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"ENHANCED TOMATO LEAF DISEASE IDENTIFICATION USING DEEP LEARNING: A COMPARATIVE REVIEW OF CNN APPROACHES"

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Abstract:

Plant diseases cause to decreases in product in agriculture. The majority of farmers find it challenging to identify and control plant diseases. It is necessary to spot diseases early in order to minimize future losses. In this paper, a deep learning method utilizing convolutional neural networks (CNNs) to identify tomato leaf diseases is described. For example, to classify tomato leaf images into one of ten categories—healthy, yellow leaf curl virus (YLCV), bacterial spot (BS), early blight (EB), leaf mold (LM), spectoria leaf spot (SLS), target spot (TS), two spotted spider mite spot (TSSMS), mosaic virus (MV), and late blight (LB)—the proposed method initially prepares the images of the leaves. A dataset which include 16021 images of tomato leaves was used to train the model. After 10 epochs, 20 epochs, and 50 epochs of training, the accuracy was 64%, 94%, and 97%, in that order.

The results provided show that the proposed approach has been effective for determining tomato leaf diseases, and that its performance gets improve with time. The early detection and prevention of tomato diseases by the use of an automated method has the capacity to boost tomato crop quality and output. The In this review paper we are going to show the different approaches that can be used to deal with the classification of tomato leaf diseases.

Keywords: Deep learning, CNN, GoogleNet, AlexNet, VGG16

II. Introduction:

Tomatoes (biological name: Solanum lycopersicum) grows on mostly any well drained soil and Nine out of 10 farmers grow tomatoes in their field. Many gardeners also grow tomatoes in their garden to use fresh grown tomato in their kitchens and get a good taste of food.

However, farmers and gardeners are sometimes unable to get proper progress of the plant growth[1]. The tomatoes may not sometime appear on plant or sometimes the tomatoes may get bad looking and disease-ful black spots at bottom part. While analyzing a tomato plant disease, people may initial look over for insects. After documenting any discrepancies in the plant, such as brown or black spots and holes, the disease can be determined.

It is forbidden to grow tomatoes and related crops like potatoes or brinjal on the same farm more than once. three-year duration . To help to maintain the soil's fertility, it is essential to plant any member of the grass family—such as wheat, corn, rice, sugarcane, etc.—before planting tomatoes[2].

Traditional disease identification techniques are time-consuming and expensive, especially on huge farms where it can be hard to keep an eye on every plant. Therefore, a more affordable and effective solution is required. Time, money, and effort can be saved by automating the detection of illnesses in leaves with the use of image processing techniques. 16021 images of 10 distinct kinds of damaged tomato leaves represent the dataset used in this study. Each image has been expanded to 256 by 256 and separated into three sections: the training dataset, the testing dataset, and the validation dataset[3]. Image processing techniques can fast and correctly diagnose diseases through analyzing the features of diseased leaves. Convolutional neural networks (CNNs), a specific kind of deep learning methodology, have been proven to be useful for image classification tasks including determining the presence of plant diseases. Over 65% of the population of India, a growing economic a catalyst, finds work in agriculture or the products of agriculture. [1] Plant diseases and insect damage cause a majority of crop losses. The approximate average yearly production tons lost at the starting point of the 21st century as the outcome of several distinct pests[4].

II. Problem Statements:

Traditional methods of recognizing diseases, such visual inspection, are susceptible to mistakes and sometimes call for a group of professionals. Furthermore, plant diseases cannot be controlled or avoided by traditional methods; early disease diagnosis is crucial. Thus, an accurate, effective, and automated technique for identifying diseases in tomato plants is required in order to enable early identification as well as effective prevention.

III. Objectives:

In recent years, there is a shift in the approach in detecting tomato leaf diseases from a more conventional machine learning methods to deep learning methods like convolutional neural networks(CNN).

