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Review of Machine Learning Implementation in Advanced Tomato Plant Disease Detection and Recognition

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Abstract

Plant disease detection prevails as one of the crucial issues in agricultural sector despite colossal research works performed to eliminate this problem encountered by farmers all over the world. Machine Learning, a subfield of artificial intelligence practice, allows computers to use a massive amount of data to train and teach themselves to make predictions, as opposed to a static system. With the help of big data, industrial 4.0 revolution, and high-performance Graphical Processing Unit (GPU), the issues mentioned has become an ideal case to be explored. This paper reviews type of common diseases appeared in tomato plant, technology employed to detect the diseases of tomato plant and the core concept of its detection using machine learning, the concise comparison of each of the existing architecture for image-based classification in determining whether the plants is healthy or affected by diseases, the vital analysis for different methods, and the key challenges faced by the endless problem faced by farmers.

Keywords: Tomato disease detection, Machine Learning, Deep Learning, Neural Network, Artificial Intelligence, Agriculture Technology.

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1 Introduction

Agriculture industry persists as one of the essential sectors all over the world. As announced by the Food and Agriculture Organization (FAO), the world population increases to 9.73 billion by 2050, and 11.2 billion by the end of the century. Therefore, the necessity to improve food production and other agricultural products is an all-embracing agenda, as the demand also increases by approximately, 50% between 2012 and 2050 [1]. While there are many problems in food production, plant disease is still a major concern among farmers and seen as one principal threat to attaining this demand.

Common causes of plant disease are basically due to the main three factors: fungi, bacteria and viruses. Some diseases might be extremely severe where the farmers suffer for the total failure of plants. While others are difficult to be detected at early stage due to its unobvious symptoms. Reference [2] mentioned that to really comprehend the nature of each disease, the processes incurred during the growth and the development of healthy plant should be thoroughly analyzed in term of its sequence of events comprising germination, vegetative growth, flowering and finally the seed production; the physiological processes which include cell division and differentiation, the fixation and utilization of energy through photosynthesis and biosynthesis, transport of water and nutrients and storage of all reserved compounds; and the metabolism pathways and molecular reactions underlying all of these processes, which are totally depending on the lighting, temperature, water and humidity and sufficient nutrients [3] - [6]. The common diseases encountered in plant, including mildew, leaf blight, leaf spot, mosaic, leaf curl, wilt, fruit rot, etc.

Conventional method, using expert’s visual to detect the presence of the disease seems to be weak especially when it involves large farms, because its high cost in term of, labour intensive and time consuming, notwithstanding their expertise generally proven to reach as high as 93% of accuracy in detecting the plant disease [7].

Direct detections [8] which consists of recognizing the causal agent of the disease were introduced in 1970s through lab-based diagnosis. Serological assays were formed to detect the thousands of pathogens, bacteria and fungi using polyclonal and monoclonal antisera. The methods include enzyme-linked immunosorbent assay (ELISA), immunostrip assays, serologically specific electron microscopy (SSEM), western blots and dot-blot immune-binding assays. There are also DNA based method which were developed for pathogens detection, such as fluorescence in situ hybridization (FISH) and some variant of Polymerase Chain Reaction (PCR) including PCR, nested PCR (nPCR), cooperative PCR (co-PCR), multiplex PCR (M-PCR), real-time PCR (RT-PCR) and DNA fingerprinting. Despite the high accurateness of the diagnosis process, none of all these laboratory-based diagnosis methods is proven ideal in term of cost-effectiveness and ability to provide instantaneous detection.

Machine Learning (ML) and Artificial Intelligence (AI) emerged a few decades ago, and widely deployed among many researchers who urge for intelligent solution for their research. It is obviously undeniable that both of them have becoming the popular option for any problem solving in various industries and research disciplines, be it in science, physics, finance, social science etc. However, people tend to get confused of how to differentiate AI and ML. According to [9], AI is likely the science and engineering to make machine to behave like human, which is called intelligence, and it can go deeper by understanding the human intelligence. In simpler phrase, if someone can write a program that make a machine have human-like behavior, it can surely be categorized as AI. However, an intelligent machine doesn't cap only at the successful process of performing given task, but it is more towards how it interacts with its surrounding because the surrounding might as well affect the final result. Thus, when it comes for machines to learn how to adapt with their surrounding using the data fed to them, this is where ML interferes.

