INTERNATIONAL JOURNAL OF ENGINEERING INNOVATIONS IN ADVANCED TECHNOLOGY

ISSN [O]: 2582-1431 VOLUME-II ISSUE-I JAN-MAR-2020

IMAGE BASED PLANT DISEASE DETECTION USING DEEP LEARNING

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Abstract:With increasing population the crisis of food is getting bigger day by day. During crisis crop diseases are a major threat to food industry, but their rapid identification remains difficult in many parts of the world due to the unavailability of the experts and necessary infrastructure. The recent expansion of deep learning methods has found solution for detection of various plant diseases.Using the dataset which contains several leaf images which were taken in various weather conditions, at different angles. Entire dataset is split into train and test sets. We do image processing using deep learning on the train set and we evaluate our trained model on the test set. During the training we want to get rid of many problems like overfitting and underfitting by make use of regularization or dropout or by increasing number of layers. This model may recognize only some diseases because of the limited dataset available, but we can use this model for detection of any type of disease by providing the large dataset which contains almost all diseases.

Keywords: Plant Disease, Deep Learning.

1. INTRODUCTION

Like every other living organism, plants are susceptible to diseases. Crop disease involves any harmful deviation or alteration from the normal functioning of the physiological processes. Therefore, diseased plants suffer disturbances from normal life processes and their vital functions.In an attempt to reach high yields and healthy crops, farmers throughout the world struggle to prevent and eradicate various diseases from their crops. Each crop is susceptible to particular diseases that affect the quality and final yield potential.Generally, it’s estimated that various pests (insects, weeds, nematodes, animals, diseases) each year cause crop yield losses of 20-40%. More precisely, there is some data that maintains that crop diseases cause average yield losses of 42% for the most important food crops. In some cases, crop diseases destroy the whole crop production. For this reason, it's extremely important for farmers to find out all they can about the crop diseases so they can manage them properly.

1.1 Causes for crop diseases

The disease usually occurs and spreads from season to season, depending on the presence of a certain pathogen, as well as environmental conditions and the characteristics of each crop variety. Essentially, crop diseases occur according to the nature of their causal agent:

1. Abiotic or Noninfectious disease agents
2. Biotic or Infectious disease agents.

Abiotic, or Noninfectious disease agents, include non-living environmental conditions or inappropriate farm management. They are not transmissable to other plants. A few universally recognized abiotic agents are:

- Extreme temperatures
- Moisture
- Wind
- Frequent and heavy rain
- Drought or flood
- Excess or deficiency of nutrients
- Soil compaction
- Chemical injury caused by pesticides or salts
- Improper water management

Biotic, or Infectious disease agents, are living organism pathogens capable of spreading from one host to another and transmitting the disease.

The pathogens are classified as:

Fungi; the most common pathogens, cause around 85% of plant diseases; examples include Black or stem rust caused by the fungus Puccina graminis tritici

Viruses; are transmitted by a vector or attack the plant through a wound; for example, the Apple mosaic virus affects apple, plum, and hazelnut,

Bacteria; mutate and multiply rapidly; they enter the plant through a wound or stomata; for instance, the Apple fire blight is caused by Erwinia amylovora

Nematodes; damage the crops causing galls on roots

Parasitic plants, live on crops, as they lack chlorophyll they obtain it from the host plant; for example, the dwarf mistletoe grows on other plants and derives nutrients from the host

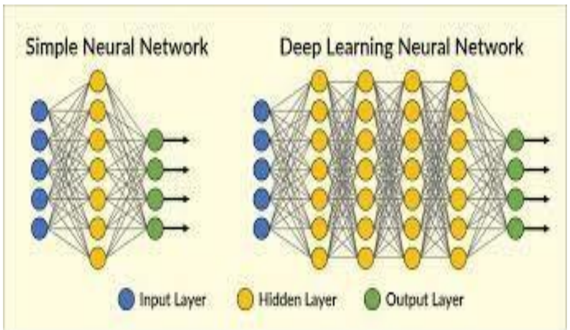
Algae; theoretically don't cause significant damage, however, the may under special circumstances.

Understanding the disease and the development process is the first step towards successful disease management. There are a few special conditions that are conducive for disease development. First, each crop is susceptible to some disease. Second, abiotic factors, namely weather, weaken the plant significantly. Therefore, the plant is vulnerable to the attack of the pathogen. So, the pathogen acts like a cherry on top. When all of the aforementioned factors (susceptible crop, abiotic stress, pathogen attack) are present together and at the same time, disease occurs. That is called the Plant Disease Pyramid.

