International Journal of Scientific Research in Science and Technology
Print ISSN: 2395-6011 | Online ISSN: 2395-602X (www.ijsrst.com)
doi : https://doi.org/10.32628/IJSRST

A Survey of CNN Based Diseases of Plant Leaves Detection Techniques

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Article Info
Volume 9, Issue 3
Page Number : 586-598

Publication Issue
May-June-2022

Article History
Accepted : 01 May 2022
Published : 12 May 2022

ABSTRACT

Today, deep learning techniques to image recognition are critical tools. Convolutional Neural Networks, a deep learning technology, has achieved a stunning success in this area. Convolutional Neural Networks are being used in a wide range of agricultural applications because of their ability to recognise images. Identifying plant species, improving yields via improved soil and water management, and detecting unwanted plants and animals are just a few of the methods available. Agricultural disease and pest detection using Convolutional Neural Networks is also being researched. As there is a vast variety of material out there on how to apply deep learning models in agriculture, selecting a suitable one might be difficult. The authors of this paper provide an overview of current research on the use of leaf images to train Deep Convolutional Neural Networks for the prediction of plant ailments. This research compares several pre-processing tactics, Convolutional Neural Network models and frameworks, and optimization methodologies for identifying plant ailments from leaf images. This article also contains the data and performance metrics needed to evaluate the model's efficacy. This research addresses both the advantages and disadvantages of various approaches and models that have been proposed in the literature. Studying plant leaf diseases using deep learning techniques will be made easier with this survey, which will aid researchers in the field.

Keywords : CNN, Leaf detection, Simulated Annealing, Leaf disease detection

I. INTRODUCTION

[1] A decrease in agricultural productivity may be caused by the presence of diseases, pests, and other unwanted elements in crops. These harmful elements have a direct effect on the quality and quantity of crops. [2] Pesticides are chemicals that are used to battle, control, and neutralise biological organisms and illnesses. The appearance, morphology, and other properties of leaves are often used in the identification of plant pests and diseases. To avoid irreversible loss of yield, this visual inspection should only be carried out and assessed by a highly qualified biologist. A professional biologist must be present to detect and prevent the spread of any illness as early as feasible in pest and disease management studies, which is often expensive [3].

"Deep learning" (DL) and "machine learning" (ML) are two concepts that have recently been introduced to describe AI techniques that enable computers to "learn" complex patterns and then take action. Deep learning and machine learning enable a program's prediction accuracy to increase over time without having been explicitly programmed to do so.

It has become possible to create sophisticated algorithms that can evaluate and identify patterns or pictures with more accuracy than the typical human. In DL, machines learn to think by mimicking the nervous system in their design, but in computer vision, computers learn to think and act with the least amount of human interaction [4].

Plant diseases may now be diagnosed utilising smartphones using AlexNet [6] and GoogLeNet [7], two network topologies that have been designed for the automated detection of plant diseases as a consequence of the foregoing. During training, the suggested model was 99.35 percent accurate in identifying leaf diseases. R-CNN diagnostic algorithm, which is quicker than CNNs, was utilised to identify early-grown maize and discriminate it from weeds in three distinct climates with an average analytical result of 97.71%. Other researchers [9] have used deep learning to recognise fruits in a strawberry-picking robot by coupling the quickest sensor with a ResNet50 neural network. The results of this study showed a 95.78% detection accuracy and an 89.55% overlapping detection area. R-CNN was found to be the most effective architecture for Fuentes and other researchers [10] when compared to various sensor families and architectures.

Pictures of plant leaves are taken, processed, segmented, and features extracted from these images in order to classify various illnesses. For illness detection, existing models work. Nevertheless, human skill in the gathering of leaf images [1] is required for accurate disease categorization. Thus, these models may be improved based on the sort of datasets and experimental settings that are accessible. As a result, the researchers in [10] are focusing on improving the models' efficiency and accuracy.

Choosing an appropriate model for a dataset, parameters, hardware setup, and experimental circumstances might be challenging due to the abundance of research on using machine learning and deep learning models in order to forecast plant diseases. In order to help researchers find the best model for data pre-processing, prediction, and categorization of plant diseases, a complete literature review is needed. This is why the authors give in this publication a comprehensive review of pre-processing approaches, DCNN frameworks, and DCNN designs methods. Other aspects of deep learning models for disease diagnosis and classification in plant leaves are discussed in this work, as well.