1. Develop a CNN model that is able to precisely identifying and classifying common diseases of tomato leaves, including target spot, yellow leaf curl virus, bacterium spot, late blight mold, early blight, two-spotted spider mite, mosaic virus, and septoria leaf spot.
2. Analyse the constructed CNN model's performance over a few epochs.
3. Contribute to sustainable agriculture by providing an automated, cost-effective method of the early identification of tomato leaf diseases, helping farmers to take preventative action and reduce crop losses. To detect unhealthy regions of plant leaves Classification of leaf disease using image Processing To analyse leaf infection with accuracy .To give remedy to the user.

V. History Of CNN:

CNN's are a class of deep feed forward artificial neural networks which are primarily used to analyse images.A CNN consist of an input layer ,an output layer and number of hidden layers depending on the problem.

The starting point of convolutional neural networks can be traced to the task of classifying handwritten digits from 0 to 9.This simple enough task for a human brain is a genuine head scratcher for the machine learning tools at that time.Eventhough feed forward neural networks (FFNNs) were used,the accuracy ceiling on FFNNs made researchers to look for a solution elsewhere.Yann LeCun's novel idea turned the image processing world upside down.His novelty was later named as LeNet-5 which applied convolutional layers to grasp the hierarchical pattern of data.

V.1 Local receptive fields: In LeNet,each neuron is connected to a small region of previous network as supposed to every other neuron like the traditional neural networks.This reduces the number of parameters and allow the network to learn local features that are useful for the task at hand.

V.2 Weight sharing: In LeNet, each neuron in a given feature map shares the same set of weights as all other neurons in that feature map.

V.3 Sub sampling: it can reduce the size of the feature maps without loosing valuable information.

V.4 Convolutional layers: Convolutional layers allows it to learn spatial invariance and help to solve the problem much easier.

The LeNet architecture consists of two convolutional layers,two sub sampling layers and three fully connected layers. In LeNet 5, the input images are of the size 32X32, if the images are different size it will be transformed to the above mentioned size. First convolutional layer consists of 6 kernals of size 5X5 and strid one, therefore the feature map is of size 28X28 after this laye and average pooling layer is used with a window size of 2X2 with strid 2 which reduces the size of the feature map by 14X14. It passes the another convolutional layer in which there are 16 kernals each of size 5X5 with strid one. There is an asymmetric connection in the network this is used to break the symmetry in the network and to keep the number of connections with in reasonable bounds.This was followed by 3 pooling layer and 3 fully connected layer. The number of the nodes and the output layer is then because this used to recognize the numerals from 0 to 9.

V.5 ImageNet Challenge: In 2007 fei-fei li met with christiane fellbaum one of the creators of wordnet which was lexical database of semantic relations between words. Inspired by the idea li wanted to put forward the largest collection of lbeled set of images called ImageNet. In 2010 ImageNet setup a compitation to classify images categorically. In 2012, AlexNet won the ImageNet largescale virtual recognition challenge, Marking a paradigm shift in image identification and classification. It was just AlexNet won te challenge it mopped the flow with all its competitors with an astounding sub 16% error rate. Since there were lot parameters that had to be trained, making the training remarkably slow or impoossible on a cpu. Hence the researchers on AlexNet turn to GPU.

Even then, the solution was in straight forward, because of the memory constaints the GPUs at that time. What was done was that AlexNet was distributed among 2 GPUs. And they also swap the typical softmax and tannex optimization function for a rectified linear unit or ReLu activation function which further include the efficiency of the model. In case of ReLu, the upper bound is unbounded so the output is normalized by local response normalization. LRN does normalization by amplifying the excited neuron, why dampening the sourrending neuron at the same time in the local neuron. There are 1000 node soft max layer in the output, there are 1000 categories of images in the ImageNet

V.6 VGG16: It was the running of ILSVRC 19 layers are available with an error rate of 7.3% VGGNET is a very deep convolutional Network of large scale image recognition which was introduced by learn sima,yan and Andrew zisserman and have altogether 140 millions parameters and a significantly deeper than Alexnet. It has 13 convolutional layer and 3 fully connected layers and the first two fully connected layers have 4096 nodes and last one has 1000 nodes become 1000 classes of ImageNet are considered and a softmax layers used as the activation function.

