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Plant Leaf Disease Detection and Fertilizer Recommendation using Deep Learning

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ABSTRACT

Plant disease, the state of a plant that interrupts its essential functions. Plant diseases are a major threat to the entire production. It is essential for farmers to effectively deal with them and check them in frequent intervals. The consequence of early disease detection can be used for disease diagnosis, control and damage assessment. Identifying the disease at the earliest and treating it accordingly is important. The objectives of this study were to investigate through experimental approach the performance of popular models of deep learning. Automatic identification methods for the early detection of disease in plants play a vital role in crop protection. Several methods have been employed in the domain of plant disease recognition. This work aid in actual identification of a plant and further detection of disease in them. The leaf images of different plants with different classes of the plant database are analyzed for the process. The core contribution of this work is to classify the plant leaf disease with the proposed network-based on VGG19, InceptionV3 and Inception ResnetV2 models. These algorithms are used to detect the plant leaf and identify the healthy and diseased plant through this network.

Keywords – Disease Diagnosis, Damage Assessment, Deep Learning, Identification Methods, Disease Recognition, VGG19, InceptionV3, Inception ResnetV2.

1. INTRODUCTION

Agriculture plays a crucial role in economy as well as it is viewed to be the backbone of economic system for developing countries. To have good quality and quantity of food, we need to protect the plant. The priority action is to spot the species of the plant followed by recognizing the diseases affecting them. Having a disease in plants is quite natural, so pointing out the diseases in plants is necessary in the field of agriculture. The seriousness of the disease is an important parameter and thus can be used to predict the yield. Proper care needs to be taken to avoid large scale effects on plants as they, in turn, show their effect on the product quality, quantity, or productivity. The diseases in plants gradually improves the loss in production of yield which results in financial loss to the farmers. The two major categories are airborne and soil-borne. In air-borne type, fungal diseases are very usual. The symptoms of a damaged plant are seen in certain parts like leaf, stem, and fruit. In soil-borne type, the effect is seen majorly on the roots of the plant. Various plant disease identification techniques are available for different classes of diseases. The basic or conventional technique is the manual inspection of the plant by naked eyes. This process was meant to be performed by experts and requires constant monitoring over a large area of the field. This process tends to be time consuming and expensive. The faster and accurate recognition of the severity of the disease will help to take preventive measures and reduce the yield losses. The detection of plant disease using pictures that are captured from devices like mobile phone camera or digital camera is also a notable challenge. To overcome this situation, we need a quick, reliable, automated, cost-effective, and accurate method to detect the disease in a plant. A technique that automatically detects the disease symptoms in the leaves of the plant is beneficial as it reduces a lot of manual work and time.

2. LITERATURE SURVEY

The authors Shanwen Zhang, Xiaowei Wu, Zhuhong You and Liqing Zhang proposed a leaf image based cucumber disease recognition using sparse representation classification. Most existing image-based crop disease recognition algorithms depend on drawing out various kinds of features from leaf images of diseased plants. They have a familiar limitation as the features selected for discriminating leaf images are usually treated as equally important in the classification process. The authors proposed a novel cucumber disease recognition approach which consists of three pipelined procedures: segmenting diseased leaf images by K-means clustering, extracting shape and colour features from lesion information, and classifying diseased leaf images using sparse representation (SR). A major advantage of this approach is that the classification in the SR space is able to effectively reduce the computation cost and improve the recognition performance. They carried out a comparison with four other feature extraction based methods using a leaf image dataset on cucumber diseases. The proposed approach is shown to be effective in recognizing seven major cucumber diseases with an overall recognition rate of 85.7%, higher than those of the other methods.

Tomato crop disease classification using pre-trained deep learning algorithm is yet another research work carried by Aravind Krishnaswamy Rangarajan, Raja Purushothaman and Aniirudh Ramesh. The wide scale generality of diseases in tomato crop affects the production quality and quantity. In order to restrain the problem early identification of diseases using a fast, reliable, nondestructive method will improve the profit to the farmers. In this study, images of tomato leaves (6 diseases and a healthy class) obtained from Plant Village dataset is provided as input to two deep learning based architectures namely AlexNet and VGG16 net. The role of number of images and importance of hyperparameters namely minibatch size, weight and bias learning rate in the classification accuracy and execution time have been analyzed.