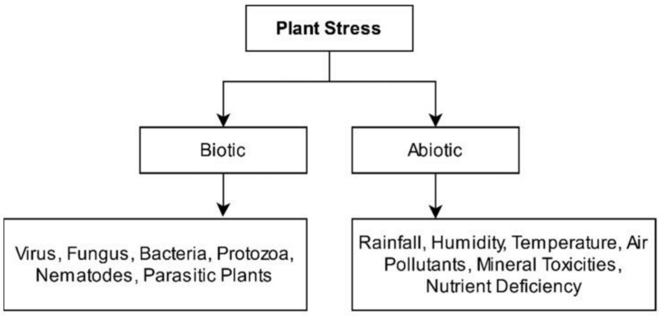

Fig. 1: Types of plant stress.

Symptoms of a sick plant include changes in colour, shape, size, and growth retardation. The severity of these signs and symptoms changes during the course of an illness. When a healthy plant begins to be affected by disease-causing factors, indications of illness begin to show gradually. It's tough to tell the difference between a healthy plant and a sick one at this point. In addition, the plant's immune system may be compromised by illness, making it more vulnerable to infection from several pathogens. In other words, two or more illnesses may have symptoms that are quite similar [15].

A disease's symptoms may be affected by elements such as temperature, wind speed, humidity, sunlight exposure, and other weather conditions. Because of these characteristics, a diseased area's form, colour, and size might vary greatly (s). Plant or plant component examinations with just the naked eye are no longer sufficient to detect illness in these instances [16]. On the other hand, sophisticated AI approaches like as Convolutional Neural Networks (CNN) and Deep Convolutional Neural Networks (DCNNs) may reduce human involvement and improve illness detection accuracy. It's still difficult to see whether a plant is infected if the backdrop is littered with weeds, branches, dead leaves and soil, leaves from other plants, insects and so on.

When photographing a plant, the lighting circumstances, cloudy conditions, location of the sun and angle of reflection, and other factors may all affect the quality of a plant picture. A low-contrast, low-quality picture does not provide enough information to identify illness [17].

The gradient of the loss function may approach 0 when adjusting the parameters, making it impossible to train the network in this manner. The earliest layers are critical for identifying the most fundamental characteristics of the incoming data. This implies that the first levels of the network will not be updated properly, resulting in a lack of accuracy across the network as a whole. When a result, the model's accuracy decreases as the network's depth exceeds a certain threshold. A shallow network's accuracy degrades when its depth rises over eight levels, according to Wang et al. [18]. The output of one layer is provided as an input to the next layer during the training of Deep Neural Networks. When the settings of one layer are altered, the succeeding layers get a different distribution of input data. Consequently, it results in a phenomenon known as Internal Covariate Shift. The training procedure is slowed considerably by this issue. Lower learning rates and more careful parameter setup are required. The Batch Normalization approach was used to reduce the Internal Covariate Shift issue [19]. Batch Normalization makes it possible to use considerably larger learning rates and to have less worry about the initiation of the process. Each hidden layer attempts to normalise the inputs it receives. As a result, the distribution of inputs is rather stable. As a result of this, deep networks can learn more quickly and accurately [20].

In the past two decades, image processing and machine learning methods have been extensively used to identify and classify plant leaf diseases. Comparative examination of CNN models used to identify plant leaf diseases is shown in Table 6. Deep learning models have been more popular since 2015 because of their ability to accurately diagnose plant leaf diseases. Table 1 compares models for machine learning and deep learning.

II. COMPARATIVE ANALYSIS

Pre-processing procedures are plentiful in literature, as seen by the variety of methods available in each category. In order for a CNN model to accurately classify a given dataset, pre-processing methods must be used to change the dataset. A single colour channel has fewer computing needs than several colour channels, which may be shown by converting RGB photos to grayscale images [21,22,23]. Data may be compressed into a smaller area by using Principal Component Analysis (PCA). Unlike PCA, Zero-Phase Component Analysis (ZCA), a whitening technique, is comparable. As a learning aid, it is used to emphasise characteristics and structures [17]. Cropping is a technique used to emphasise a certain area of interest in a picture [26]. Before using the correlation coefficient approach to segment an area, contrast stretching is performed [27]. Improves the appearance of a sick area. Leaf pictures are segmented using Otsu's technique [28]. Details regarding current pre-processing methods are revealed in the next section of the article.