The people around the world are surrounded by technologies in their daily life. Various kind of data are able to be collected massively and they are becoming more significant and contextually relevant for various kind of researches. Thus, this situation has marked a new breakthrough for ML and AI, particularly when Deep Learning (DL) has been widely explored among researchers [10]. The presence of Industrial Revolution 4.0 has made the researches in this kind of discipline becoming indispensable and fitting. Researchers in agriculture who center around an enhanced plant disease detection will benefit from this compelling approach. Image-based detection is used as one of the indirect detection approaches, which observe on the impact of the disease through physiological plant response rather than recognizing the causal agent of the disease.

Thus, this paper consists of reviewing and comparing existing works done by the several researchers regarding the implementation of ML's image-based to firstly recognize what type of common diseases in tomato plants, followed by the methods used for the detection of their diseases.

2 Image Based Machine Learning

As mentioned in introduction, image-based of plant disease detection is categorized under indirect detection, which focused on the physiological impact of the diseases, practically has effects on the leaf texture, fruit, root etc.

For image-based technique, the basic steps taken for plant disease detection are illustrated in Figure 1.

Image acquisition consists of collecting images captured using digital camera, be it RGB image, spectral, thermal or fluorescence imaging. The images are then pre-processed to remove undesired distortions, enhance certain features of the image and focus only on the significant region. The pre-processed images are then grouped by similar features for significant representation and facilitate the analysis process. The features of image which should be defined include color, shape, texture etc. Finally, images are classified using neural network to get the diagnosis of the related disease [11].

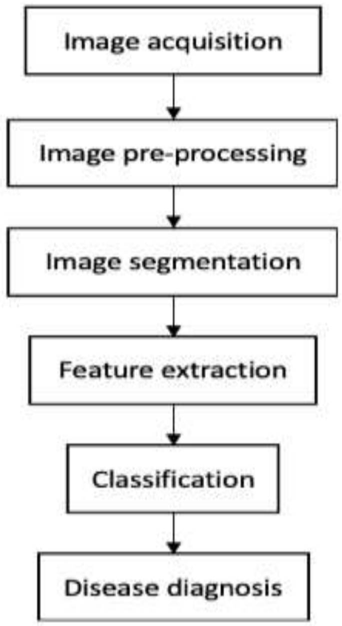

Figure 1 Steps for Disease Detection through Mage-Based Technique

2.1 Image Acquisition

The suitable image acquisition technique should be considered in order to facilitate the process of detecting and recognizing the plant disease. RGB technique is explored to diagnose ascochyta blight in cotton [12]; cercospora leaf spot, rust, ramularia leaf spot and phoma leaf spot in sugar beet [13]; scab in apple and anthracnose in tobacco [14]. Spectral technique is examined to detect head blight [15], [16] and yellow rust [17], [18] in wheat; late blight in tomato [19]; cercospora leaf spot [20] - [22], rust [21], powdery mildew [21] and root rot [23], [24] in sugar beet; scab in apple [25]; net blotch [26], brown rust [26] and powdery mildew [26], [27] in barley; orange rust in sugar cane [28]. Thermal technique is employed to detect cercospora leaf spot in sugar beet [29]; downy mildew [30] and powdery mildew [31] in cucumber; scan in apple [32]; and downy mildew in rose [33]. Lastly, fluorescence imaging technique is used to diagnose powdery mildew [34] and leaf rust [35] in wheat; cercospora leaf spot in sugar beet [36], [37]; and gummosis in cashew [38].