This paper uses the deep learning for the classification of plant diseases by taking the different images of diseased plants. Data should be preprocessed and this preprocessing stage must be done before the model training phase.

1.2 Deep Learning

Deep learning is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence (AI) that has networks capable of learning unsupervised from data that is unstructured or unlabeled. Also known as deep neural learning or deep neural network. Deep learning learns from vast amounts of unstructured data that would normally take



humans decades to understand and process.

1.3 Neural Networks

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so the network generates the best possible result without needing to redesign the output criteria.

Fig.1. Simple and Deep Neural Network

1.4 Feed Forward Neural Networks

Feed forward neural network is an artificial neural network wherein connections between the nodes do not form a cycle. As such, it is different from its descendant: recurrent neural networks. The feed forward neural network was the first and simplest type of artificial neural network devised.

Data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, that is when it acts as a classifier, there is no feedback between layers. This is why they are called feed forward neural networks.

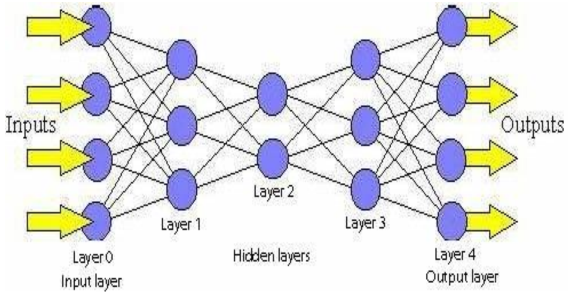


Fig.2. Feed Forward Neural Networks

2. LITERATURE SURVEY

Jie Hang, Dexiang Zhang, Peng Chen, Jun Zhang and Bing Wang proposed a paper on “Classification of Plant Leaf Diseases Based On Improved Convolutional Neural Network”. An accurate and timely detection of diseases and pests in plants can help farmers in applying timely treatment on the plants and thereby can reduce the economic losses substantially. Recent developments in deep learning based convolutional neural networks (CNN) have greatly improved image classification accuracy. This work proposed a deep learning-based method to identify and classify plant leaf diseases. The proposed method can take the advantages of the neural network to extract the characteristics of diseased parts, and thus to classify target disease areas. To address the issues of long training convergence time and too-large model parameters, the traditional convolutional neural network was improved by combining a structure of inception module, a squeeze-and-excitation module and a global pooling layer to identify diseases. Through the Inception structure, the feature data of the convolutional layer were fused in multi-scales to improve the accuracy on the leaf disease dataset. Finally, the global average pooling layer was used instead of the fully connected layer to reduce the number of model parameters. Compared with some traditional convolutional neural networks, our model yielded better performance and achieved an accuracy of 91.7% on the test data set. At the same time, the number of model parameters and training time have also been greatly reduced.

S. Mohan Sai, G. Gopichand, C. Vikas Reddy, K. Mona Teja proposed a paper on “High Accurate Unhealthy Leaf Detection”. This work proposed a model which is made into five sessions. Image preprocessing includes the enhancement of the low light image done using inception modules in CNN. Low resolution image enhancement is done using an Adversarial Neural Network. This also includes Conversion of RGB Image to YCrCb color space. Next, this work presents a methodology for image segmentation which is an important aspect for identifying the disease symptoms. This segmentation is done using the genetic algorithm. Due to this process the segmentation of the leaf Image this helps in detection of the leaf mage automatically and classifying. Texture extraction is done using the statistical model called GLCM and finally, the classification of the diseases is done using the SVM using different Kernels with the high accuracy.

Sharada Prasanna Mohanty, David Hughes, and Marcel Salathe proposed a paper on “Using Deep Learning For Image-Based Plant Disease Detection”. The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify 14 crop species and 26 diseases. The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach. When testing the model on a set of images collected from trusted online sources - i.e. taken under conditions different from the images used for training the model still achieves an accuracy of 31.4%. While this accuracy is much higher than the one based on random selection (2.6%), a more diverse set of training data is needed to improve the general accuracy.

Chowdhury Rafeed Rahmanc, Preetom Saha Arkoa, Mohammed Eunus Alia, Mohammad Ashik Iqbal Khanb, Sajid Hasan Apona, Farzana Nowrinb, Abu Wasif proposed a paper on “Identification And Recognition Of Rice Diseases And Pests Using Convolutional Neural Networks”. In this paper, they present deep learning based approaches to detect diseases and pests in rice plants using images captured in real life scenario. We have experimented with various state-of-the-art CNN architectures on our large dataset of rice diseases and pests collected manually from the field, which contain both inter-class and intra-class variations and have nine classes in total. The results show that we can effectively detect and recognize rice diseases and pests using CNN with the best accuracy of 99.53% on test set using CNN architecture, VGG16. Though the accuracy of CNN models built on VGG16 or other similar architectures is impressive, these models are not suitable for mobile devices due to their large size having a huge number of parameters. To solve this problem, we propose a new CNN architecture, namely stacked CNN, that exploits two stage training to reduce the size of the model significantly while at the same time maintaining high classification accuracy. Our experimental results show that we achieve 95% test accuracy with stacked CNN, while reducing the model size by 98% compared to VGG16. This kind of memory efficient CNN architectures can contribute in rice disease detection and identification based mobile application development.