2.1 Reducing the Dimensions

The dimensions of the images we've obtained from various sources vary. The model's training time is increased because of the model's size disparity. Before using a CNN model, it is necessary to resize recorded and/or collected pictures. It's important to keep picture sizes consistent by padding zeros in tiny photos and cropping big ones. Picture resizing is performed using the CNN model's input layer, as shown in the Inception-v3 [29] and Xception [30] models by resizing an example image to 299 299 pixels.

A. Increasing the Size of the Effect

For Deep Neural Networks, training a model is largely reliant on the quantity of data that is utilised to train the model. Data augmentation is required when just a little dataset is available. It is possible to enhance data in a variety of ways, from changing the brightness to cropping to PCA jittering [39] to shearing to rotation to affine transformations [25].

B. The normalisation of values

Simplifying an image's appearance by scaling its dimensions or pixel intensity levels to a predetermined range is known as normalisation. An 8-bit RGB picture has pixel values ranging from 0 to 255, which is an example of an 8-bit RGB image. Lights and shadows may distort a picture if they aren't properly normalised. It increases the model's learning pace, quality, and accuracy by giving equal weight to each feature. Decimal scaling, Min–Max normalisation, and Z-score normalisation are a few of the normalising methods.

C. Annotated text

To train a model, photos are annotated by giving labels to them. To identify plant illnesses, professionals who have a thorough understanding of the disease are required to annotate leaves. You may use bounding box annotations and picture annotations in a variety of ways. It's not uncommon to annotate with a bounding box. It is common practise to construct a tight rectangle or cuboid to fit tightly around the item being studied this way. The problem of this method is that it adds noise to the confined box.

D. Rejection of Outliers

The process of removing outliers from a dataset entails removing erroneous or irrelevant photos. Criteria for rejection include things like poor resolution, low intensity, blurriness, noise, irrelevance, and duplicate pictures [25]. OrganNet, a CNN model built by the authors, was used to remove incorrect or undesired photos from a dataset.

E. The Denoising Process

Denoising is the process of removing noise from a picture while maintaining the image's original characteristics. In a noisy environment, it enhances the performance of an image classification approach. Gaussian, Mean, Wiener and Small-window median denoising filters are among the approaches used by researchers to remove noise from images

F. Models and Datasets for CNN

Deep learning models were utilised to identify and classify plant illnesses from a variety of datasets. PlantVillage, the dataset created by the authors, was used to train a CNN model. Researchers collected leaves from plants and laid them out on a black or grey sheet for this dataset. A digital camera (Sony DSC-Rx100/13 20.2 megapixels) was used to take photos of leaves in various lighting circumstances, such as intense sunshine and clouds. The camera's settings are optimised to ensure that the best possible picture is captured. To train the CNN model, the researchers utilised 54,306 pictures from 14 crops with 26 distinct illnesses. The PlantVillage dataset was used in a series of studies by Mohanty et al. The original 'PlantVillage' dataset, which included coloured photos, is referenced in the first set. The 'PlantVillage' dataset has been grayscaled in the second batch. Images of segmented leaves from the PlantVillage dataset are included as part of the third collection. The CNN model was trained using 80% of the dataset and tested with 20% of the dataset. The GoogLeNet architecture with transfer learning was used to get the maximum accuracy of 99.35% on colourful leaf pictures [23]. PlantVillage datasets were used to conduct tests on three different datasets.

Models that use deep learning have a distinct advantage over those that use simple feature learning. Feature extraction is done automatically by these models. In order to improve classification accuracy, they need massive datasets. Researchers utilise pre-trained models when there aren't enough datasets. Deeper networks, according to [33], are more efficient in training and provide better outcomes.

2.2 The most common CNN designs

In 1998, LeNet ushered in a new era for CNN. In 2012, AlexNet became well-known as it took first place in the 'ImageNet Large Scale Visual Recognition Challenge. The accuracy rate and the error rate are both increased by further advances in designs. Image categorization is another area in which CNN architectures are finding use. A particular piece of data or set of experimental settings may need a particular design due to its distinct benefits or qualities. The following is a list of the most common picture categorization architectures.

A. LeNet-5.

One of the first, seven-tiered and very simple architectures is depicted in Figure 5. Each layer has three convolutional layers, two pooling (S2) and four fully connected (F6) layers, as well as an output. Detailed information on it may be found at [2].