The research article proposed by T. Rumpf , A.-K. Mahleinb, U. Steiner, E.-C. Oerke b, H.-W. Dehne, L. Plümer on early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance started the following discussion. Automatic methods for an early identification of plant diseases are crucial for crop protection. The main contribution of the paper is a procedure for the early detection and differentiation of sugar beet diseases based on Support Vector Machines and spectral vegetation indices. The aim was to discriminate diseased from nondiseased sugar beet leaves, to differentiate between the diseases Cercospora leaf spot, leaf rust and powdery mildew, and to identify diseases even before specific symptoms became visible. Hyperspectral data were listed from healthy leaves and leaves immunized with the pathogens Cercospora beticola, Uromyces betae or Erysiphe betae causing Cercospora leaf spot, sugar beet rust and powdery mildew, respectively for a period of 21 days after inoculation. For the automatic classification, a total of nine spectral vegetarian indices associated to physiological parameters were used. Early distinction between healthy and immunize plants as well as among specific diseases can be achieved by a Support Vector Machine with a radial basis function as kernel. The distinction between healthy sugar beet leaves and diseased leaves resulted in classification accuracies up to 97%. The multiple classification between healthy leaves and leaves with symptoms of the three diseases still obtained an accuracy higher than 86%. Furthermore, the capability of presymptomatic detection of the plant diseases was demonstrated. Depending on the type and stage of disease the classification accuracy was between 65% and 90%.

The authors Jitesh P. Shah, Harshadkumar B. Prajapati, Vipul K. Dabhi proposed a survey on detection and classification of rice plant diseases. Rice plant diseases can experience huge amount of loss in agriculture if enough attention is not given. Using computer and communication technologies, an automated system can be built which can provide prior alerting of the disease. In the same direction, they tried to provide their contributions in image processing and machine learning aspects of such system. They have studied that various alternatives exist for various operations in image processing and in machine learning. The paper reviewed and summarized techniques of the image processing and machine learning that have been used in disease identification. They found that extraction of disease region from the leaf image is the driving step, for which they have studied and compare various segmentation techniques. They utilized their survey and study, presented in this paper, to propose their work in the same direction. The paper presented detailed schematic diagram of the proposed work and discussed important steps. At present, they are working on completing the implementation of the proposed work. A incorporation of image processing and machine learning techniques can give a chance to researchers to address problems in various domains that affect to society directly or indirectly.

3. METHODOLOGY

A. Deep Learning

Deep learning can be treated as a subset of machine learning. This domain is based on learning and improving on its own by examining computer algorithms. While machine learning uses simpler concepts, deep learning works with artificial neural networks, which are designed to imitate how humans think and learn. Until recently, neural networks were limited by computing power and thus were limited in complexity. However, advancements in Big Data analytics have allowed larger, experienced neural networks, allowing computers to observe, learn, and react to complex situations faster than humans. Deep learning has assisted image classification, language translation, speech recognition and many other subsets of machine learning. It can be adapted to work out any pattern recognition problem and without human intervention. Artificial neural networks that have many layers tend to adapt deep learning. Deep Neural Networks (DNNs) are the types of networks where every layer can perform complex operations such as representation and abstraction that show a sense of images, sound, and text. Deep learning is considered as the fastest-growing field in machine learning and it represents a truly disruptive digital technology, and it is being used by increasingly more companies to create new business models.

VGG-19

VGG-19 is a convolutional neural network which consists of 19 layers. You can load a pretrained version of the network that is trained on more than a million images taken from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. The layers in VGG19 model are Conv3x3 (64), Conv3x3 (64), MaxPool, Conv3x3 (128), Conv3x3 (128), MaxPool, Conv3x3 (256), Conv3x3 (256), Conv3x3 (256), Conv3x3 (256), MaxPool, Conv3x3 (512), Conv3x3 (512), Conv3x3 (512), Conv3x3 (512), MaxPool, Conv3x3 (512), Conv3x3 (512), Conv3x3 (512), Conv3x3 (512), MaxPool, Fully Connected (4096), Fully Connected (4096), Fully Connected (1000) and SoftMax.