2.2 Image Pre-processing

As for image pre-processing, it focalizes more on the enhancement of the image, be it through the conversion of RGB to Lab, filtering etc. This process is performed to increase the contrast of images, hence, facilitate the next process followed. Image smoothing is done through filtering techniques, including median filter, average filter, Gaussian filter etc. [39].

2.3 Image Segmentation

Image segmentation is a process where the image is divided into smaller regions. This will facilitate the process to extract only the significant data from the image. There are various methods of doing it, such as, region-based segmentation, partition clustering or well known as K-means clustering technique, edge detection, Otsu's algorithm and thresholding and others [40], [41].

2.4 Feature Extraction

Once the segmentation work is done, there are only the data of significant areas which left. Thus, the feature from these areas should be extracted to get the real meaning of the picture. Color, shape and texture are among the most utilized feature extraction of an image [42]. However, with the presence of Deep Learning (DL) recently, feature extraction is done automatically through training of images to the architecture model [43].

2.5 Classification and Diagnosis

Image classification consists of a complex procedure which relies on different components. In plant disease detection, it will receive the image as the input and produce the output classification for identifying if the plant has disease, and what kind of disease presented. The examples of the existing classifiers which are widely used include Neural Network (NN), Support Vector Machine (SVM), Fuzzy Logic and Genetic Algorithm. Each of them has their own advantage as well as limitation [44], [45].

3 Existing Detection Methods

Almost all the researches done recently employ Convolutional Neural Network (CNN) based architecture to detect the presence of pests and diseases in crop due to the fact that it is a DL architecture, able to easily identify and classify objects with minimal pre-processing, successfully analyzing visual image and easily extracting the required features with its multi-layered structure [43]. CNN consists of four main layers which are convolutional layer, pooling layer, activation function layer and fully connected layer. Its architecture is illustrated in Figure 2.

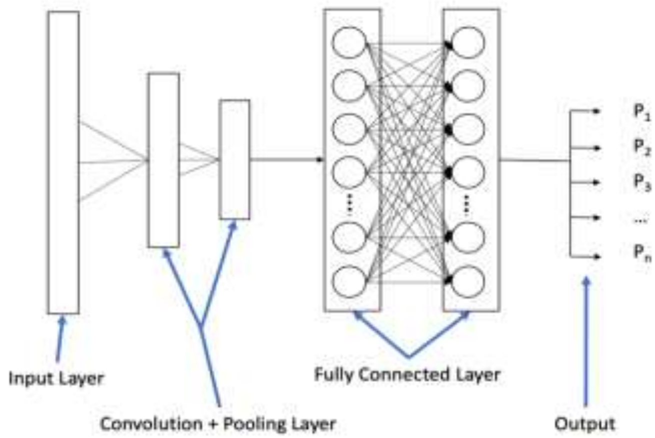

Figure 2 Basic Concept of CNN

CNN's name came from the convolutional layer, in which, a series of mathematical operations are performed to extract the feature map of the input image [46]. Filter is used to reduce the size of the image. It is shifted step by step from the upper left corner of the image. At each step, the multiplication of image value and filter matrix value is performed, and the result is then summed up to get a new matrix with certainly a smaller size [43] as illustrated in Figure 3.

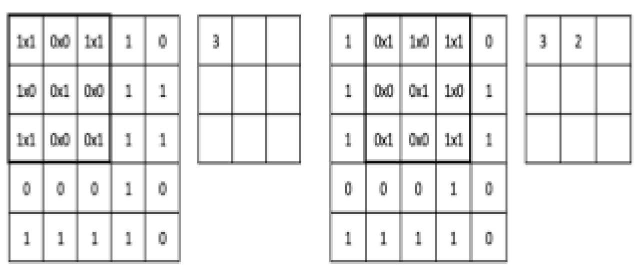

Figure 3 Convolution process for 5x5 input with 3x3 filter

As for pooling layer, it consists of reducing the size of the output matrix of convolutional layer. Generally, the size 2x2 is applied for the filter. The existing pooling functions are as max pooling (widely used), average pooling and L2-norm pooling [43]. Max pooling, for example, consists of selecting the highest number in sub-partition of matrix and transfer it to the new matrix as shown in Figure 4.

