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Plant Disease Detection Techniques Based on Deep Learning Models: A Review

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Abstract: *To avoid these diseases, plants need to be monitored at a very early stage in their life cycle. The traditional method used for this monitoring is visual observation, which requires more time and expensive expertise. Therefore, to accelerate this process, disease detection systems must be automated. Disease detection systems should be developed using image processing techniques. Many researchers have developed systems based on various techniques of image processing. This paper examines the potential of methods of plant leaf disease detection systems to promote the development of agriculture. It includes various steps such as image retrieval, image segmentation, feature extraction, and classification. Plant disease detection is a technique applied to detect disease in infected plants. Plant disease detection technology consists of two steps: segmentation of the first stage of an open input image to detect a sick part in the input image. A feature extraction technique is applied that extracts the features of the image and classifies the extracted features using various classifiers. In this paper, we will examine and explain various techniques of segmentation, feature extraction and classification from the viewpoint of various parameters.*

Keywords: Plant disease detection, image processing, image acquisition, segmentation, feature extraction, classification.

Introduction

Plant diseases are described as any disruption of a plant's normal physiological function that results in noticeable symptoms. A symptom is an event that occurs in relation to something and is used to prove its existence. Pathogens that cause plant disease may be present in plant leaves, stems, bulbs, fruit, and roots. Changes in the size, shape, and appearance of leaves, branches, flowers, and fruits are all symptoms of disease. Figure 1. depicts the leaf diseases of soybean, potato, and maize. It depicts how the disease has altered the green sheet, including colour, form, and rough texture transitions.

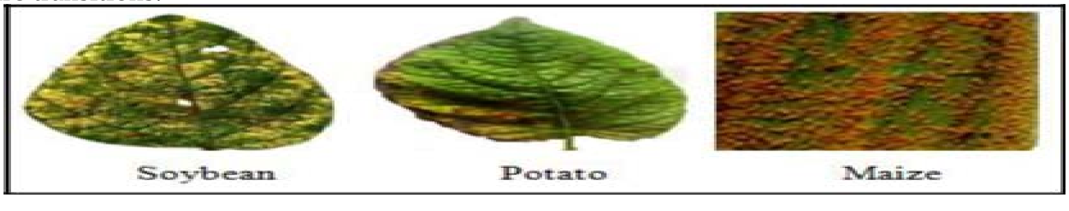


Figure 1: different Plant diseases.

Plant diseases are classified into various groups based on their frequency, severity, and cause [3,4]. The type of plant disease is classified as either localized or systemic. On the basis of natural propagation and mode of infection, plant disease is often classified as soil-borne disease, airborne disease, or seed-borne disease. A variety of diseases are included in a classification category based on symptoms. Rust, smuts, spotting leaves, mildew, mildew, powdery mildew, and so on are examples. By host plant, plant diseases are also known as cereal, vegetable, fruit, and forest diseases. On the basis of agriculture, plant diseases are referred to as maize diseases, soybean diseases, and so on. Root and fruit diseases, foliage diseases, and shooting diseases are the three types of plant diseases classified by organ. Plant diseases are classified as chronic, epidemic, seasonal, or pandemic depending on the occurrence and spread of the disease. It is widespread in a particular area when a disease is consistently moderately present year after year. Epidemic disease manifests itself in a severe form in large crop areas on a regular basis. Sporadic illness manifests itself in sporadic and unpredictable ways. It's formed in a mild to serious way. Pandemic diseases have spread throughout the continent. Pathogen production distinguishes monocyclic, polycyclic, and polyyetic diseases. Monocyclic diseases occur only once in a harvest season (for example, smut in meat), while polycyclic diseases occur several times in a cropping season (e.g. Late Blight in Potato). Polyyetic diseases are polycyclic diseases with a disease cycle of more than a year (e.g. Rust Apple).On the basis of cause, vegetable diseases are commonly referred to as fungal diseases, bacterial diseases, and so on. Nutritional deficiencies are also a cause of certain herbal diseases. Khaira in rice disease, for example, is caused by a lack of zinc.

Plant disease is unavoidable, and in the field of agriculture, the understanding of such diseases plays a significant role[3]. Plant pathology, also known as phytopathology, is the study of plant diseases. Emerging plant health issues are disrupted. Herb means phyton, disease/ailment means pathos, and discourse/knowledge means logos. Phytopathology is a branch of agriculture that studies the causes and effects of disease. Plant pathology is the scientific study of plant parasites, diseases, and conservation factors [4]. It is also possible to explain the study of nature, as well as the causes and prevention of plant diseases. Disease is a form of plant state disorder that interferes with normal functions like poisoning, sweating, photosynthesis, germination, and impregnation. Plant pathology is consumed in order to achieve the key objectives. To investigate the causes of illnesses, living and non-living, as well as recyclable materials Instruments for studying disease development to investigate the relationship between plant pathogens and environmental factors in order to improve plant monitoring methods. Plant pathologists focused on a variety of crop and plant diseases, as well as mitigating losses caused by transferable agents. They were supposed to get rid of the agent-caused lesion.

