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PLANT DISEASE CLASSIFICATION USING DENSENET-121 ARCHITECTURE AND FLASK

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Abstract:

In terms of economic viability and human existence, agriculture is a nation's backbone. We aim to prevent plant diseases to maintain high agricultural production efficiency. In order to improve the outcome without adding complexity, the suggested method will optimise the data from the resources that are now accessible. The Dense Convolution Neural Network (DCNN) is the neural network that is employed for classification. For training in this project, a pre-trained neural network model (densenet-121) imported from the keras library was employed. An input that results in activation may be subjected to a convolution by the straightforward application of a filter.

A feature map, which shows the positions and intensity of a detected feature in an input such as an image, is produced by repeatedly applying an analogous filter to an input. The convolutional networks assist in automatically learning a large number of filters relevant to a training dataset in simultaneously. The country's economy benefits as a consequence of this algorithm's ability to identify plant illnesses effectively. The densenet-121 has been used to classify the 29 various illnesses for 7 plants (potato, tomato, maize, bell pepper, grape, apple, and cherry) using 34599 photos from the Huges DP Plant-Village dataset from Kaggle.

In my research, the original picture is transformed into HSV colour form, after which the thresholding-generated masked image is delivered to the suggested model for training and classification, yielding an average accuracy 98.23% (theoretical). We obtained an average accuracy of 94.96% for 50 epochs with a learning rate of 0.002 when all classes of plant disease were provided to the model for training using the Google Colab platform (Tesla-T4 processor).

IndexTerms -**Metallic surface, VGG-16, Neural Networks, defect detection**

1. INTRODUCTION

A plant disease is a physiological abnormality. Once a plant suffers from any disease it shows up certain symptoms. symptoms are the outward changes in physical appearance that are gradually developed and can be witnessed by naked eyes.

In India about 70% of the populace relies on agriculture. Identification of plant diseases is important in order to prevent the losses within the yield. It's terribly troublesome to observe plant diseases manually. It needs a tremendous quantity of labor, expertize within the plant diseases, and conjointly need the excessive time interval. Hence, image processing and machine learning models can be employed for the detection of plant diseases. In this research , we have described the technique for the detection of plant diseases with the help of their leaf pictures. Image processing is a branch of signal processing that can extract the image properties or useful information from the image.

Machine learning is a sub part of artificial intelligence which works automatically or give instructions to do a particular task. The main aim of machine learning is to understand the training data and fit that training data into models that should be useful to the people. So it can assist in good decisions making and predicting the correct output using the large amount of training data. The color of leaves, amount of damage to leaves, area of the leaf, texture parameters are used for classification. In this project we have analyzed different image parameters or features to identifying different plant leaves diseases to achieve the best accuracy. Previously plant disease detection is done by visual inspection of the leaves or some chemical processes by experts.

For doing so, a large team of experts as well as continuous observation of plant is needed, which costs high when we do with large farms. In such conditions, the recommended system proves to be helpful in monitoring large fields of crops. Automatic detection of the diseases by simply seeing the symptoms on the plant leaves makes it easier as well as cheaper.