Hee –Jin Yu and Chang-Hwan proposed a paper on “Apple Leaf Disease Identification Through Region- Of Interest-Aware Deep Convolutional Neural Network”. A new method of recognizing apple leaf diseases through region-of interest-aware deep convolutional neural network is proposed in this paper. The primary idea is that leaf disease symptoms appear in the leaf area whereas the background region contains no useful information regarding leaf diseases. To realize this idea, two sub networks are first designed. One is for the division of the input image into three areas: background, leaf area, and spot area indicating the leaf diseases, which is the region of interest (ROI), and the other is for the classification of leaf diseases. The two sub networks exhibit the architecture types of an encoder–decoder network and VGG network, respectively; subsequently, they are trained separately through transfer learning with a new training set containing class information, according to the types of leaf diseases and the ground truth images where the background, leaf area, and spot area are separated. Next, to connect these sub networks and subsequently train the connected whole network in an end-to-end manner, the predicted ROI feature map is stacked on the top of the input image through a fusion layer, and subsequently fed into the sub network used for the leaf disease identification. The experimental results indicate that correct recognition accuracy can be increased using the predicted ROI feature map. It is also shown that the proposed method obtains better performance than the conventional state-of- the-art methods: transfer-learning-based methods, bilinear model, and multi scale-based deep feature extraction and pooling approach.

3. SYSTEM ANALYSIS

System analysis is a process of collecting and interpreting facts, identifying the problems, and decomposition of a system into its components. System analysis is conducted for the purpose of studying a system or its parts in order to identify its objectives. It is a problem solving technique that improves the system and ensures that all the components of the system work efficiently to accomplish their purpose. Analysis specifies what the system should do. To know the kind of disease the plant has, we need to give the image of that plant leaf to the system. The system can extract features from this image and recognize the patterns in the image. The recognized patterns compared with the already existing features of the images that are present in our training dataset in order to make predictions.

3.1 Methodology

The system performs several operations under the hood. Let us discuss the methodology of the system.

3.1.1 Pre-processing the data

Dataset contains noise and some unwanted data. Image enhancement, image compression these are the kinds of pre-processing to extract the hidden information or not to lose any information or to normalize the pixel data.

3.1.2 Extract the features of the Image

Feature extraction is a very important process in every machine learning and deep learning mechanisms. System should able to extract some features like edges and disease location and the type of leaf and so on. Feature extraction is a built in process in the deep learning mechanism. Feature extraction is a necessary step and should be done properly because if this step goes wrong entire system definitely fails.

3.1.3 Pattern Recognition

Patterns in the images can be recognized using the deep learning algorithms. The pattern of the disease in the leaf should be recognized to predict the type of disease.

3.1.4 Compare Patterns

After predicting patterns in the leaf, they are to be compared with the existing patterns of the images captured by the deep learning algorithms. The comparison made based on calculating the distance between the patterns.

3.1.5 Make a Prediction

In order to make the prediction the distance between patterns is calculated and compared with the threshold value to find the type of disease that leaf has.

The system contains some components which are to be used to achieve the above mentioned operations. Let us discuss those components.

3.2 Dataset-Description

The dataset used in this system contains 38 different kind of diseases belongs to different plants. Every image in the system contains three channels i.e. Red, Green, Blue. The training dataset contains 19, 543 images and the validation dataset contains 6,542 images. The example image of the Apple plant with Scab disease.

Fig.3. Apple Leaf Contain Scab Disease

3.3 Layers

The layers are the building blocks of a Convolutional Neural Networks (CNNs). Let us discuss those layers.

