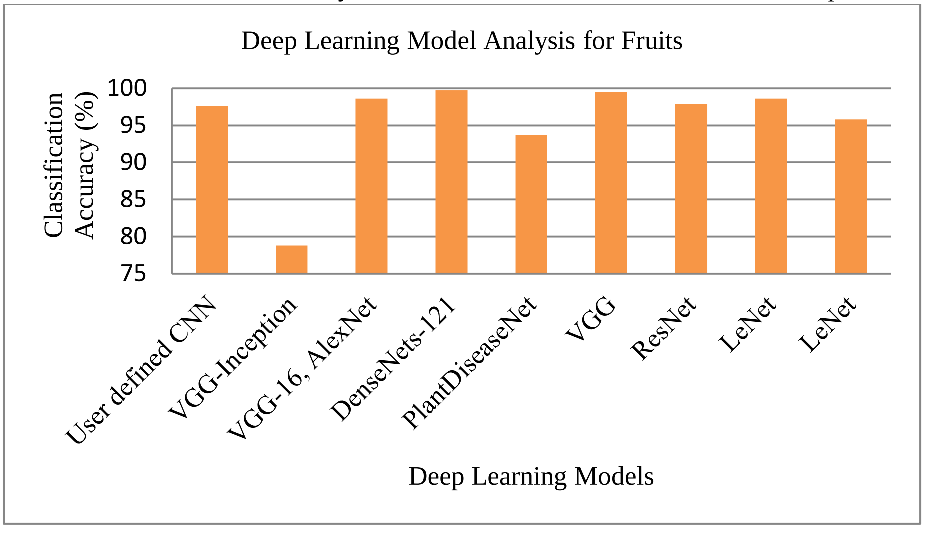

Figure 9 Classification accuracy graph of different DL Models used in fruits

Some experiments were performed to identify diseases particularly in vegeTable and crop plants. Figure 10, shows the models used for vegeTable plants like tomato, radish, cucumber and cassava. Analysis shows that AlexNet and GoogleNet have achieved maximum accuracy of 99.95% over plant village dataset comprising of 56,000 images belonging to common vegetables.

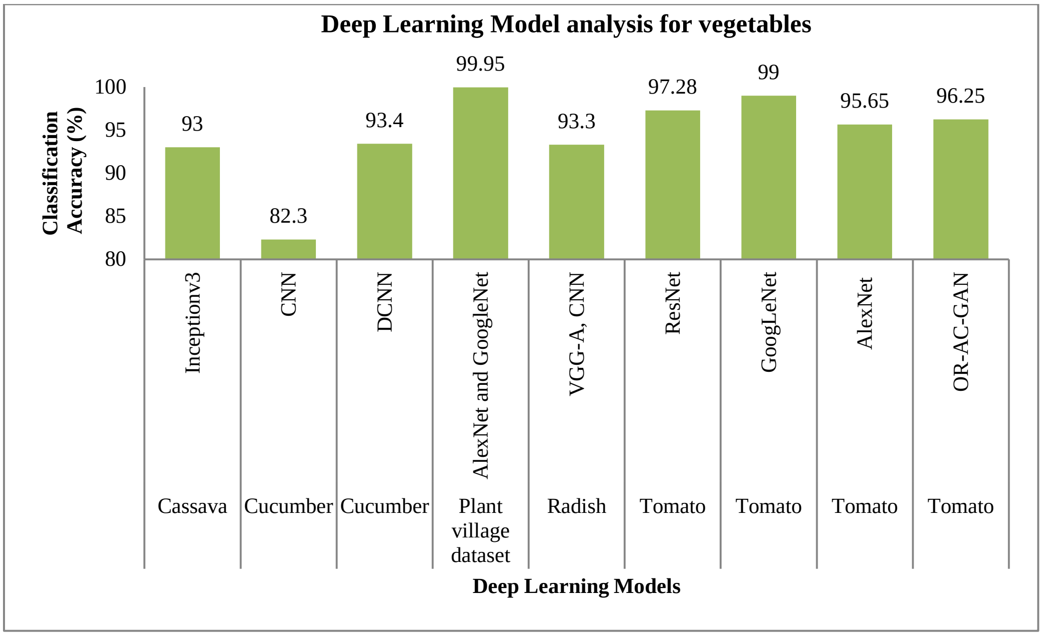

Figure 10 Classification accuracy graph of different DL Models used in vegetables

Some models were used to identify diseases in common food crop plants such as wheat, maize, soybean etc and study shows that LeNet, GoogleNet and VGG networks performed remarkably better to identify diseases in them. Figure 11 shows the graphical representation of models used and their respective accuracies achieved. Here also the DL models achieved high average classification accuracy i.e. more than 95 %.