B. AlexNet - a search engine

Similar to LeNet, but with more than 60 million parameters, this design is more complex. [42] discusses the top-five mistake of 15.3%, which is lower than the second-best entry's 26.2 % error rate. AlexNet has five convolutional layers and three layers that are completely linked. A ReLU activation function is used in this process. Training a network is done with the help of the MaxPooling layer, local response normalisation, and a large number of graphics cards

C. VGGNet

The Visual Geometry Group at Oxford University developed VGGNet [31]. It came in second place in the ILSVRC-2014 competition. The accuracy of this model's localization and classification improves as the model's depth grows. The VGGNet network is a more basic one. Small 3 3 convolutional filters with a stride of one are used in all layers of the algorithm. It has a max-pooling layer of 2 x 2 with a two-step stride. It takes as input an RGB picture with dimensions of 224 224 3. The mean average value of RGB is removed from each pixel in the training dataset to conduct pre-processing, as shown in the figure. Convolutional layers and five max-pooling layers are applied to a pre-processed picture. First two completely linked layers with 4096 channels and a third layer with 1000 channels are used. The final classification layer uses a 1000-way classification system. The last step uses a softmax layer to calculate multi-class probability.

D. Search Engine Lenny

ILSVRC-2014 champion Inception module [49] is the inspiration for GoogLeNet [48]. It has a more complex and expansive design. For each layer, there are 22 convolutions of 1 to 1, 3 to 3, and 5 to 5, which are all extremely tiny. Convolutions, max-pooling, and convolution-max-pooling are all used in GoogLeNet to extract various types of features. Linearly layered, it contains nine initialization components. There are five convolutional layers in Inception, each with its own outputs concatenated into one single output vector. Two major alterations to an initial inception module are made by GoogLeNet.

E. ReSect

ResNet was created by Kaiming and colleagues. At 3.57 percent, it had the highest mistake rate in the ILSRVC-2015 competition [32]. The deterioration issue that arises as a result of adding additional layers to a network is the driving force behind this advanced residual learning approach. The vanishing gradient issue makes it difficult to train a deep network. Weighted gradients of loss are computed during backpropagation. Moving forward in a network, gradients tend to become smaller. With 50 convolutional layers, ResNet-50 is a recursive convolutional network. About 25.6 million variables are included. In ResNet-101, there are 44.5 million parameters. In ResNet-152, there are 60.2 million parameters [50].

F. DenseNet

DenseNet, a densely linked network, was suggested by G.Huang et al. As seen in Figure 9, it comprises of two modules: dense blocks and transition layers. Using a Feed-Forward topology, this network connects every layer to every other. DenseNet of N layers has direct connections of N(N + 1)/2. [33] Feature maps from previous levels are used as inputs for each new layer. Batch Normalization, ReLU activation, and 3 x 3 Convolution make up a Dense Block. Dense blocks are separated by transition layers [33].

G. SqueezeNet

Eight fire modules sandwiched between two convolutional layers make up SqueezeNet [53], as seen in Figure 10. With a 1 1 filter, a squeeze convolutional layer serves as the basis for the fire module. Expanded layers are provided to it. One-by-one and three-by-three convolutional filters make up this layer.

H. LeafNet

LeafNet, a CNN model built by J. Chen et al. to diagnose illnesses in tea leaves, was recently published [54]. This model is a step up from AlexNet in terms of accuracy. Rather of using more convolutional or fully linked nodes, this method relies on fewer filters. As a result, the issue of overfitting may be avoided by limiting the number of network parameters.

2.3 Comparison of Frequently Used CNN Designs

One of the most effective methods for learning is deep learning. In comparison to standard Neural Network methods, it utilises ANNs with a greater number of processing layers [24]. Among deep learning approaches, Convolutional Neural Networks (CNNs) are among the most popular. Using just raw data, it learns to identify essential characteristics. Color and texture aspects of a picture are used to identify and classify images in this network.

Classification of nine tomato plant diseases by Brahimi et al. was 99.66 percent accurate [35]. To better comprehend the signs of a disease, the authors used visualisation approaches to pinpoint diseased leaf areas. In an open dataset of 87,848 photos, Ferentinos [24] used CNN to identify and diagnose plant illnesses. The collection includes 25 different plant species and 58 separate disease categories for each of them.

The selection of a good CNN model relies on the kind of dataset, the size of the dataset, and the circumstances under which the experiment is conducted. There is a comparison of CNN models used to identify illnesses in plant leaves shown in Table 3 by the authors. Architectures depending on plant kind and accuracy are shown in Figure 11 by various authors.