Potato Late Blight [9, 10]**:** It is one of the most dangerous diseases that can affect potatoes. Figure 2 depicts the effect on a potato leaf. In the mid-nineteenth century, Ireland was afflicted with the disease (1845-1847). At that time, approximately 1.5 million people died of hunger.About 1,5 million people have been forced out of Ireland from other countries at the same time.

Figure 2: Potato Late Blight.

Citrus Canker: It's been dubbed one of Citrus's most dangerous diseases. It's common in places like Florida, Alabama, Georgia, Louisiana, South Carolina, Texas, Brazil, and Mississippi, to name a few. Many countries have started to combat devastation since 1915. Between 1999 and 2008, 2.327.772 plants were destroyed [11]. Moreover, over 116 million dollars was spent in the last decade on the removal of polluted or exposed plants. Figure 3 shows examples of cancer-infected leaves.

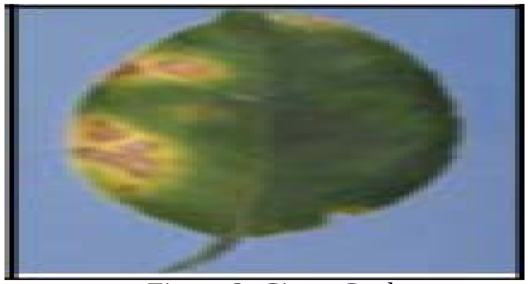


Figure 3: Citrus Canker.

Figures 4 show that the disease not only affects the color of the leaf, but also changes its morphs/stripes (e.g. shape). Diseases are often referred to as characteristics. The amount of green leaf content decreases because it includes diseases. It interferes with plant photosynthesis, lowering the process of forming plant food and, as a result, overall performance. The late blight disease on potato leaves demonstrates how leaf characteristics such as shape and edges have changed. In comparison to a healthy leaf, the diseased leaf has a strongly rolling surface. Another example of the effect of viral disease on a soybean leaf is seen in Figure 4 (b), which shows teeth of the margin on one side.

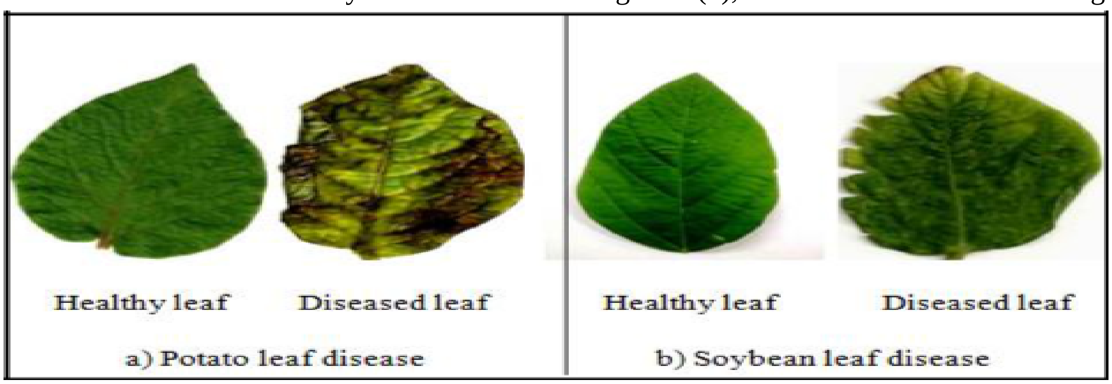


Figure 4: Effect of Disease on Leaf Traits like Shape and Margin.

Disease Diagnosis : Plant diseases spread through the air, water, and insects. Disease incidence and distribution are often influenced by environmental factors. Although humans have little power over climate change, growing crops in greenhouses may provide some control. Both growers, however, would be unable to cultivate in a greenhouse. Greenhouse maintenance and expenses are prohibitively expensive for large farms. It is only necessary for farmers to keep a close eye on their crops in order to manage diseases and pests, including early detection and treatment of plant diseases. According to an ICR survey [12], 93 percent of Indian farmers only use pesticides to control crop diseases and pests. A crop is given between 1 and 15 pesticide sprays after harvest, according to the survey. Crop losses range between 11 and 40 percent for farmers. Overuse of pesticides has a negative impact on the food chain, can result in secondary pests, is hazardous to human health, and can cause acute and chronic illnesses. The ability to diagnose a disease early allows for timely treatment. It also aids in the surveillance of disease transmission, which increases over time and spreads through wind, water, birds, and insects. Once the disease has been detected, a variety of disease-control strategies may be used. Pesticide use, biological control organisms, and Integrated Pest Management (IPM) are examples of these strategies The diagnosis method necessitates the presence of a particular individual in order to diagnose the disease and explain its treatment and protection. Recognizing a disease is a daunting task. It needs not only plant and disease awareness, but also experience. If the disease signs are correct, disease recognition is correct. As a result, farmers need a competent and expert system. This system is designated as an Expert System. An expert system could be:

- An expert farmer
- Agricultural advisor
- Electronic or Computerized expert system

A professional farmer can understand the changes in the crops by regularly observing the growing crops. According to the most recent update, they deal with cultivation. Farmers have the ability to gain insight into subtle changes in crops through observation and long cultivation experience. This knowledge is difficult to hand on to future generations. If farmers decide to seek advice from an agricultural expert on how to handle plant diseases in order to boost productivity, the following will occur. Farmers must occasionally travel long distances to visit experts. Experts will not be accessible if the farmer travels such a long way. The expert will not always be able to provide factual advice to the farmers. Seeking expert advice in such a situation is both costly and time consuming. Disease diagnosis may be done using imaging or computer vision techniques based on the results of a visual inspection. Expert systems for electronics are the name given to the device created using these techniques.

II. Literaure Survey

Many methods were used to correctly diagnose the disease in the plants in the photographs. The majority of them are concerned with image processing in general, SVM classification, K-mean, genetics, and so on. We couldn't have asked for a more positive outlook. Some researchers have recently used neural network-based methods in this area. When opposed to traditional image-processing methods, deep neural networks are effective at detecting image disease. Mango disease control is a vital part of environmental protection since it is so closely related to the health and production of the crop. India is particularly important in today's fast-growing world. The prevalence and simplicity of certain major diseases pose major challenges in the management and control of these conditions. As a result, the most recent study is crucial. Disease is a major impediment to fruit development, resulting in both qualitative and quantitative losses. It is important to understand the origin, persistence, and spread of the pathogens that cause disease in order to enforce management measures quickly. The various causes of the epidemic must also be recognized, and these diseases must signal the appearance of preventive or treatment chemicals, as well as their timely implementation. The most suitable diagnostic system will be used to diagnose the disease on fruit seeds efficiently and reliably. In order to reduce the loss of fruits in the region, during traffic and in the field, as well as the development of various diseases that affect fruits, detailed etiological, epidemiological, and control research is needed.

Xinda Liu et.al (2021) Infectious diseases are very important in agriculture because they are necessary for increasing yields. Recent advances in image processing provide a new way to solve this problem by analyzing disease in visible plants. However, there is not much work in this area, let alone ongoing research. In this article, we discuss with the system the problem of disease recognition in plants in the diagnosis of disease. Compared to other types of photographs, plant photographs usually show divided lesions, different symptoms and complex backgrounds, so it is difficult to obtain discriminatory information. To promote research on the identification of plant diseases, we have compiled a database of major diseases, which includes 271 disease categories and 220,592 images. Based on these data, we solve the problem of plant disease identification by re-evaluating the visible area and the loss to highlight the diseased part. We first calculate the value of the blocks with each section per image according to the cluster distribution of these blocks to indicate the level of discrimination per block. Then, during a weak control exercise, we weighed the losses for each pair of patch marks to determine the study distinguishing the part of the disease. We extract the patch features from the network that has undergone weight loss training, and use the LSTM network to patch the sequence of the heavy-duty pipelines into a complete feature set. Excessive evaluation of this information fund and other public funds proves the benefits of the proposed method. We hope that this research will further advance the program for the detection of diseases in plants in the field of image processing.

Xulang Guan et.al (2021) this study developed a new disease detection method by combining four CNN models. The experiment used an open source database containing 36258 images, divided into 10 plant species and 61 healthy and diseased plant species. Figure 36258 is divided into two data sets, including Figure 31718 in the training and Figure 4540 in the validation results. Four CNN models, Inception, Resnet, Inception Resnet, and Densenet are broadcast, and the results of the CNN model are set. Using the adjusted method achieves 87% accuracy, which is a significant improvement compared to the results of using a single CNN model. The high accuracy rate indicates that the integration of the CNN model with the implant method may be a viable method, which can be extended to real cultivation as an early warning tool of disease.

Deepa et.al (2021) Plant diseases are a factor in low yields and reduce incomes for farmers. Currently, researchers are doing their best to find mechanics to automatically diagnose plant diseases. Accurately diagnosing plant diseases can help with treatment as quickly as possible to control the loss. This article attempts to create a new way to predict plant diseases through the use of machine learning technology. Experimental results show that plant diseases can be successfully detected.

