A Review and Challenges of Leaf Disease Prediction Using Machine Learning and Deep Learning Approach

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Abstract:- Even in situations of rapid population increase, agriculture provides food for everyone. It is recommended that plant diseases be anticipated early in the agricultural process in order to supply food for the whole population. On the other hand, it is regrettable to predict infections in immature crops. When examining plant diseases, a number of obstacles must be overcome, including the need for high-quality leaf images, publicly accessible datasets, noisy data influencing leaf samples, the possibility of disease identification through segmentation, but sample testing, training, and classification are also necessary. A range of diseases can be observed in different types of plants, and environmental factors can alter the color of the leaves. Various leaf diseases are categorized using machine learning (ML) and deep learning (DL) models. A workflow framework to support research in this topic is presented in this publication. While popular deep learning models for detecting leaf disease include Convolutional Neural Networks (CNN), Visual Geometry Group (VGG), ResNet (RNet), GoogLeNet, Deep CNN (DCNN), and Back Propagation Neural Networks (BPNN), popular machine learning (ML) models for predicting leaf disease include Support Vector Machine (SVM), Random Forest, and Multiple Twin SVM (MTSVM). This review would be helpful to researchers in this field who are searching for multiple efficient ML and DL-based classifiers for leaf disease detection.

Keywords: *Convolution Neural Networks (CNN), Visual Geometry Group (VGG), ResNet (RNet), GoogLeNet, Deep CNN (DCNN), and Back Propagation Neural Networks (BPNN), SVM*

1. Introduction

Delivering high-quality food is essential, and the agriculture sector is the main driver of growing economies and populations. Plant diseases have the power to eradicate species diversity and drastically diminish food production. Early plant disease diagnosis can lower costs and increase the quality of food produced by using accurate or automatic detection techniques. In recent years, object detection and picture classification algorithms have seen a huge boost in identification accuracy because to deep learning[4]. Every crop has a particular disease that can lower its quality and yield, and farmers often have to spend a lot of money controlling disease in their crops. On the other hand, poor technology can have severe consequences, degrade soil, and result in inefficient disease management. Furthermore, plant diseases wreak havoc on the natural ecology, affect the food chain's food supply, and aggravate environmental issues [6].

Previously, disease identification was done manually with assistance from agricultural groups or local plant clinics. However, farmers find it difficult to correctly detect the disease due to their lack of competence. Furthermore, manual identification is labor-intensive, less exact, and requires doing tiny sections at a time. Taking into consideration the challenges associated with plant disease detection, a novel deep learning automated method for early identification of the underlying disease is also suggested.

Machine learning, which is basically a three-layer neural network, includes deep learning as a subset. While these neural networks attempt to mimic the structure and functions of the human brain, they are far from matching it, which prevents the human brain from being able to "learn" from large amounts of data. Even though a neural network with only one layer can still produce approximate predictions, more hidden layers can aid in fine-tuning and refining for accuracy. Deep learning powers a plethora of artificial intelligence (AI) applications and services, augmenting automation by performing mental and physical activities without human interaction. For picture categorization, there are numerous deep learning algorithms available, including CNNs, RNNs, GANs, MLPs, and others.

ConvNets, also called CNNs, are mainly used for object detection and image processing. They consist of multiple layers. CNNs process the data by passing it through multiple layers and extracting features in order to perform convolutional operations. The feature map is corrected using Rectified Linear Units (ReLUs), which are a component of the convolutional layer. The pooling layer is used to adjust these feature maps for the upcoming feed. A common down-sampled sampling technique that lowers the feature map's dimensionality is pooling. Subsequently, the output is generated as 2-D arrays composed of a single linear vector that is long, continuous, and flat within the map. The next layer, called the Fully Connected Layer, classifies and identifies the image using the input of the flattened matrix or 2-D array that was obtained from the Pooling Layer.

One type of artificial neural network that is primarily used to find patterns in data sequences is the Recurrent Network (RNN). RNNs are primarily utilized in time series analysis, image captioning, data translation for machines, and handwritten data recognition. Recurrent neural networks with the unique ability to learn long-term dependencies are known as long short-term memory networks, or LSTMs. Long-term dependencies refer to the frequent occurrence of only needing recent data to answer a question in a model. However, we might also require data that has already been collected.