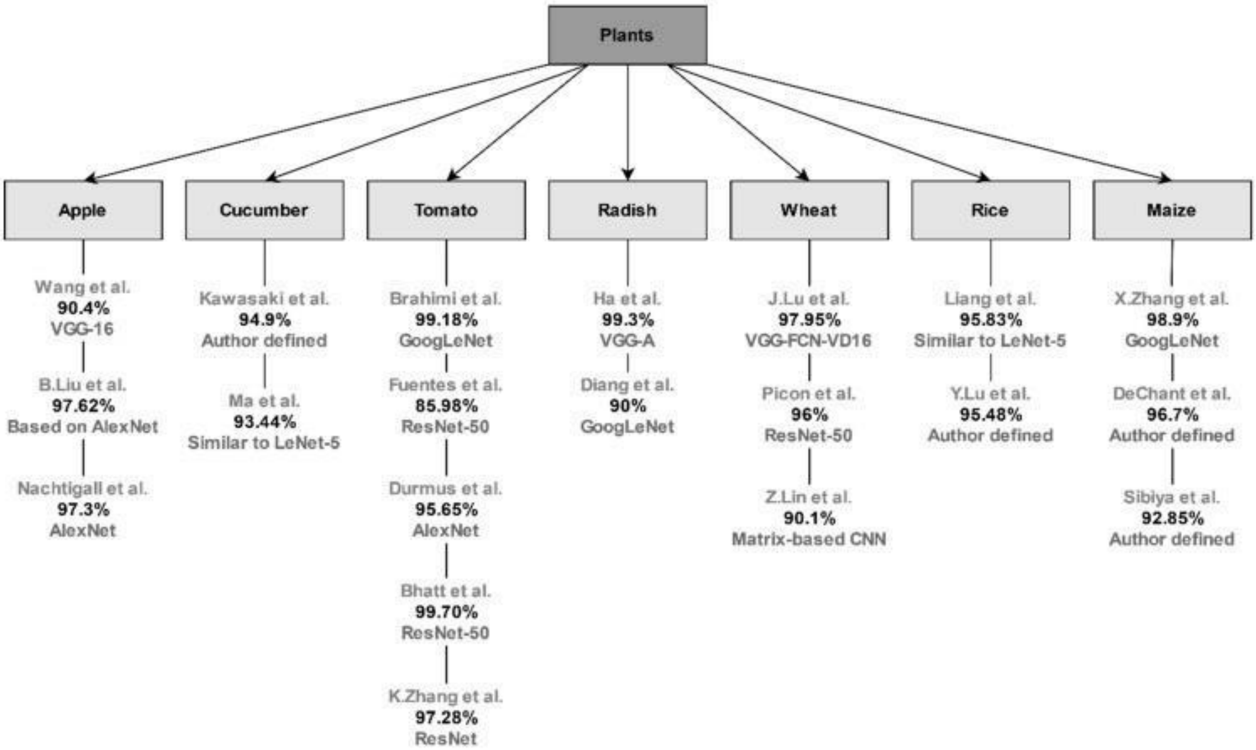

Fig. 11: Comparison of CNN architectures based on plant types and accuracy.

Table 3: Comparison of popular CNN architectures.