Bincy Chellapandi et.al (2021) The facts have proved that artificial intelligence has played a major role in most all industries. Recently, the demand for food has increased, but there is still a lack of supply. To meet these growing demands, prevention and early detection of crop diseases are measures that must be put in place in agriculture to save crops in the short term and thus reduce overall food loss. . In this article, we use an in-depth study-based model and a migration study-based model to classify the images of diseased plant leaves into 38 plant species based on defects in the data. Our research uses eight pre -trained models, namely VGG16, VGG19, ResNet50, InceptionV3, InceptionResnetV2, MobileNet, MobileNetV2, DenseNet, and customized models. We found that DenseNet achieved the best results with the test data, with a 99%accuracy rate.

Faizan Akhtar et al. (2021) Plant diseases have an impact on the spread of species, so prior research is very important. However, until the advent of machine learning, i.e., in-depth learning, this research area often has a lasting power in improving accuracy. Developed / modified in-depth measurements are used in terms of multiple vision techniques to detect and differentiate the symptoms of plant diseases. In addition, many degrees work on examining these systems / methods. This review provides a complete summary of the in -depth study models used to characterize three disease eyes. In addition, some analytical gaps are known, although their symptoms are not yet obvious, the measurements determine their specific characteristics of the identified diseases in the plant.

PE Rubini et.al (2021) Agriculture is a major activity in many parts of the country. Agriculture is an important part of the economic system of the country. Farming not only provides basic food and raw materials, but also a source of livelihood for farmers. Today, farmers face many challenges in using their farmland. The focus of this research work is on one of the major challenges in agricultural land, i.e. disease prediction. Crop diseases affect agricultural production, so a model has been proposed to predict plant diseases and encourage farmers to take appropriate action. In this work, in addition to assigning disease types, an in -depth study model was also proposed, which can accurately classify whether the diseased leaves have images. Images of tomato plants were taken from the Plant Village data, and trained models such as VGG16 and Dense Net were used for training through migration studies, and compared. Therefore, the proposed system, in addition to the interpretation and measurement of the dimensions, can help the farmer in the pre -identification of diseased leaves.

Akshai KP et.al (2021) Agriculture plays an important role in the Indian economy. Early detection of plant diseases is very important to prevent crop loss and spread of disease. Most plants, such as apples, tomatoes, cherries and grapes show obvious symptoms on the leaves. These visual patterns can be identified to accurately predict the disease and take precautionary measures to prevent it. The traditional method is for the farmer or observer to inspect the plant's leaves and identify the type of disease. In this project, an in-depth study model was trained to classify various plant diseases. The convolutional neural model (CNN) is used because of its great effectiveness in image classification. Compared to the study of plant leaves, the in -depth study model can provide faster and more accurate predictions. In this work, CNN models and trained models such as VGG, ResNet and DenseNet models were trained using the data. Among them, the DenseNet model has the most accuracy.

N Radha et al. (2021) Cluster farming is a widely used farming method today. Poly-housing will provide the water and fertilizer needed to increase production. Movement in bad air causes insects. To avoid this problem, it is necessary to regularly monitor the crop. Therefore, control parameters such as temperature and hardness are essential for effective farming because they can indicate the amount of water, nutrients and pesticides needed at the right time. This will prevent the occurrence and spread of the disease indirectly as well. Therefore, driven by this complex task, our goal is to offer solutions to monitor plants and identify plant-borne diseases. Automatic plant detection technology helps to relieve the symptoms of the disease in large farms. The data used for this work include images of various plants with diseased and healthy leaves. Convolutional Neural Networks (CNN) are used to train models for the diagnosis of neurological diseases. The plants considered include corn, strawberries, grapes, tomatoes and potatoes. The model predicts the status of most plants with an optimal predictive ability of 85%, and the losses observed during the training data are negligible by 0.25.

Satoi Kanno et al. (2021) Photographic identification of vegetation is a difficult task because it is easy to detect symptoms. This cracking can cause the system to overheat because it sometimes responds to unwanted areas of the image, such as conditions or sunlight. Therefore, this will result in a significant reduction in performance when diagnosing disease in different test areas. A method of generating large amounts of data through Generative Adversarial Networks (GAN) has been proposed to solve this extreme problem. But, due to the limited type of images created, the performance improvement is limited. This research proposes a reproductive and pathogenic imaging technology (PPIG), which is a system to create high -quality plant imaging to train the diagnostic system. PPIG consists of two stages: the mass production process and the pathogenic process. In the first stage, a number of healthy leaf images were prepared to form the basis for image production. Then, in the second step, the symptomatic feature is added to the leaf portion of the obtained healthy image. In this study, we conducted an experiment to evaluate PPIG using test images taken from different areas of the training image, assuming that cucumber leaves have six disease categories. The proposed PPIG can create images that appear natural, healthy and patient, and the use of these images to improve the data improves the robustness of the diagnostic system. Examination of 8,834 images taken from 53,045 training images in different domains shows that our proposal improves the diagnostic efficiency of F1 model yellow eyes by 9.4%. In addition, it is 4.5% higher than the previous data improvement method.