Generative Adversarial Networks (GANs) are used to render 3D objects, produce realistic images and cartoon characters, and take pictures of people's faces. MLPs, or multilayer perceptions. Activation functions are present in multiple layers of perceptrons in MLPs, which are a type of feed forward neural network. An input layer and an output layer that are fully connected make up an MLP. They may have more than one hidden layer and have the same number of input and output layers. They can be used to create machine translation, speech recognition, and image recognition software. Networks of Deep Beliefs (DBNs) Generative models called DBNs are made up of several layers of latent, stochastic variables. Latent variables, also known as hidden units, are binary variables. Each RBM layer communicates with both the layer before it and the layer after it, and DBNs are a stack of Boltzmann Machines with connections between the layers. Motion capture, video, and image recognition are all handled by Deep Belief Networks (DBNs).

2. Objectives

To provide a survey about various machine learning and deep learning models for identifying plant leaf diseases for supporting researchers and discuss the various challenges involved in identifying leaf diseases.

3. Methods

I. Machine Learning

Artificial intelligence's machine learning field enables systems to pick up knowledge and grow from experience without explicit programming. Because it has so many real-world applications across numerous industries, it has grown in popularity in recent years. The machines are fed high-quality data, and they are trained on this data using a variety of algorithms to create machine learning models. The kind of data at hand and the kind of task that needs to be automated determine which algorithm is best. Intelligent systems that can make decisions and predictions based on data can be created with machine learning. This can assist businesses in improving their operations, coming up with new goods and services, and making better decisions.

Types of Machine Learning Algorithms

1. Supervised Learning

2. Unsupervised Learning

3. Semi supervised Learning

4. Reinforcement Learning

Supervised Learning

One kind of machine learning algorithm is supervised learning, in which the model or algorithms are trained using labeled datasets. In order for the algorithm to be able to predict or classify new, unseen data, it must first learn a mapping from the input data to the output labels.

- Linear regression
- Logistic regression
- Decision tree
- SVM algorithm
- Naive Bayes algorithm
- KNN algorithm
- K-means
- Random forest algorithm
- Dimensionality reduction algorithms
- Gradient boosting algorithm and AdaBoosting algorithm

Unsupervised Learning

Unsupervised learning, sometimes referred to as unsupervised machine learning, is the process of analyzing and grouping unlabeled datasets using machine learning algorithms. These algorithms find hidden relationships or patterns in the data without requiring human assistance.

- Gaussian Mixture Models
- Convolution neural network

The machine learning algorithms K-Means Clustering, Support Vector Machine, Random Forest, and Multiple TWIN are used to predict leaf diseases. K-means clustering

a. K-means clustering

K clusters are always present. Every cluster contains a minimum of one item. There is no hierarchy among the clusters, and they don't overlap. Because closeness does not always involve the "centre" of clusters, each member of a cluster is closer to its cluster than it is to any other cluster. A cluster analysis technique called k-means clustering seeks to divide n observations into k clusters, each of which is comprised of the observations that are closest to the mean.

One of the most straightforward unsupervised learning algorithms for resolving the well-known clustering problem is K-means[20]. The process assumes that there are k fixed clusters a priori and uses a straightforward and easy method to classify a given data set using a specific number of clusters. Determining k centroids—one for each cluster—is the main idea. These centroids should be positioned cleverly since different locations yield different

Outcomes. Placing them as far apart as possible is therefore the better option. The next action is to identify the closest centroids for every point in a given data set. The first step is finished and an early group age is finished when there are no points left to earn. Now, in order to determine the barycentre of the clusters produced by the preceding step, we must recalculate k new centroids. A new binding between the same data set points and the closest new centroid must be completed once we have these k new centroids. Something has created a loop. We might observe that the k centroids gradually shift their locations as a result of this loop until no more adjustments are made. Stated differently, centroids are immobile. A predetermined number of flat, disjoint clusters are produced by K-Means clustering. The K-Means method is iterative, non-deterministic, unsupervised, and numerical. Segmenting images using hierarchical clustering is another common application. Among image segmentation techniques, k-means clustering is the most widely used.