Architecture	Layers	Parameters	Highlights	Reference
AlexNet	8 (5 Convolution + 3 Fully Connected)	60 million	AlexNet is similar to LeNet-5, but it is deeper, contains more filters in each layer, and uses stacked convolutional layers. Winner of ILSVRC-2012.	[44]
VGGNet	16–19 (13–16 convolution + 3 FC)	134 million	The depth of a model is increased by using small convolutional filters of dimensions 3 × 3 in all layers to improve its accuracy. First runner-up in ILSVRC-2014 challenge.	[31]
GoogLeNet	22 Convolution layers, 9 Inception modules	4 million	A deeper and wider architecture with different receptive field sizes and several very small convolutions. Winner of ILSVRC-2014.	[48]
Inception v3	42 Convolution layers, 10 Inception modules	22 million	Improves the performance of a network. It provides faster training with the use of Batch Normalization. Inception building blocks are used in an efficient way for going deeper.	[29]
Inception v4	75 Convolution layers	41 million	Inception-v4 is considerably slower in practice due to many layers.	[108]
ResNet	50 in ResNet-50, 101 in ResNet-101, 152 in ResNet-152	25.6 million in ResNet-50, 44.5 million in ResNet-101, 60.2 million in ResNet-152.	A novel architecture with 'skip connections' and heavy batch normalization. Winner of ILSVRC 2015.	[32]
ResNeXt-50	49 Convolution layers and 1 Fully Connected layer	25 million	Use ResNeXt blocks based on the strategy of 'split–transform–merge'. Despite creating filters for a full channel depth of input, the input is split into groups. Each group represents a channel.	[51]
DenseNet-121	117 Convolution layers, 3 Transition layers and 1 Classification layer	27.2 million	All layers are connected directly with each other in a feed-forward manner. It reduces the vanishing-gradient problem and requires few parameters.	[33]
SqueezeNet	Squeeze layer and Expand layers	50 times fewer parameters than AlexNet.	SqueezeNet is a lightweight model of size 2.9 MB. It is approximately 80 times smaller than AlexNet. Achieves the same level of accuracy as AlexNet. Reduces the number of parameters by using a smaller number of filters.	[53]
LeNet-5	7 (5 Convolution + 2 FC)	60 thousand	Fast to deploy and efficient in solving small-scale image recognition problems.	[43]

Table 4 : Advantages and disadvantages of various optimization techniques.

Name	Advantages	Disadvantages
BGD	Easy to compute, implement and understand.	It requires large memory for calculating gradients on the whole dataset. It takes more time to converge to minima as weights are changed after calculating the gradient on the whole dataset. May trap to local minima.
SGD	Easy to implement. Efficient in dealing with large-scale datasets. It converges faster than batch gradient descent by frequently performing updates It requires less memory as there is no need to store values of loss functions.	SGD requires a large number of hyper-parameters and iterations. Therefore, it is sensitive to feature scaling. It may shoot even after achieving global minima.
AdaGrad	Learning rate changes for each training parameter. Not required to tune the learning rate manually. It is suitable for dealing with sparse data.	The need to calculate the second-order derivative makes it expensive in terms of computation. The learning rate is constantly decreasing, which results in slow training.
RMSProp	A robust optimizer has pseudo curvature information. It can deal with stochastic objectives very nicely, making it applicable to min-batch learning.	The learning rate is still handcrafted.
Adam	Adam is very fast and converges rapidly. It resolves the vanishing learning rate problem encountered in AdaGrad.	Costly computationally.

III. OPTIMIZATION TECHNIQUES

For a CNN model to be successful, an appropriate optimization strategy must be used. Table 4 shows a comparison of the most popular optimization methods. Optimization using Batch Gradient Descent (BGD).

Here, a whole training dataset is used to update the parameter (x) in Equation (1). (5). Scan millions or billions of samples in a training dataset takes a long time to calculate gradients. It is also difficult to input all samples at once to a model owing to the restricted computational memory. Because of these disadvantages, Batch Gradient Descent isn't the best choice for updating the parameters of a deep learning network, according to [39].

A. Stochastic Gradient Descent (SGD)

An approach that uses Stochastic Gradient Descent (SGD) updates the model's parameters in the wrong direction. For each training sample, it calculates the gradient and changes the model's parameters. Instead of computing the total cost of all data points, it randomly selects one data point and its accompanying gradient. The steps are swiftly updated and the minimal time period is soon reached using this method. That's why this optimization method is so often employed. SGD is slowed down by a tiny step size, which helps it find a suitable equilibrium point. When using GPUs to do computations, the efficiency is hampered by the frequent commutation of data between the GPU's memory and the system's memory.

B. Framing

A variety of tools and platforms are being developed in artificial intelligence (AI) that may be used to implement deep learning in diverse scenarios.

C. TensorFlow

In the context of deep learning applications, TensorFlow is the most often utilised framework, as discussed in [10]. A widely used open-source software library C++ and Python are used to create it. The library for artificial neural networks is developed by

Google. Using data flow diagrams, it aids in numerical calculations on a CPU, GPU, server, desktop, or mobile device. For the identification of cassava disease, Ramcharan et al. used TensorFlow to construct an image recognition algorithm. TensorFlow was utilised by Picon et al. to develop mobile apps for agricultural disease categorization [38]. Keras Deep Learning framework and TensorFlow on the backend were utilised by the authors of [29].