Majji V Applalanaidu et.al (2021) Check the latest progress in the development of medical systems and classification systems according to machine learning (ML) and deep learning (DL) models. In this study, we collected more than 45 papers that were published between 2017 and 2020. These papers were from journals reviewed by colleagues in various databases, such as the use of machine learning to detect, diagnose and classify plant diseases and other keywords. The structured methods of the various disease classification models are presented in a well-organized table. In this article, we have conducted a systematic literature review on the application of the most advanced ML and DL algorithms, such as support machine (SVM), fuel network (NN), nearest K neighbor (KNN), and Bayes (NB) is meaningless. , Many other popular ML algorithms and AlexNet, GoogLeNet, VGGNet and many other popular DL algorithms are used to classify the disease. Each dedicated algorithm passed a corresponding processing method (e.g. image sharing, feature extraction) and experimental parameters (e.g. total training / testing data used, number of diseases considered, the type of classification used, and the accuracy of the classification This work will be a useful source of information for researchers to identify which specific plant species by means of data retrieval methods.

Iqbal et al. in Leafy plants should be categorized and graded, according to several reports. In the review, the authors cover every aspect of disease management, including image processing concepts, technology, difficulties, benefits, and drawbacks..for example. Several neural network methods for recognising and classifying diseases in plant photographs have been proposed in the literature [2]. Models, models, forms, mechanics, and groups are all used in hyper-spectral images and many other visual representations in this work. Ma et al. listed four types of poultry from the leaves, including anthracnosis, pink fast, powdery mildew, and leaf soup. [4] Collects all images in real time and classifies them using deep neural networks (DCNN). Ferentinos proposed classifying the VGG convolutional neural network's index for plant leaves in [5.] The method for presenting an image to patients categorizes it. The results are compared to the rigorous research procedure's validity in a large data set. Four convolutional network structures, including VGG 16, Inception V4, ResNet, and DenseNets, are used to classify the disease in [6]. The photographs were taken from records on the rice field that included 38 different health categories. In contrast to other media outlets, the DenseNets network has high coverage in high classification and requires little time.

ChutinanTrongtorkidet.al (2018): The study has shown success in the Barracuda Mango, which is one of Thailand's most important agricultural products, as well as a specialist organization diagnosing plant diseases (Nam-Dok Mai). However, since Thailand is a tropical nation, climate change has an effect on mango tree growth and plant disease changes. Due to a lack of farming varieties, farmers are unable to properly categories plant species. Furthermore, no decision-making process is used to decide how farm diseases are avoided or dealt with. A variety of errors have occurred as a result of the handling of infected plants. As a result, the system was created to assist farmers in identifying the plants and quickly resolving their issue. Farmers could be used as high-end applications for a specific disease procedure. Information architecture and model-based data extraction techniques are included in the plant diagnostics application. You will find a model set for a rule-based picture here. The model is made up of 129 mango pictures obtained from the University of Maeda under quality control and standard equivalent, and the test results for category 3 tablets (anthracnosis, algal position, standard) are 89.92 percent accurate. Experiments have shown that the principles-based model can be applied to plant marches.

UdayPratap Singh et.al (2019): Fungal diseases affect not only the weight of plants and their products, but also their ecological value. Fruit trees are affected by anthracnose, which affects their fruits and leaves in particular. The aim of this article is to expand the treatment of the illness and its symptoms in an acceptable and efficient manner, resulting in early and prompt assistance. Because of their superior work in calculus and precision, computer vision and systematic learning methods have become common in recent years in various disease classifications. It is proposed that anthracnose-infected blue leaves be identified using a neural convolutional neural network (MCNN). It is based on real data from India's J&K Katra University, which includes images of Shri Mata Vaishno Devi and blue trees. The results include images of healthy leaves as well as images of diseased leaves. The proposed MCNN model outperforms other advanced accuracy models, according to the findings.

Sunayana Arya et.al (2019): Deep Learning (DL) is one of the most quickly acquired skills. CNN analyses images in great detail in order to provide the most accurate solutions to global problems. AlexNet, Google Net, Dense Net, Squeeze Net, ResNet, and VGGNet are only a few of the architecture-trained CNNs. The present report compared the accuracy and effectiveness of CNN and AlexNet laboratories in detecting diseases in blue and potato leaves. A 4004-page diagram was used in this project. A photograph of potatoes was taken for the Village Village website, and a photograph of the blue one was taken for the GBPUAT website. The results show that the AlexNet framework's CNN architecture has superior precision.