3.3.1 Convolutional Layer

The convolutional layer is the core building block of a CNN.A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons. In other words, the filter is slid across the width and height of the input and the dot products between the input and filter are computed at every spatial position. The output volume of the convolutional layer is obtained by stacking the activation maps of all filters along the depth dimension. Since the width and height of each filter is designed to be smaller than the input, each neuron in the activation map is only connected to a small local region of the input volume. The most important parameters are the number of kernels and the size of the kernels. A convolutional layer acts as a fully connected layer between a 3D input and output. The input is the "window" of pixels with the channels as depth. This is the same with the output considered as a 1 by 1 pixel "window". The kernel size of a convolutional layer is

$$k\_w * k\_h * c\_in * c\_out.$$

where k_w = kernel width

k_h = kernel height

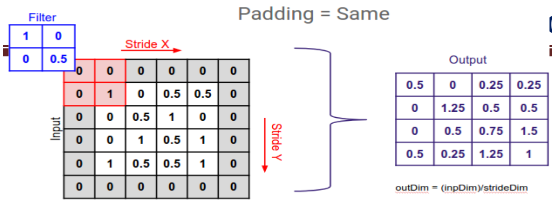
c_in = number of channels in input image

c_out = number of channels in output image

In this system we used 5 convolutional layers.

3.3.2 Pooling Layer

A pooling layer is another building block of a CNN. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. Pooling layer operates on each feature map independently. The most common approach used in pooling is max pooling. In our system we used 5 pooling layers.



- Pooling layers are used to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters to learn and the amount of computation performed in the network.
- The pooling layer summarizes the features present in a region of the feature map generated by a convolution layer. So, further operations are performed on summarized features instead of precisely positioned features generated by the convolution layer. This makes the model more robust to variations in the position of the features in the input image.

Two common functions used in the pooling operation are:

- Average Pooling: Calculate the average value for each patch on the feature map.
- Maximum Pooling (or Max Pooling): Calculate the maximum value for each patch of the feature map.

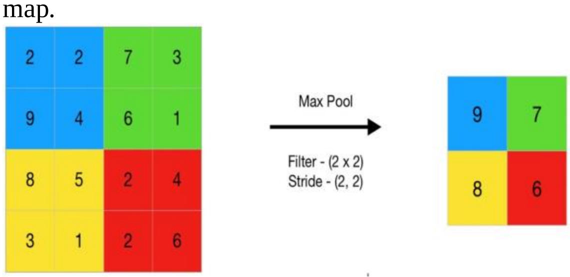
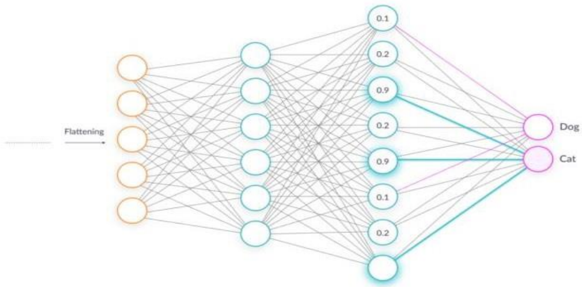


Fig.4. Max Pooling

3.3.3 Fully connected layers

Fully connected layers are an essential component of Convolutional Neural Networks (CNNs), which have been proven very successful in recognizing and classifying images for computer vision. The CNN process begins with convolution and pooling, breaking down the image into features, and analyzing them independently. The result of this process feeds into a fully connected neural network structure that drives the final classification decision. Fully Connected Layer is simply, feed forward neural networks. Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer. In our system we used 4 fully connected layers.

The objective of a fully connected layer is to take the results of the convolution/pooling process and use them to classify the image into a label (in a simple classification example). The output of convolution/pooling is flattened into a single vector of values, each representing a probability that a certain feature belongs to a label. For example, if the image is of a cat, features representing things like whiskers or fur should have high probabilities for the label "cat". The image below illustrates how the input values flow into the first layer of neurons. They are multiplied by weights and pass through an activation function (typically ReLu), just like in a



classic artificial neural network. They then pass forward to the output layer, in which every neuron represents a classification label.

The fully connected part of the CNN network goes through its own back propagation process to determine the most accurate weights. Each neuron receives weights that prioritize the most appropriate label. Finally, the neurons "vote" on each of the labels, and the winner of that vote is the classification decision.

Fig.5. Fully Connected Layer in CNN

3.4 CNN Components

There are some components in CNN. Let us discuss those components.

3.4.1 Padding

Padding is a term relevant to convolutional neural networks as it refers to the amount of pixels added to an image when it is being processed by the kernel of a CNN. For example, if the padding in a CNN is set to zero, then every pixel value that is added will be of value zero. If, however, the zero padding is set to one, there will be a one pixel border added to the image with a pixel value of zero.

Padding works by extending the area of which a convolutional neural network processes an image. The kernel is the neural networks filter which moves across the image, scanning each pixel and converting the data into a smaller, or sometimes larger, format. In order to assist the kernel with processing the image, padding is added to the frame of the image to allow for more space for the kernel to cover the image. Adding padding to an image processed by a CNN allows for more accurate analysis of images.