D. Infinite Theano

Python's Theano library packs a lot of punch. For example, it may be used to describe numerical operations such as multidimensional arrays, and to evaluate and optimise them [113]. NumPy integration, transparent GPU utilisation, dynamic C code creation, performance optimization, and efficient symbolic differentiation are all included in this programme. Theano's syntaxes are difficult to decipher. However, its highly tuned performance means that it is still widely used. Theano is used in conjunction with Keras or other Deep Learning libraries in the backend.

E. Keras

For deep learning implementation, there's Keras is a free and easy-to-understand package. TensorFlow [30] and the Microsoft cognitive toolkit may both be used with it. VGGNet, AlexNet and GoogLeNet are just a few of the prominent architectures that can be found in Caffe and Theano.

F. Caffe

UC Berkley's Yangqing Jia created Caffe [14], an open-source deep learning framework. It has an excellent Matlab, C++, and Python interface. To develop Convolutional Neural Networks for image classification, it is highly quick and efficient. It is possible to use Neural Networks using this tool without writing any code. Deep architectures may be evaluated using this framework, since it is the most user-friendly [15]. Using an NVIDIA DIGITS 5 toolkit [26].

G. Torches

Torch7, an open-source library is built on the Lua programming language. Programmers may use this tool to do indexing, transpose and slice operations, as well as linear algebra and n-dimensional array operations. Using Torch7, Ferentinos [24] evaluated the efficacy of several CNN models for the identification and diagnosis of plant diseases. They used an NVIDIA GTX1080 GPU to make it work. PyTorch, a framework comparable to Torch, was created by Facebook. This framework is one of the most versatile. This tool's popularity grows because to its characteristics such an easy-to-use API and support for the Python programming language.

H. The neuropeptide

This framework is a complete system. Create and deploy neural networks using the NetBeans Platform IDE and the Java Neural Network library. With this framework, you don't need to know any programming languages like C, Python, or MATLAB to develop an accurate CNN model [31].

I. Deeplearning

Deeplearning is a Java-based deep learning library delivered via the internet. Kotlin, Python, Scala, and Clojure are all supported API languages. It is as quick as Caffe on many GPUs when it comes to image identification using Deeplearning4j. Keras-created Deeplearning4j can also import models from Tensorflow and other Python frameworks. When evaluating their model for categorising banana leaf illnesses, for example, Amara et al. employed the deeplearning4j framework [21].

J. Pylearn

Pylearn2 is seldom used, according to the research, since it is ineffective in dealing with large-scale issues.

K. MATLAB Toolbo

Extensive training Deep neural networks may be designed and implemented using the MATLAB Toolbox. This framework is available for Linux, macOS, and Windows, and is developed in MATLAB, is all included in the toolbox's library of pre-trained models. Analyses of DCNNs for the detection of plant leaf disease.

In this table, we compare DCNN's ability to identify plant leaf diseases with other methods.