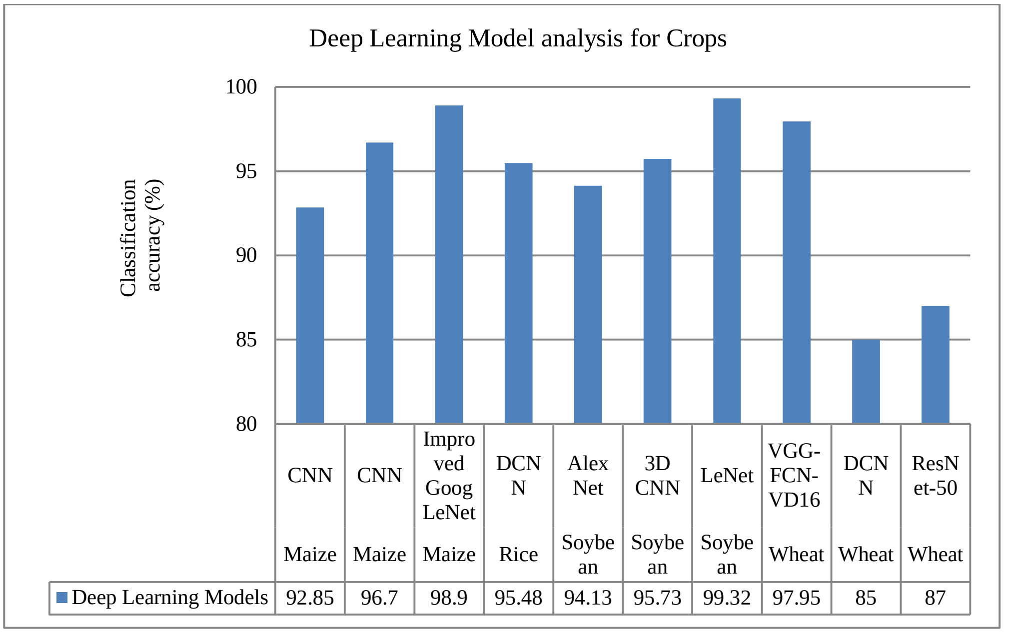

Figure 11 Classification accuracy graph of different DL Models used in Crops

5. Conclusion

The paper outlines the basics of deep learning, along with the model architecture to understand the deep learning classification technique. The study provides the required attention towards some common diseases found in maize and encourages using deep learning approach in image classification problem to achieve good classification results. It is observed that DL models like ResNet, ALexNet, GoogleNet, LeNet have performed really well in plant disease identification. Figure 12 clearly describes that highest classification accuracy which is 98%, is achieved by GoogleNet model belonging to DCNN architectures. It is evident that DCNN architectures can be the best approach to be used in plant disease detection systems.

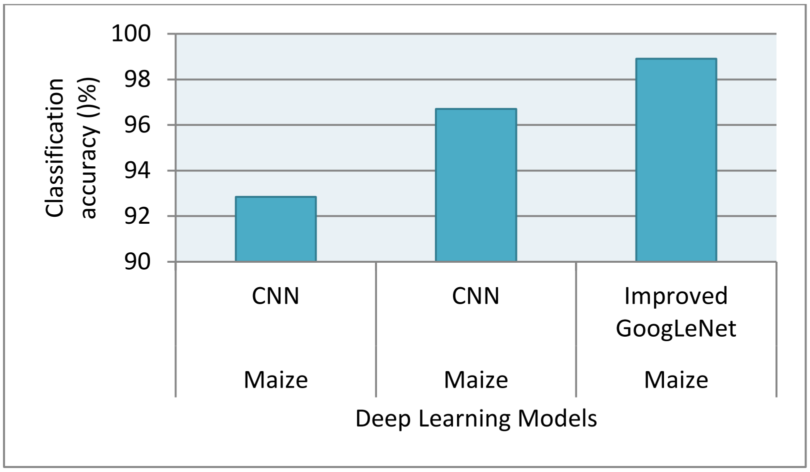

Figure 12 Classification accuracy results for maize

The comprehensive review of the work done on image based disease identification draws some conclusion and future ideas which are as follows:

- Deep learning methods are effective in image classification problems and have proved to achieve high accuracy rates (>90%).
- Deep learning methods eliminates the data preprocessing steps and provides results faster.
- Foliar diseases are very common in maize and require automated classification solutions to accurately diagnose disease symptoms.
- The algorithms are not just confined to be used for image classification but research can also be extended to feature and object detection, severity analysis etc.
- Various frameworks are available to use pre-built DL models to perform comparison studies, enhance the efficiency and accuracy of models by hit and trial methods.

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