Gina S. Tumang et.al (2019) : By recognising the plagues and diseases of leaves and fruit, the study improved the management of specific crops used in pest farming and discussed one of the leading causes of the pest. Mango production in the Philippines is declining, and blue farmers from Pampanga are assisting. In times of plague, farmers are sceptical of pesticides. Multi-SVM and GLCM are used in image processing to detect anthracnose, fly, and raspberry moulds with 85 percent accuracy. Contrasts, courtesy, rubbing, and entropy are all taken into account. This research can be used as a model for other trees or as a foundation for local agricultural management (especially blue farming using data science).

III. Deep Learning Models

Now that you've learned the fundamentals of CNN cables, we'll show you how to read CNN's new architecture. Each component is a key CNN system structure in this chapter, as well as a basic model for research construction projects and distributed systems (or currently). Each of these networks is a long-term design, and they're all ImageNet winners or contestants. Since 2010, the ImageNet competition has served as a metric for the effectiveness of computer surveillance studies. These models include the AlexNet, the first large-scale transmission network to overcome the traditional challenges of computer vision with major vision problems; VGG networks, which use several blocks of repetitive components; and the NiN network, which can create the entire neural network. Although the concept of a deep network (with several bundles) is similar, the architecture and hyper parameter selection will differ significantly. The neural networks described in this chapter result in intuition, mathematical interpretation, and a lot of trial and error. These models are presented to assist you in comprehending the storey and developing your own sense of the area, as well as possibly establishing your own framework. Batch normalization and residual concatenation, for example, are two common ideas for further training and profound modeling discussed in this chapter.

Classification network

In real natural environment, the great differences in shape, size, texture, color, background, layout and imaging illumination of plant diseases and pests make the recognition a difficult task. Due to the strong feature extraction capability of CNN, the adoption of CNN based classification network has become the most commonly used pattern in plant diseases and pests classification. Generally, the feature extraction part of CNN classification network consists of cascaded convolution layer pooling layer, followed by full connection layer (or average pooling layer)+softmax structure for classification. Existing plant diseases and pests classification network mostly use the pertained network structures in computer vision, including AlexNet and GoogleNet By inputting a test image into the classification network, the network analyses the input image and returns a label that classifies the image. According to the difference of tasks achieved by the classification network method, it can be subdivided into three subcategories: using the network as a feature extractor, using the network for classification directly and using the network for lesions location.

Google Net

Google Net was proposed by research at Google (with the collaboration of various universities) in 2014 in the research paper titled “Going Deeper with Convolutions”. This architecture was the winner at the ILSVRC 2014 image classification challenge. It has provided a significant decrease in error rate as compared to previous winners AlexNet (Winner of ILSVRC 2012) and ZF-Net (Winner of ILSVRC 2013) and significantly less error rate than VGG (2014 runner up). This architecture uses techniques such as *1×1* convolutions in the middle of the architecture and global average pooling.

The Google Net architecture consists of 22 layers (27 layers including pooling layers), and part of these layers are a total of 9 inception modules Have a quick review of the table before reading more on the table's characteristics and features. The input layer of the Google Net architecture takes in an image of the dimension 224 x 224.

Type: This refers to the name of the current layer of the component within the architecture

Patch Size: Refers to the size of the sweeping window utilized across conv and pooling layers. Sweeping windows have equal height and width.

Stride: Defines the amount of shift the filter/sliding window takes over the input image.

Output Size: The resulting output dimensions (height, width, number of feature maps) of the current architecture component after the input is passed through the layer.

Depth: Refer to the number of levels/layers within an architecture component.

#1x1 #3x3 #5x5: Refers to the various convolutions filters used within the inception module.

#3X3 reduce #5x5 reduce: Refers to the numbers of 1x1 filters used before the convolutions.

Pool Proj: This is the number of 1x1 filters used after pooling within an inception module.

Params: Refers to the number of weights within the current architecture component.

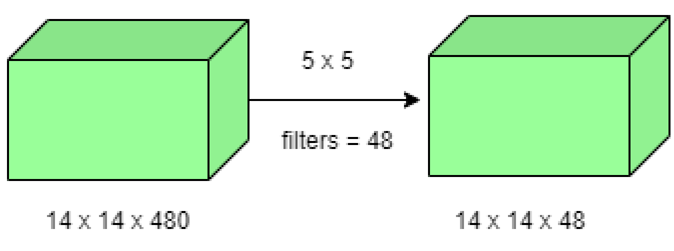
Ops: Refers to the number of mathematical operations carried out within the component.