When k is smaller, the algorithms produce good outcomes. Larger values of k result in extremely coarse segmentation, with many clusters appearing in the images at discrete locations. Different final clusters may arise from different initial partitions.The K Means algorithm's simplicity and efficiency are its main advantages. When clusters are not well separated from one another, it functions well. [19]

b. Support Vector Machine (SVM)

Encouragement Vapnik's (1998) statistical learning theory serves as the foundation for the potent classification technique known as Vector Machine. Generally speaking, the goal of classification algorithms is to identify patterns related to label classes in empirical data (training or input data). To forecast new unlabeled data, the generated classification model is employed. The process of supervised learning ultimately aims to identify a function f that provides the best fit to the training set of data. Since there are an infinite number of functions that can equally well describe the discrete data, finding such a function is considered a "ill-posed problem." However, machine learning is more concerned with the class of unseen data prediction (i.e., the classifier's ability to generalize) than it is with fitting the training data. The need to restrict the class of feasible functions f is a fundamental understanding of machine learning. In this sense, choosing the function class involves making a trade-off between maintaining enough modest complexity to prevent overfitting and achieving good generalization. SVMs provide an optimal solution for both problems (Vapnik, 2000). SVMs use a hyperplane, defined by its normal vector w and bias b, to divide two distinct classes. SVMs can distinguish non-linear discrimination by utilizing a kernel function; this ability is necessary for the classification of plant diseases, particularly for early-stage plant disease discrimination between healthy and diseased plants.[7] Multi-birth SVM (MBSVM), a variation of this method, has also produced noteworthy outcomes. Bhange and Hingoliwala achieved 92% successful accuracy when using the SVM model to identify pomegranate leaf disease. Another version of the SVM technique that has shown great success in this study is neural network ensemble SVM. Using radial basis function

c.Random Forest

This algorithm consists of two stages: creating a random forest in the first step, and using the values from the first step to make predictions in the second step. Choose m features from n features in this case where m<n. Find the node d with the best split point among the m features. Once the k number of nodes has been reached, split the node later into child nodes and repeat the previous steps. To create z trees, repeat each of the previous steps z times to build the forest. When comparing the Random Forest algorithm to RF, SVM, DT, KNN, NB, and KNN, it offers 89% accuracy [8].

II. Deep Learning

Deep learning is an artificial intelligence (AI) technique that trains computers to interpret data in a way that is similar to the human brain. In order to produce accurate analyses and forecasts, deep learning models are able to recognize complex patterns in text, audio, image, and other kinds of data. Deep learning is used in medical image analysis to automatically identify diseases for diagnosis.

Deep learning algorithms used for Leaf Disease Detection are,

1. conventional neural network (CNN)

- ✓ AlexNet
- ✓ MobileNet
- ✓ Inception-v3

2. Ant Colony Optimization with Convolution Neural Network (ACO-CNN, Back Propagation Neural Networks (BPNN)

a. Conventional Neural Network (CNN)

An artificial neural network (ANN) that is used for image recognition is called a convolution neural network (CNN). Its primary function is to process pixel input. Three layers make up a convolution neural network: the fully connected layer, the pooling layer, and the convolutional layer. Convolution layer: uses a filter to scan multiple pixels at once in the image to create an activation map. The pooling layer makes better use of storage space by reducing the volume of data produced by the convolutional layer. Fully connected input layer: The output of the layers before it is "flattened" into a single vector, which serves as an input for the layer after it. In order to predict the correct label, the first fully connected layer adds weights to the inputs from the feature analysis. The fully connected output layer provides the final probability for every label. In basic images of both damaged and healthy plants, conventional neural network (CNN) models were developed to identify and diagnose plant leaf disease. CNN's accuracy rate is 95.6% [18].

b. AlexNet

AlexNet is an eight-layer convolutional neural network. The ImageNet database contains a pretrained version of the network that was trained on over a million images.

AlexNet, a CNN architecture, was selected as the 2012 LSVRC competition champion. Research teams test their algorithms on a large dataset of annotated images (ImageNet) in the Large Scale Visual Recognition Challenge, where the goal is to improve accuracy on a variety of visual recognition tasks. More than 1.2 million images are used for training, 50,000 for validation, and 150,000 for testing. The model creators imposed a fixed size of 256×256 pixels on each image by deleting the central 256×256 patch.

Eight convolutional layers make up AlexNet's architecture; there are three ANN layers and five convolutional layers total. Each of the convolution layers is followed by a max pooling layer.

Features of AlexNet:The convolution layer kernels in the second, fourth, and fifth layers are connected to the kernels in the layers before them that are located on the same GPU.There is interconnectivity among the neurons found in the fully connected layers.ReLu activation is incorporated into the basic artificial neural network structure and applied to each convolution layer's output.