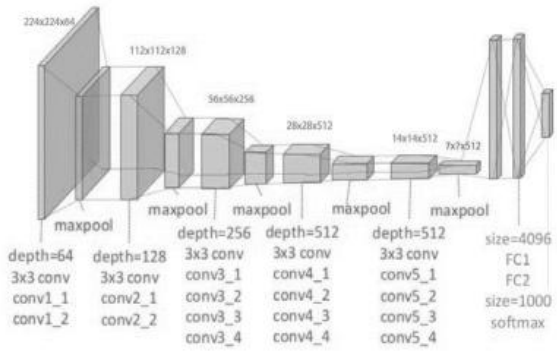

Fig. 1. Network Architecture of VGG-19 Model

A fixed size of (224 * 224) RGB image is given as input to this network which means that the matrix is of shape (224,224,3). The only pre-processing that is done is that the difference between the mean RGB value from each pixel, computed over the whole training set. The kernels that are incorporated are of (3 * 3) size with a stride size of 1 pixel. This permitted them to cover the whole notion of the image. Spatial padding is used to maintain the spatial resolution of the image. Max pooling was carried out over a 2 * 2-pixel windows with stride 2. This is followed by Rectified linear unit (ReLu) to introduce non-linearity to make the model classify better and to improve computational time as the previous models used tanh or sigmoid functions this proved much better than those. Implemented three fully connected layers from which first two are of size 4096 and after that a layer with 1000 channels for 1000-way ILSVRC classification and the final layer is a SoftMax function.

C. InceptionV3

Inception v3 comes under one of the image recognition models that showed greater than 78.1% accuracy on the ImageNet dataset. The model is the summit of many ideas introduced by many researchers over the years. It has 42 layers in total and shows lower error rate than its predecessors. The major modifications done on the Inception V3 model are factorization into smaller convolutions, spatial factorization into asymmetric convolutions, utility of auxiliary classifiers and efficient grid size reduction.

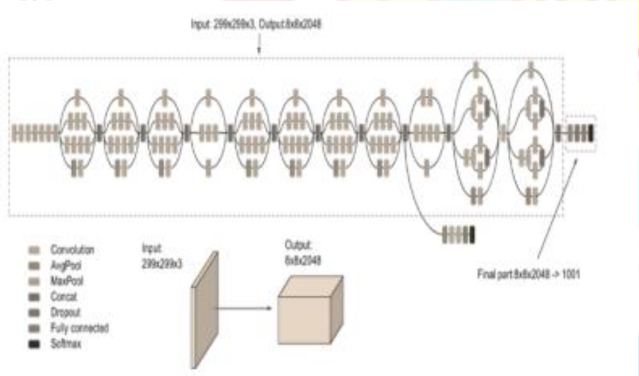

Fig. 2. The final InceptionV3 Model

It has many assets and the main asset is the generous dimension reduction. The larger convolutions in the model are factorized into smaller convolutions. The basic module of the inception V1 module has a 5×5 convolutional layer which is computationally expensive. So, to reduce the computational cost the 5×5 convolutional layer is replaced by two 3×3 convolutional layers. To be precise, consider the process of using two 3×3 convolutions that reduces the number of parameters. It results in reducing the number of parameters and computational costs also gets reduced. This factorization of larger convolutions into smaller convolutions obtained a relative gain of 28%.

Though the larger convolutions are resolvable into smaller convolutions. Asymmetric convolutions can be a better alternative to increase the efficiency of the model. Asymmetric convolutions are of the form n×1. So, they replace the 3×3 convolutions with a 1×3 convolution followed by a 3×1 convolution. This is same as sliding a two-layer network with the same receptive field as in a 3×3 convolution. The two-layer solution is 33% cheaper for the same number of output filters with number of input and output filters being equal. The aim of using an auxiliary classifier is to improve the convergence of very deep neural networks. The core purpose of auxiliary classifier is to combat the vanishing gradient problem showed in very deep networks. The auxiliary classifiers did not result in any improvement in the early stages of the training. But towards the end, the network with auxiliary classifiers revealed higher accuracy compared to the network without auxiliary classifiers. Thus, the auxiliary classifiers act as a regularised in Inception V3 model architecture.