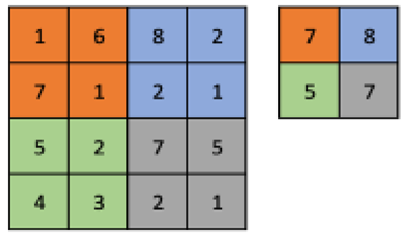

Figure 4 Max pooling with 2x2 filters and stride 2

Activation functions, e.g. linear, sigmoid, hyperbolic tangent and Rectified Linear Unit (ReLU), provide curvilinear relationship between the input and output layers [43]. Non-linear learning of the network is performed by these activation functions. ReLU, is however, the most employed activation function in CNN. ReLU performed the equation as stated in (1).

$$f(x)=\begin{cases}0, & \text{if } x<0\\ x, & \text{otherwise}\end{cases} \qquad (1)$$

Once the output matrix from the convolutional, pooling and activation layer is generated, it is fed to the fully connected layer, which will calculate the class probabilities or scores. The output of this layer will be the input of classifier, e.g. softmax classifier [47].

In [39], there were some works done to detect the diseases of tomato plant using CNN with 7 convolutional layers, together with ReLU activation function. The diseases covered were Septoria leaf spot, early blight, late blight, mosaic virus, bacterial spot, bacterial canker and bacterial speck. The 520 images were divided into 90%-10% of training-testing data, recorded an accuracy of 76%.

In [43] proposed to use CNN-based architecture embedded with LVQ algorithm. This method was used to detect four tomato plant’s diseases, which are, bacterial spot, late blight, Septoria leaf spot and yellow leaf curl virus. The images from Plant Village were used for the training purposes. There were 500 images with 5 classes (including healthy leaf). CNN is used for the training, comprising of convolutional layers, pooling layers and activation layers. The output of these layers should basically go to the fully connected layers. However, the proposed work used LVQ instead which make all layers are not fully connected. LVQ consists of input layer, kohenan layer and output layer. The input and kohenan layer are fully connected, while kohenan and output layer are partially connected. The concept 80%-20% training-testing data splitting had been put in place. As the result, it produced 86% of accuracy.

In [47], there are two architectures used to train the model with tomato image data acquired from Plant Village, which are AlexNet and SqueezeNet. This work consisted of detecting the tomato plant diseases, e.g. bacterial spot, early blight, late blight, leaf mold, leaf spot, spider mites, target spot, mosaic virus and yellow leaf curl virus as shown in Figure 5.

Figure 5 Sample images from Plant Village dataset, first row left to right labelled as bacterial spot, early blight, healthy, late blight, leaf mold; Second row left to right labelled as septoria leaf spot, spider mites, target spot, mosaic virus, yellow leaf curl virus

AlexNet registered an accuracy of 95.65% better than SqueezeNet with 94.3%.

The proposed work done in [48] to detect and recognize the tomato plant diseases using DL algorithm, recorded the highest accuracy of 95.75% for data validation. This work focused on detecting three types of diseases, which are, phoma rot, leaf miner and target spot. There were 4,923 images of healthy and diseased tomato leaf (80% used for training, and 20% used for testing), captured under controlled environment, using a motor-controlled image capturing box, from four different angles. CNN-based approach has been used to identify the type of diseases presented. The training of anomaly and disease detection were done through transfer learning using pre-trained network AlexNet. As the result, the transfer learning disease recognition model achieved the accuracy of 95.75%, and the automated image capturing system implemented in actual registered the accuracy of 91.67%.

Another research done in [49] which also used image data from Plant Village to detect the presence of 10 different diseases of tomato plant, which are, bacterial spot, early blight, late blight, leaf mold, leaf spot, spider mites, target spot, mosaic virus, yellow leaf curl virus and gray spot. There are 11 classes (including healthy leaf) which contain 640 images for each, thus, giving a total of 7040 images. The proposed algorithm is to implement CNN-based architecture on VGG16 by fine tuning the initial model with 3 fully connected layers to only 2 fully connected layers instead. This results an increasing from 88% of accuracy to 89%.