ReLu Activation in AlexNet

Deep learning networks typically use the sigmoid or tanh function as an activation function. Rectified Linear Unit activation, on the other hand, is a non-linear activation function used by AlexNet. Non-linearity in ReLu facilitates efficient learning because the previous activation functions saturate quickly and are difficult to train on GPUs. The operational functionality of ReLu is provided by the following equation: $= max(0, x)$

If x > 0, the derivative of the above equation is 1, and in all other cases, it is 0. The ReLu function has only two values for its derivative, in contrast to the sigmoid and tan h functions, which have a specific boundary of derivative values. ReLu activation avoids the vanishing gradient descent issue that arises when sigmoid and tan h functions are used.

Local Response Normalization in AlexNet

For neural networks that employ nonlinear activation functions, normalization is an essential component. Since the unbounded activation outputs of nonlinear activation functions are not bounded like those of linear activation functions, we utilize normalization to limit them. Normalization of local responses facilitates generalization. ReLU was selected as the activation function in place of the then-common tanh and sigmoid, which resulted in the AlexNet architecture using "local response normalization" (LRN).Apart from the previously mentioned rationale, the application of LRN was suggested to encourage lateral inhibition. In neuroscience, a neuron's capacity to reduce the activity of its neighbors is a concept. The lateral inhibition function in DNNs is utilized for local contrast enhancement, whereby the layers that follow are stimulated locally by the highest pixel values. Using LRN, a non-trainable layer, the pixel values of a feature map of a nearby neighborhood are square-normalized.

Issues with AlexNet

Using this CNN can lead to overfitting because the original AlexNet architecture was created with a lot of data. Techniques for dropout and data augmentation were applied to solve this issue. The CNN architecture's performance was observed to increase with the use of dropout layers. The complex co-adaptations of neurons are diminished by the dropped attributes since they do not take part in forward and backward propagation. As a result, the network is able to learn more complex features. In the first two layers of AlexNet's fully connected architecture, dropout is utilized. AlexNet offers reasonably accurate image classification.

MobileNets

- One of the TensorFlow pretested models is MobileNets are Inception-v1, Inception-v2, and Inception-v3, it has been enhanced on a number of structures to expedite its use by researchers in diverse fields. In this work, MobileNet has reported a successful model for image classification. The analysis of MobileNet's performance with bean leaf diseases yields a very good classification result. The new plant diseases dataset fits the MobileNet model well; its training and validation accuracy are 99.07 and 97.52%, respectively.[9]

Inception V3

a CNN model using the Inception V3 architecture and the Adam Optimizer to identify and categorize potato plant diseases like early and late blight. It provided achieve 90% classification accuracy over the test dataset. This model enables a farmer to construct a computer setup from which he can effectively monitor plant health issues, increase crop yield, and identify and diagnose diseases in their early stages.[18]

Ant Colony Optimization with Convolution Neural Network

a cutting-edge deep learning method called Ant Colony Optimization with Convolution Neural Network (ACO-CNN) for the detection and classification of diseases. Ant colony optimization was used to examine how well disease diagnosis in plant leaves worked (ACO). The CNN classifier is used to remove color, texture, and plant leaf arrangement from the given images. [10]

III.Challenges

1.One of the most difficult areas of research in computer vision, machine learning, and image processing (IP) is the identification of leaf diseases [2, 3, 4, 5].

2.It is very difficult to remove noise from the leaf using image processing.

4.One of the main obstacles in this experiment is defocused images, which are typically taken by electronic devices. Defocused images become blurry, making this type of image impossible to see clearly.

5.In general, the majority of researchers use datasets that are spread across numerous repositories. For the purpose of their experiments, very few of them take pictures of infected leaves from agricultural fields, but taking pictures itself presents another challenge. In addition, these researchers must deal with a variety of challenging factors, such as varying occlusion-based images, weather variations, the direction in which to take pictures, and the separation between electronic devices and infected leaves.

6. A number of images can be obtained for various configurations through the use of different electronic devices, such as digital cameras and mobile phones. Making the right electronic device selection is also crucial. Images from mobile phones are primarily distorted because they are unable to focus objects clearly. Similar to this, a digital camera can also take pictures of infected leaves, but there are additional challenges with the device's direction and distance from the subject of the picture.

7. Another challenging task is handling Large images lead to leaf disease detection being blurred.

4. Result

This study provided the summary of the different deep learning and machine learning algorithms to enhance the performance of on large biological databases for faster and more accurate disease detection and challenges of leaf disease prediction. There are still certain difficulties in identifying leaf diseases despite the efforts of numerous ML and DL models. Pre-trained models like GoogLeNet, AlexNet, VGGNet, and ResNet, as well as the training data from ImageNet [410], [411] (Image Database), have been used in numerous published research studies. These models have produced higher accuracy than other models that are currently in use.

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