VGGNet uses 3x3 convolutional filters with strid 1 and fad 1inorder to have the feature map of as size as the input image. The amount of parameter is reduced in VGGNet by taking smaller filer than AlexNet. That is in VGGNet 3X3 convolutional layer which are used which has the same effective respective to held as one 7X7 convolutional layer and at the same time then reduce the parameters.

V.7 GoogleNet: Googlenet was discovered in 2015 by christen szegedy et al and it is deeper than VGGNet, GoogleNet was the winner of 2014 ILSVRC competition it is more efficient than the previous counterparts and is much more deeper. There are 22 layer in GoogleNet.

In GoogleNet, an inception module is repeated over and over again and it is fundamental unit of GoogleNet. There are 9 inception modules in GoogleNet. The inception module covers a bigger area but at the same time preserves even the smallest of information along with 9 inception modules there are two auxiliary lyers which solves the vasuality GoogleNet had Reduced the error rate to 8.7%.

VI Methodology

Using CNN for the identification of Tomato leaf disease requires collecting datasets, preprocessing them, differentiating them into three categories: train, valid, and test datasets, and using dataset statistics.

VI.1. Methodology Flowchart:

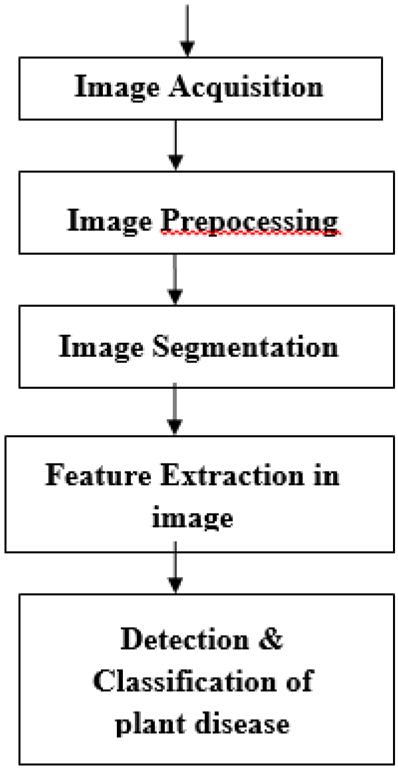

Fig: Basic steps for plant leaf disease

Acquiring images for tomato leaf disease detection involves several steps to ensure high-quality data for accurate analysis. Here's a general outline of the process:

VI.1.1 Image Acquisition Equipment: Obtain a suitable camera or imaging device capable of capturing high-resolution images. This could be a digital camera, a smartphone with a high-quality camera, or specialized imaging equipment designed for agricultural applications. Selection of Tomato Plants: Choose healthy tomato plants as well as those showing symptoms of various diseases for imaging. It's important to have a diverse set of images representing different stages and severities of diseases.

VI.1.2.Image Capture Environment: Control environmental factors such as lighting, background, and camera angle to ensure consistent and uniform images. Natural lighting conditions are preferred, but if indoors, use diffused artificial lighting to avoid harsh shadows.

VI.1.3.Image Preprocessing: Preprocess the images to enhance quality and remove noise if necessary. This may include tasks such as cropping, resizing, color correction, and noise reduction.

VI.1.4.Feature Extraction in Image: Feature extraction in image processing refers to the process of extracting meaningful information or features from raw pixel data in images. These features can then be used for various tasks such as image classification, object detection, segmentation, and more.

VI.1.5. Image Segmentation: To increase the diversity of your dataset and improve the robustness of your model, consider augmenting your images through techniques such as rotation, flipping, zooming, and adding noise.

VI.1.6. **Detection & Classification of plant disease:** Detection and classification of plant diseases involve several steps, including image acquisition, pre processing, feature extraction, model training, and evaluation.

VII. CNN Model Architecture:

.A Convolutional Neural Network (CNN) is a deep learning model commonly used for image recognition and classification tasks. CNNs are particularly well-suited for tasks involving spatial data, such as images, due to their ability to automatically learn hierarchical patterns and features directly from raw pixel data. Here's a basic architecture of a CNN:

VII 1. Input Layer: The input layer receives the raw pixel values of the input image. The dimensions of the input layer correspond to the dimensions of the input image (e.g., height, width, and number of color channels).