A research in [50] which again used the image data from Plant Village to detect nine diseases of tomato plant, which are, bacterial spot, early blight, late blight, leaf mold, leaf spot, spider mites, target spot, mosaic virus and yellow leaf curl virus. In this work, each original image from Plant Village was transformed into three different versions: the original image in color, grayscale image and segmented image. AlexNet and GoogLeNet were used as the architecture to train two different models, transfer learning and training from scratch. The training had been repeated using 80%-20%, 60%-40%, 50%-50%, 40%-60% and 20%-80% of training-testing data splitting. This comes up with the 99.27% and 97.82% accuracy for transfer learning and training from scratch, respectively using AlexNet. While for GoogleNet, it recorded slightly higher accuracy, which are 99.34% and 98.36% for transfer learning and training from scratch, respectively.

Last research [51] which employed image data from Plant Village were done to detect the same diseases as [50]. The concept used is illustrated in Figure 6.

Figure 6 Proposed Technique in [51]

AlexNet, GoogLeNet and the variation of LeNet (additional block of convolutional) were implemented to detect the presence of tomato plant disease. LeNet variation registered an accuracy of 94.85% compared to other implemented architectures.

A robust DL-based tomato plant diseases detector and pest recognition has been developed in [52]. The images are captured on site from multiple angles of cameras. The implementation of three deep neural network approaches had been put in place to detect nine different diseases/pests, e.g. canker, gray mold, leaf mold, low temperature, miner, nutritional excess, plague, powdery mildew and whitefly. They were Faster Region-based Convolutional Neural Network (Faster R-CNN), Single Shot Multibox Detector (SSD) and Region-based Fully Convolutional Network (R-FCN). The research work proposed a meta-architecture which concatenates feature extractor (e.g. VGG-16, ResNet-50, ResNet-101, ResNet-152) and the classifiers listed above.

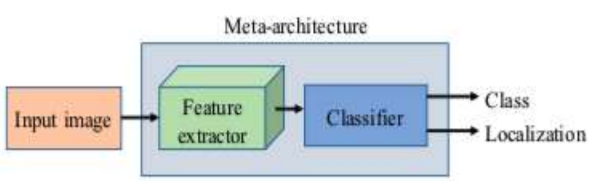

Figure 7 Meta-architecture Proposed in [52]

Without data augmentation, the average precision recorded was only 55.64%. However, the reading is increased to 83.06% thanks to the implementation of data augmentation.

Finally, a recent study in [53] employed Adaptive Neuro-Fuzzy (ANFIS) Classification to detect the presence of five different diseases of tomato plant: bacterial canker, bacterial leaf spot, fungal late blight, leaf curl and septoria leaf spot. Gray Level Co-occurrence Matrix (GLCM) was used as feature extractor. There were 650 images (80%-20% training-testing data split). The algorithm proposed was to convert segmented RGB plant images to grayscale, compute GLSM, store extracted feature into Feature Vector, Fm, then submitted to ANFIS. The proposed architecture came up with the accuracy of 90.7%.

4 Analysis on Existing Solution

Based on all the reviewed works done, here are some analysis which might be useful for improvement of future works. Table 1 illustrates the occurrence of diseases in reviewed papers.