Table 6: Comparative analysis

Plant	Disease	Architecture	Datasets	Results
Banana	Black sigatoka and Black speckle	LeNet [21]	PlantVillage: 3700 images	Accuracy: 99%
Apple	Black rot on Apple leaves	VGG16, VGG19, Inception-v3 and ResNet50 [18]	PlantVillage: 2086 images	VGG16: 90.4%, VGG19: 90.0%, Inception-v3: 83.0%, ResNet50: 80.0%
Tomato	9 different diseases in tomato	AlexNet, GoogLeNet [35]	PlantVillage: 14,828 Images	GoogleNet: Accuracy: 99.18% AlexNet: Accuracy: 98.66%
Cucumber	Melon Yellow Spot Virus (MYSV), Zucchini Yellow Mosaic Virus (ZYMV)	Author-defined CNN [36]	800 images of cucumber leaves captured by Saitama Prefectural Agriculture and Forestry Research Center, Japan	Average accuracy: 94.9%, MYSV Sensitivity: 96.3%, ZYMV Sensitivity: 89.5%,
Rice	10 different diseases	Author-defined CNN [19]	The author created a database of 500 images captured from experimental rice fields of Heilongjiang Academy of Land Reclamation Sciences, China	Accuracy: 95.48%
Tomato	9 different types of diseases and pests	VGG-16, ResNet-50, ResNet-101, ResNet-152, ResNetXt-50, [82]	The author created a dataset of 5000 images captured through a camera from tomato farms located in Korea	VGG-16: 83.06%, ResNet-50: 75.37%, ResNet-101: 59.0%, ResNet-152: 66.83%, ResNetXt-50: 71.1%
Olive	Olive Quick Decline Syndrome (OQDS)	Authors-defined LeNet [28]	PlantVillage	Accuracy of 99%
Radish	Fusarium wilt	VGG-A [26]	139 Images captured by a commercial UAV equipped with an RGB camera	Accuracy: 93.3%
Wheat	Septoria, Tan Spot and Rust	ResNet50 [8]	Author-defined dataset of 8178 images	Accuracy: 96.00%
Cassava	3 diseases: Brown leaf spot, Brown streak, and cassava mosaic 2	Inception-v3 [14]	Author-defined dataset. Originally: 2756 images. Leaflet: 15,000 images	Accuracy: 93.00%
Wheat	6 different diseases	Author-defined architecture named M-bCNN (Matrix-based CNN) [85]	16,652 images collected from Shandong Province, China	Accuracy: 90.1%
Maize	Northern Leaf Blight	Five CNNs were trained on the augmented data set with variations in the architecture and hyperparameters of the networks [64]	1796 images of maize leaves grown on the Musgrave Research Farm in Aurora, NY	Accuracy: 96.7%,
Grapevine	Esca disease	LeNet-5 [77]	The dataset consists of 70,560 learning patches by the UAV system with an RGB sensor	The best results were obtained with the combination of ExR, ExG and ExGR vegetation indices using (16 × 16) patch size reaching 95.80%
Tea	7 Diseases: Red leaf spot, Algal leaf spot, Bird's eye spot, Gray blight, White spot, Anthracnose, Brown blight	Author-defined CNN model named LeafNet (Improvement over AlexNet) [84]	A total of 3810 tea leaf images captured using a Canon PowerShot G12 camera in the natural environments of Chibi and Yichang within the Hubei province of China.	Accuracy: 90.16%

IV. CONCLUSION

Transfer learning may be used to fine-tune deep learning models for diagnosing crop diseases using natural colour images. This study develops a deep learning framework and procedures for selecting the optimum band combinations of multispectral imaging for training crop and crop-disease classification models by transfer learning, i.e., by fine-tuning just a few layers of pre-trained deep learning models. This study presents a unique way for detecting and classifying agricultural illnesses before they are evident to the human eye. This early identification of "invisible" agricultural illnesses is predicted to cut disease treatment costs and boost crop yields. This research's architecture and process may be used for monitoring o In this publication, the authors review studies on identifying and categorising plant leaf diseases (DCNN). Authors chose relevant research publications to compare DCNN designs. The study focuses on plant diseases, datasets used, dataset size, image pre-processing techniques, CNN architectures, CNN frameworks, performance measures, and experimental results of many models used to identify and classify plant leaf diseases. The above-mentioned techniques yielded excellent results. Training data amount and quality affect DCNN model performance. If training data is sparse, fine-tuned pre-trained models may perform better than models constructed from scratch. Deep Convolutional Neural Network (DCNN) designs show that choosing a CNN or DCNN model depends on the dataset, dataset size, and experimental settings. SqueezeNet is clever for tiny networks with high precision. As layers increase, efficiency decreases. ResNet uses skip connections for deeper networks. DenseNet works if all layers are feed-forward coupled. It reduces vanishing gradient and requires a few parameters. The existing literature suggests that researchers constructed CNN models on top-side leaf images using cameras or drones. Current research focuses on sickness diagnosis and classification, but not disease localization.

This aim was not met due to a lack of multispectral aerial cassava canopy images and crop disease calendars documenting when infections were diagnosed. Even low-resolution photos couldn't be obtained since this research couldn't determine when crops in the study locations were infected. This work used real colour leaf photos of various crops to assess transfer learning's feasibility in crop-disease classification algorithms.

Training crop classification models required four-band multispectral imagery. Due to the restricted number of spectral bands, the investigations focused on three-band combination models. The crop-classification training data came from field crops of varied ages and stages. Since crop reflectance changes with age and growth stage, it was unable to establish how this influenced crop categorization models.

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Cite this article as :

Shagun Agrawal, Dr. Mukesh Rawat, Dr. Vimal Kumar, "A Survey of CNN Based Diseases of Plant Leaves Detection Techniques", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 9 Issue 3, pp. 586-298, May-June 2022.
Journal URL : https://ijsrst.com/IJSRST2229315