VII.2.ConvolutionalLayers: Convolutional layers are the core building blocks of a CNN. Each convolutional layer consists of multiple filters (also known as kernels) that convolve across the input image to extract spatial features. As the filters convolve across the image, they learn to detect patterns such as edges, textures, and shapes. The output of a convolutional layer is referred to as a feature map.

VII 3.Pooling Layers: Pooling layers are used to downsample the feature maps produced by the convolutional layers, reducing the spatial dimensions (e.g., height and width) while retaining the most important features. Common pooling operations include max pooling and average pooling.

VII 4.Fully Connected Layers: After several convolutional and pooling layers, the feature maps are flattened into a 1D vector and passed through one or more fully connected (dense) layers.
These layers perform classification by learning complex patterns in the feature vectors and mapping them to class labels.

VII 5.Output Layer: The output layer produces the final predictions or class probabilities. The number of neurons in the output layer corresponds to the number of classes in the classification task, and the activation function used depends on the task (e.g., softmax for multi-class classification).

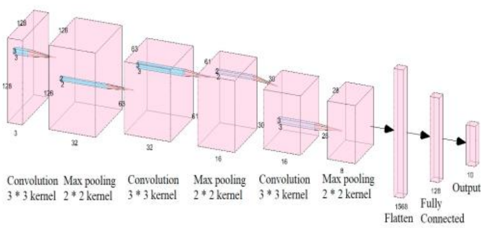

Fig 2. CNN Model Architecture

VIII. Tomato Plant leaf Diseases

Tomato plants are susceptible to various diseases that can affect their leaves. Some common tomato leaf diseases include:

VIII.1.Early Blight (Alternaria solani): Early blight is a fungal disease that affects the lower leaves of tomato plants. It causes dark, concentric lesions with a target-like appearance. As the disease progresses, the leaves may turn yellow and eventually die.

VIII.2.Late Blight (Phytophthora infestans): Late blight is a destructive fungal disease that affects tomato leaves, stems, and fruits. It causes water-soaked lesions on leaves, which rapidly turn brown and may develop a fuzzy texture. Infected leaves may collapse and spread the disease to other parts of the plant.

VIII.3.Septoria Leaf Spot (Septoria lycopersici): Septoria leaf spot is a fungal disease characterized by small, circular lesions with dark centers and yellow halos. It primarily affects the lower leaves of tomato plants and can lead to defoliation if left untreated.

VIII.4. Tomato Yellow Leaf Curl Virus (TYLCV): TYLCV is a viral disease transmitted by whiteflies. Infected tomato plants exhibit yellowing and curling of the leaves, stunted growth, and reduced fruit production. The disease can cause significant yield losses in tomato crops.

VIII.5.Bacterial Spot (Xanthomonas campestris pv. vesicatoria): Bacterial spot is caused by the bacterium Xanthomonas campestris pv. vesicatoria. It produces small, dark lesions on tomato leaves, which may enlarge and coalesce under favorable conditions. Severe infections can cause defoliation and reduce fruit quality.

VIII.6.Powdery Mildew (Oidium spp.): Powdery mildew is a fungal disease that appears as white, powdery patches on tomato leaves. It can inhibit photosynthesis and lead to reduced plant vigor and yield.

VIII.7. Tomato Mosaic Virus (ToMV): Tomato mosaic virus is a viral disease that causes mottling, distortion, and yellowing of tomato leaves. Infected plants may also exhibit stunted growth and reduced fruit size and quality.

IX. Conclusions:

In this paper, they have presented a approach for tomato leaf disease detection using CNN. Used a dataset of tomato leaf images that we gathered a multiple sources to build a deep learning model. The common tomato leaf diseases are- bacterial spot, early blight, late blight, leaf mold, spectorial leaf spot , Yellow leaf curl virus,mosaic virus and others. Could all accurately detected by the trained model. The suggested technique is designed to provide a effective way to recognize the diseases on tomato leaves.

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