Table 1 List of Diseases for Tomato

Name of tomato plant disease	No. of appearance	Reference
Bacterial canker	3	[39] [52] [53]
Bacterial speck	1	[39]
Bacterial spot	6	[39] [43] [47] [49] [50] [51]
Early blight	5	[39] [47] [49] [50] [51]
Gray mold	1	[41]
Gray spot	1	[49]
Late blight	7	[39] [43] [47] [49] [50] [51] [53]
Leaf miner	2	[48] [52]
Leaf mold	5	[47] [49] [50] [51] [52]
Leaf spot	6	[47] [49] [50] [51] [53]
Low temperature	1	[52]
Mosaic virus	5	[39] [47] [49] [50] [51]
Nutritional excess	1	[52]
Phoma rot	1	[48]
Plague	1	[52]
Powdery Mildew	1	[52]
Septoria leaf spot	3	[39] [43] [53]
Spider mites	4	[47] [49] [50] [51]
Target spot	5	[47] [48] [49] [50] [51]
Whitefly	1	[52]
Yellow leaf curl virus	6	[43] [47] [49] [50] [51] [52]

Based on the table above, the common diseases in tomato plant detected are late blight, early blight, bacterial spot, leaf spot, yellow leaf curl virus, leaf mold, mosaic virus and target spot. Figure 8 shows Common Disease in Tomato Plant.

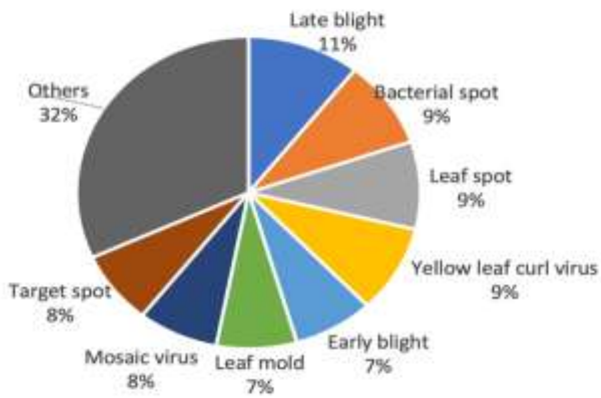

Figure 8 Common Disease in Tomato Plant

In terms of architecture employed by researchers to detect the tomato plant disease, it is illustrated in Table 2.

Table 2 List of Model Architecture Employed

Model architecture	No. of occurrence	Best Accuracy	No/Source of Images	No of Diseases
AlexNet	3	99.27%	Plant Village	9
ANFIS	1	90.70%	650	5
FR-CNN	2	83.06%	NA	9
GoogLeNet	2	99.34%	Plant Village	9
LeNet	1	94.85%	Plant Village	NA
ResNet	1	83.06%	NA	9
R-FCN	1	83.06%	NA	9
SqueezeNet	1	94.30%	Plant Village	9
SSD	1	83.06%	NA	9
VGG-16	2	89.00%	Plant Village	10

Based on Table 2, AlexNet is the most employed architecture used to train the system and it states among the best accuracy recorded which is 99.27%. However, GoogLeNet recorded the highest accuracy which is 99.34%, slightly higher than AlexNet's. Since most of the research works use the same sources of data, which is from Plant Village, it can be concluded that the accuracy reading is relevant and comparable.

5 Conclusion and Key Challenge

Based on the reviews done in this paper, it is concluded that there are some common diseases of tomato plant that can be detected using image-based Machine Learning architecture. They are late blight, early blight, bacterial spot, leaf spot, yellow leaf curl virus, leaf mold, mosaic virus and target spot.

In terms of the method used, most of the solution provided employed the CNN-based architecture which proven to give a high accuracy detection. GoogLeNet and AlexNet remain those with highest accuracy reading amongst other architectures which use the same samples of plant leaves.

In terms of research gap, almost all the high accuracy detection recorded were using pre-recorded images and mostly from Plant Village. These images are already cropped and there is no disturbance from the environmental factor. There are few researches which go further by testing their models with the on-site images under non-controlled environment and it registered not impressive accuracy compared to those with pre-recorded images. It is certainly due to the many environmental factors interfered during the detection and recognition of actual on-site images. Thus, there are still room of improvements to be explored in such matter.

Furthermore, in certain cases, even though the same source of data and model architecture is used, the recorded accuracy differs. This might be due to the different parameters used for each model. Thus, these parameters should be defined accordingly in order to produce the best accuracy.

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