Features of Google Net:

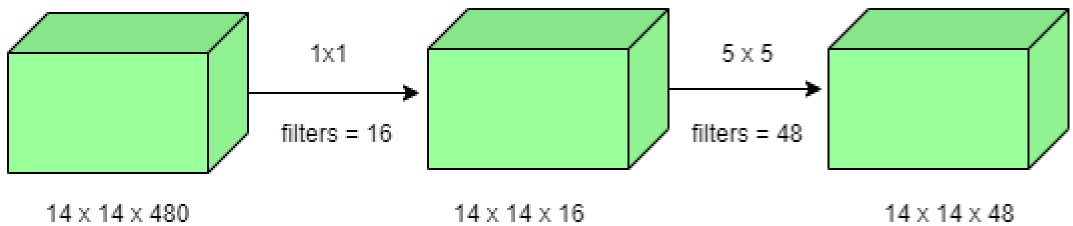
The Google Net architecture is very different from previous state-of-the-art architectures such as AlexNet and ZF-Net. It uses many different kinds of methods such as *1×1* convolution and global average pooling that enables it to create deeper architecture. In the architecture, we will discuss some of these methods:

***1×1* convolution:** The inception architecture uses *1×1* convolution in its architecture. These convolutions used to decrease the number of parameters (weights and biases) of the architecture. By reducing the parameters we also increase the depth of the architecture. Let's look at an example of a *1×1* convolution below:

For Example, If we want to perform *5×5* convolution having 48 filters without using *1×1* convolution as intermediate:



Total Number of operations: *(14 x 14 x 48) x (5 x 5 x 480) = 112.9 M* With 1×1 convolution :



(14 x 14 x 16) x (1 x 1 x 480) + (14 x 14 x 48) x (5 x 5 x 16) = 1.5M + 3.8M = 5.3M which is much smaller than 112.9M.

Global Average Pooling

In the previous architecture such as AlexNet, the fully connected layers are used at the end of the network. These fully connected layers contain the majority of parameters of much architecture that causes an increase in computation cost. In GoogLeNet architecture, there is a method called global average pooling is used at the end of the network. This layer takes a feature map of 7×7 and averages it to 1×1. This also decreases the number of trainable parameters to 0 and improves the top-1 accuracy by 0.6%

ALEXNET (2012)

AlexNet is one of the most popular neural network architectures to date. It was proposed by Alex Krizhevsky for the ImageNet Large Scale Visual Recognition Challenge (ILSVRV), and is based on convolutional neural networks. ILSVRV evaluates algorithms for Object Detection and Image Classification. In 2012, Alex Krizhevsky et al. published ImageNet Classification with Deep Convolutional Neural Networks. This is when AlexNet was first heard of.

The challenge was to develop a Deep Convolutional Neural Network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 dataset into more than 1000 different categories. The architecture achieved a top-5 error rate (the rate of not finding the true label of a given image among a model's top-5 predictions) of 15.3%. The next best result trailed far behind at 26.2%.**AlexNet.** The architecture consists of eight layers: five convolutional layers and three fully-connected layers. But this isn't what makes AlexNet special; these are some of the features used that are new approaches to convolutional neural networks:

ReLU Nonlinearity. AlexNet uses Rectified Linear Units (ReLU) instead of the tanh function, which was standard at the time. ReLU's advantage is in training time; a CNN using ReLU was able to reach a 25% error on the CIFAR-10 dataset six times faster than a CNN using tanh.

Multiple GPUs. Back in the day, GPUs were still rolling around with 3 gigabytes of memory (nowadays those kinds of memory would be rookie numbers). This was especially bad because the training set had 1.2 million images. AlexNet allows for multi-GPU training by putting half of the model's neurons on one GPU and the other half on another GPU. Not only does this mean that a bigger model can be trained, but it also cuts down on the training time.

Overlapping Pooling. CNNs traditionally "pool" outputs of neighboring groups of neurons with no overlapping. However, when the authors introduced overlap, they saw a reduction in error by about 0.5% and found that models with overlapping pooling generally find it harder to overfit.

The Over fitting Problem. AlexNet had 60 million parameters, a major issue in terms of over fitting. Two methods were employed to reduce over fitting:

Data Augmentation. The authors used label-preserving transformation to make their data more varied. Specifically, they generated image translations and horizontal reflections, which increased the training, set by a factor of 2048. They also performed Principle Component Analysis (PCA) on the RGB pixel values to change the intensities of RGB channels, which reduced the top-1 error rate by more than 1%.

Dropout. This technique consists of "turning off" neurons with a predetermined probability (e.g. 50%). This means that every iteration uses a different sample of the model's parameters, which forces each neuron to have more robust features that can be used with other random neurons. However, dropout also increases the training time needed for the model's convergence

AlexNet Architecture

The architecture is comprised of eight layers in total, out of which the first 5 are convolutional layers and the last 3 are fully-connected. The first two convolutional layers are connected to overlapping max-pooling layers to extract a maximum number of features. The third, fourth, and fifth convolutional layers are directly connected to the fully-connected layers. All the outputs of the convolutional and fully-connected layers are connected to ReLu non-linear activation function. The final output layer is connected to a softmax activation layer, which produces a distribution of 1000 class labels.