Convolutionally, max pooling and average pooling were used to reduce the grid size of the feature maps. In order to efficiently reduce the grid size in the inception V3 model, the activation dimension of the network filters is expanded. Suppose that we have a d×d grid with k filters after reduction it results in a d/2 × d/2 grid with 2k filters which is done using two parallel blocks of convolution and pooling that are later concatenated.

Therefore, the inception V3 model is made up of 42 layers which is a bit higher than the previous inception V1 and V2 models. But the efficiency of this model is really impressive.

D. Inception ResnetV2

Inception ResnetV2 is a convolutional neural network that is trained on more than a million images from the ImageNet database. The Inception ResnetV2 network is 164 layers deep. It can classify images into 1000 object categories, such as the monitor, keyboard, mouse, pen drive, pencil, and also many animals. This brings to the point that the Inception ResnetV2 network has learned rich feature representations for a vast range of images. The network takes an image input size of 299*299 and the output will be a list of estimated class probabilities. This is formulated based on a combination of the Inception structure and the Residual connection.

Convolutional filters of multiple sizes are combined with residual connections in the Inception Resnet block. Besides avoiding the degradation problem caused by deep structures, the residual connection also reduces the training time.

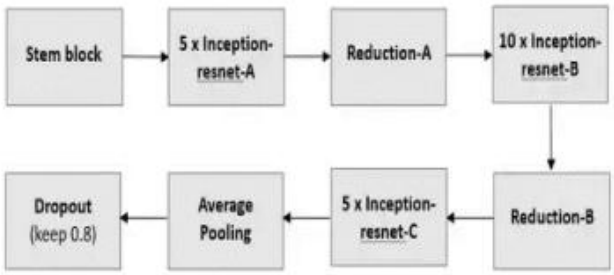

Fig. 3. The basic architecture of Inception ResnetV2

E. System Architecture

Three models via., VGG19, InceptionV3 and Inception ResnetV2 were used in this project. The dataset was taken from Kaggle, which contains 38 different classes with a total of 70000 images. Later, the dataset was divided into training, validation and testing parts. Also, the dataset was loaded into TensorFlow. During this, the ImageDataGenerator was used to produce new images from one image by variations such as rotating, zooming in, zooming out and flipping. This made the model to be trained on every type of image and accuracy can also be enhanced. Moving further, the learning rate was set to a specific value. The objects were objects were created for all the three models. These were basically the pre-training models. Also, the layers were added to the models. Now, the training phase started on the three models using the training dataset. Different layers were included such as pooling layer, flatten layer, normalization layer and others. Greater the number of layers greater will be the accuracy of model. SoftMax and other activation functions were used. During training, a number of epochs were considered to make sure the models can be trained well and accuracy can be improved. After the training phase has ended, the models were tested using the dataset. The VGG19 model showed about 33% accuracy, InceptionV3 model showed around 50% and Inception ResnetV2 got almost a 100% accuracy. Depending on the results observed, the Inception ResnetV2 model was considered for further testing and detection phases.

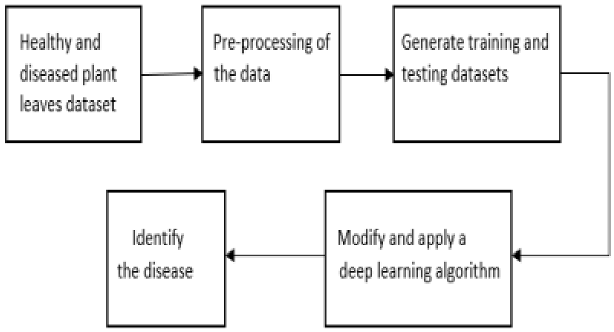

Fig. 4. System Architecture

F. CNN Architecture

Convolutional Neural Network comprises of two core elements via., Feature Extraction and Classification. Convolution tool identifies and separates different features of the image. These are then used for analysis in a process called as Feature Extraction. The Feature Extraction network consists of many sets of convolutional or pooling layers. A fully connected layer uses the output given by the convolution layer. Later, it predicts the class of the image depending on the features that are extracted in past stages. The goal of CNN model of feature extraction is to lower the number of features present in a dataset. It generates new.