Fig.6. Padding

3.4.2 Stride

Stride is a component of convolutional neural networks, or neural networks tuned for the compression of images and video data. Stride is a parameter of the neural network's filter that

modifies the amount of movement over the image or video. For example, if a neural network's stride is set to 1, the filter will move one pixel, or unit, at a time. The size of the filter affects the encoded output volume, so stride is often set to a whole integer, rather than a fraction or decimal.
Imagine a convolutional neural network is taking an image and analyzing the content. If the filter size is 3x3 pixels, the contained nine pixels will be converted down to 1 pixel in the output layer. Naturally, as the stride, or movement, is increased, the resulting output will be smaller.
Stride is a parameter that works in conjunction with padding, the feature that adds blank, or empty pixels to the frame of the image to allow for a minimized reduction of size in the output layer. Roughly, it is a way of increasing the size of an image, to counteract the fact that stride reduces the size. Padding and stride are the foundational parameters of any convolutional neural network.

3.4.3 Filtering

In image processing filters are used to smoothing the image, enhancing or detecting the edges of the image. Filtering is a technique for modifying or enhancing an image. Filtering include smoothing, sharpening and edge enhancement. Filtering is a neighborhood operation, in which the value of any given pixel in the input image is determined by applying some algorithm to the values of the pixels in the neighborhood of the corresponding input pixel.

4. RESULT ANALYSIS

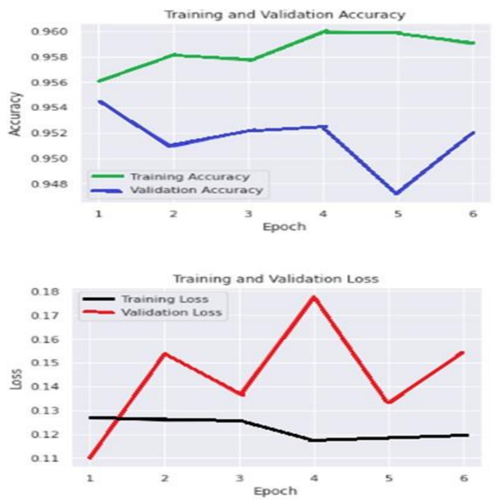


Fig.7. Output Demonstrating the Accuracy and Loss per Epoch

The above outputs depicts how the model accuracy and loss changes for each and every epoch.

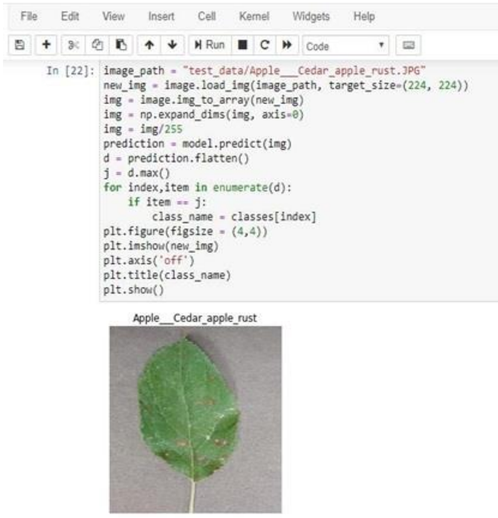


Fig.8. Prediction of the Apple Leaf Cedar Rust Disease

The input for the model is apple plant's leaf contains Cedar rust disease. The trained model predicts the given input correctly as Apple Cedar_apple_rust.

5. CONCLUSION

This paper is developed for the identification of disease affected plants and healthy plants is done and this proposed work is focuses on the accuracy values during the real field conditions, and this work is implemented by having seveal plant disease images.
This paper proposes a deep learning approach to automatically discover the discriminative features for fine-grained classification, which enables the end-to-end pipeline for diagnosing plant disease severity. Based on few training samples, we trained small convolutional neural networks of different depth from scratch and fine- tuned four state-of-the-art deep models. Comparison of these networks reveals that fine-tuning on pretrained deep models can significantly improve the performance on few data. The fine-tuned VGG16 model performs best, achieving an accuracy of 90.4% on the test set, demonstrating that deep learning is the new promising technology for fully automatic plant disease severity classification.
In future work, more data at different stages of different diseases will be collected with versatile sensors, like infrared camera and multispectral camera. This deep learning model can be associated with treatment recommendation, yield prediction, prediction of the damage for crop in upcoming stages of the disease.

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ISSN [O]: 2582-1431 VOLUME-II ISSUE-I JAN-MAR-2020

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