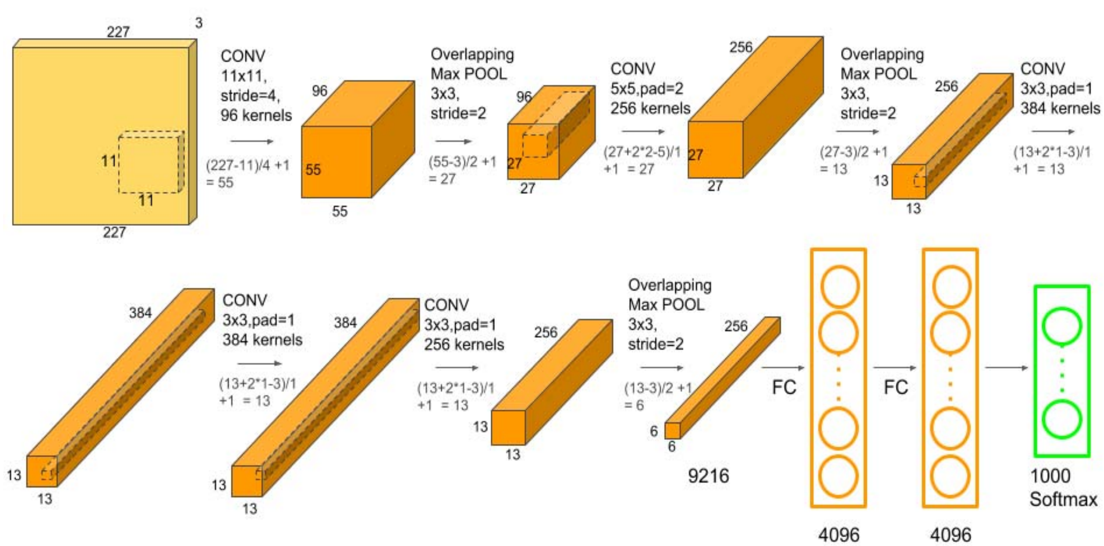


Figure 5: AlexNet Architecture.

The input dimensions of the network are (256 × 256 × 3), meaning that the input to AlexNet is an RGB (3 channels) image of (256 × 256) pixels. There are more than 60 million parameters and 650,000 neurons involved in the architecture. To reduce overfitting during the training process, the network uses dropout layers. The neurons that are "dropped out" do not contribute to the forward pass and do not participate in back propagation. These layers are present in the first two fully-connected layers

Let's now see one more example of a convolutional neural network. The second convolutional neural network that we are going to present is AlexNet neural network. An input to this neural network is 227×227×3. We have a color image as an input and that is why we have 3 channels.

AlexNet architecture layer

Let's explore the architecture of this convolutional neural network.

Conv1
First, we will apply convolutional layer: filter size is f=11, and a number of filters is 96. In this convolutional layer we will also use a stride of 4. This stride of 4 will decrease dimensions of an input volume by a factor of 4, so after this first convolutional layer we will get 55×55×96 volume.
Maxpool1
The next layer is Maxpooling layer. In this layer we will use a 3×3 filter and a stride of 2. This will reduces the dimensions of 55×55×96 volume to 27×27×256, because we are using a stride of 2.
Conv2
Next layer is a convolutional layer with a filter size f=5 so we are also using a same convolution, so we will get the same dimensions 27×27×256.
Maxpool2
After this same convolution, we will apply Maxpooling with a 3×3 filter and a stride of 2. This will reduce the height and width to 13.
Conv3,Conv4,Conv5
Next, we will apply 3 3×3 same convolution layers with padding = 1 and a stride = 1. In the first two convolutional layers we will use 384 filters and in the third (in Conv5 layer) we will use 256 filters.
Maxpool3
Next, we will apply the third Maxpool layer with a stride of 2, so we have the volume with dimensions 6×6×256. If we multiply out these numbers 6×6×256=9216. We're going to unroll this into 9216 nodes. FC6,FC7,FC8.

IV. Conclusion

This review paper concludes that these disease detection techniques show a efficiency and accuracy such that they have the ability to run the system developed for detection of leaf diseases besides having some limitations. Therefore, there is a lot that can still be done in this field for enhancement of the existing works. In this work, it is been concluded that plant disease detection is the technique to detect infected portion from the leaf. The plant disease detection consist of two steps, in the first step the image segmentation is done and in the second step technique of feature extraction and classification is applied which will classify diseases and normal portion in the image. In this paper, various techniques of plant disease detection is reviewed and discussed in terms of various parameters.

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