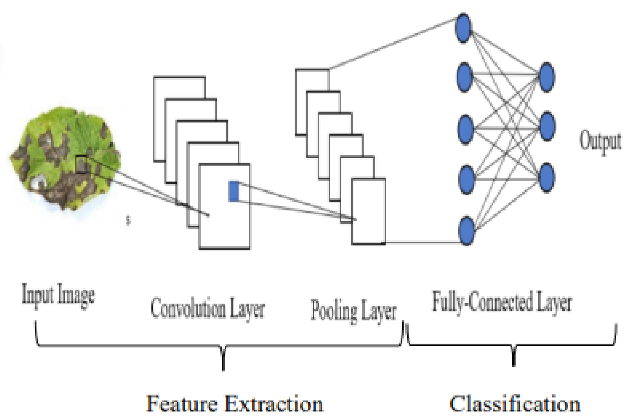

Fig. 5. Basic CNN Architecture

4. EXPERIMENTAL RESULTS

Therefore, an Inception ResNet V2 model for detecting the diseases in leaf of a plant is developed. This model can not only be used by farmers but also can be implemented by many large-scale industries. Identifying the diseases in plants in early stage prevents major loss of yield and improves profit when used on timely basis. We also created a simple web application for easy access to farmers so that they can get sufficient information about the disease and know a few disease management techniques. Accuracy of the model can be increased by running more epochs and also by trying new datasets. A few images of the application developed are shown below.

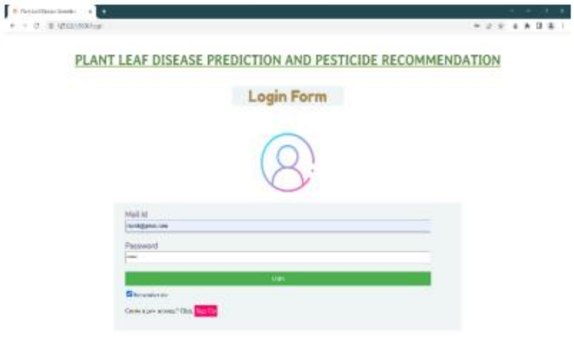

Fig. 6. Login Page Interface for the user

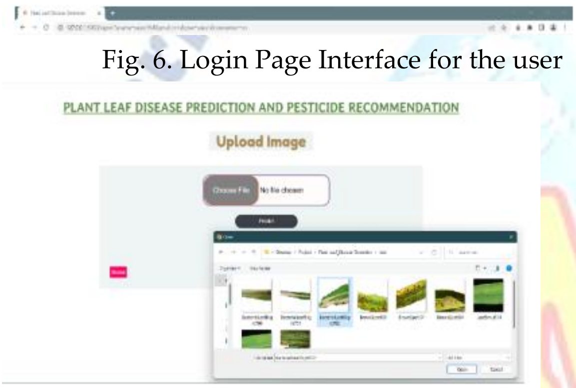

Fig. 6. Login Page Interface for the user

Fig. 7. Image Upload Interface to upload the diseased leaf

Fig. 8. Disease Information Page to know about the disease

5. CONCLUSION

In this project, combination of healthy and diseased plant leaf data is used for training the model. Transfer learning is used for the pre-trained AlexNet network for a different amount of data for training of the network, and results are validated with a VGG19, InceptionV3 and InceptionResnetV2. The classification accuracy can be improved by increasing the dataset as the deep learning models can efficiently work on them.

6. FUTURE SCOPE

In future work, the feature extraction techniques in preprocessing of the data can be chosen that can be best suited for the deep learning model for better performance. The performance can further be improved by using a fast computing device like GPU as the work carried out here is on a single CPU.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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