2. LITERATURE SURVEY

Over the past several years, a number of machine vision-based strategies have been proposed to recognise various diseases, pests, and stresses in a range of crops. Anamietal. [1] used Sequential Forward Floating Selection (SFFS) to compare the accuracy of classifier models like Support Vector Machine (SVM), Back Propagation Neural Network (BPNN), and k - Nearest Neighbour (k-NN) and reduce the overlap between the colour features for detecting paddy diseases and stresses.To identify yellow stemborer and leaf folder moths in the paddy field, Muppala et al. [2] suggested a four-layer deep neural network with search and rescue optimisation (DNN-SAR) pest detection approach. All image processing methods used to identify plant diseases have been compiled by Sethy et al. [3] and Kartikeyan, Pet al. [4]. These publications were excellent resources for evaluating a variety of modern image processing methods. For the purpose of paddy disease identification, Ramesh et al. [5] employed a dataset of 575 pictures. The Optimised Deep Neural Network with Jaya Optimisation Algorithm (DNN-JOA) was used to classify the illnesses. A approach to diagnose tomato illnesses has been put out by Khan et al. [6] that combines colour balancing, k-means clustering, super pixel operations, Histogram of Gradients (HOG), Grey Level Co-occurrence Matrix (GLCM) features, and Random Forest (RF) methodology. Both downloaded and real-time datasets are included in their data collection. In order to diagnose fungal illnesses in bananas, Mathew al et al. [7] created a unique neural network model by enhancing images, segmenting them, and extracting feature vectors using DWT (Discrete Wavelet Transform) and DTCWT (Dual Tree Complex Wavelet). Convolution Neural Network (CNN) models have been developed by Rahman et al. [8] and Sharma et al. [9] to classify paddy illnesses using segmented and whole photos. After converting live photos to HSV colour format, Bakar et al. [10] worked on identifying rice plant illnesses into three groups using multi-level thresholding. The similar kind of network is also utilised in [11] to create a model for smart agriculture. When using the Deep Convolution Neural Network (DCNN), [12] obtained an accuracy of 88.46% using the same neural network model that had been trained to identify maize plant disease. To recognise three distinct maize diseases, a CNN model was created in [13]. Using ResNet-18, the blackleg detection in potatoes was created. VGG19, a well-known CNN model, was used to mimic the detection of potato disease [15]. [16] uses a Multi-class SVM based classifier to diagnose tomato illness. Santhosh et al. [16] created a classifier for tomato disease using the CNN model. The use of additional neural networks, such as the back propagation neural network (BPNN), [17] describes the extraction of 24 texture characteristics using GLCM for categorising potato disease diagnosis. Using the same dataset [32] we used to test our model, the feature set based multi-diseases classification (FSMDC) [18] operated using a specially derived feature set based on the picture dataset. The state-of-the-art methods are compared using SVM, MLP, and LR approaches. Regarding the image processing method, they employed a model to create masks for pictures using a growing area, and their results demonstrated an average accuracy of 93.2%. Iyyanaret al. [19] developed a CNN network-based model to categorise various diseases in rice, tomato, and potato. A survey of the developments in plant and vegetable disease detection has been done by Jadhav et al. [20]. In [21] HSV based apple disease classification using machine learning was performed and compared with other color spaces. Ghorai A. K. et al.[22] has reviewed all major diseases and deficiencies of crops along with various machine learning techniques used in the years. Patil et al. [23] has analyzed and complied 16 existing image processing and classification techniques for pomegranate disease detection. We have taken their data for comparison with our model. As for the neural architecture all information is referred from [26, 27, 28] for dense net model as a whole is analyzed and explained.

3. KEY TECHNOLOGIES

A. Deep Learning

Deep learning is a class of machine learning techniques that employs many layers to extract higher level information from the data at hand. Deep learning is a type of machine learning that instructs computers to filter data across several levels. The filtering of information by the human brain is demonstrated via deep learning. The neural network designs are used in several deep learning approaches. The term "deep" refers to the multiple concealed layers that are present in neural networks. Deep neural networks can include as many as 150 hidden layers, as opposed to the 2-3 hidden layers in a standard neural network.

B. Convolutional Neural Network

Convolutional neural networks (CNN) are a kind of deep neural networks. A CNN makes this architecture more appropriate for processing 2D data, such as pictures, by combining well-read features with input data and using 2D convolutional layers. CNNs do away with the need for manual feature extraction and removal during the categorization of the pictures. The CNN model itself pulls features directly from pictures. The characteristics that are retrieved are well-read when the network is being trained on a small number of picture groups; they are not pre-trained. The Convolutional Neural Network (CNN) model contains several layers, including Input layer, Output layer, Convo layer, Fully connected layer, Soft-max layer, and Pooling layer, which process images using convolutional layers.

C. Introduction to DenseNet

In a traditional feed-forward Convolutional Neural Network (CNN), each convolutional layer except the first one (which takes in the input), receives the output of the previous convolutional layer and produces an output feature map that is then passed on to the next convolutional layer. Therefore, for 'L' layers, there are 'L' direct connections; one between each layer and the next layer.

However, as the number of layers in the CNN increase, i.e. as they get deeper, the 'vanishing gradient' problem arises. This means that as the path for information from the input to the output layers increases, it can cause certain information to 'vanish' or get lost which reduces the ability of the network to train effectively.

DenseNets resolve this problem by modifying the standard CNN architecture and simplifying the connectivity pattern between layers. In a DenseNet architecture, each layer is connected directly with every other layer, hence the name Densely Connected Convolutional Network. For 'L' layers, there are L(L+1)/2 direct connections.

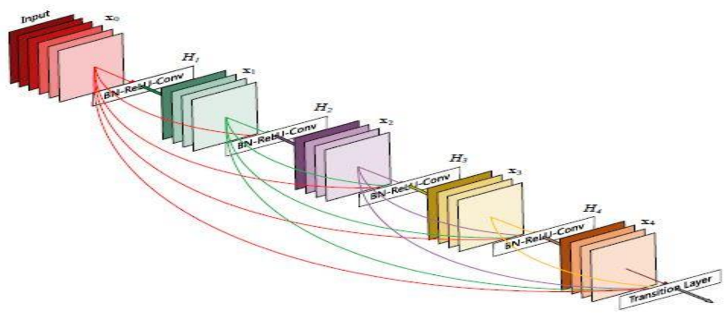

Figure 1: Block Diagram of DenseNets

D. Flask

Python allows the use of Flask to create such an API. Flask is basically a micro framework that has been written in python. It needs no special tools. It has provisions for use of render templates to enable the Api over multiple HTML pages. Flask is based on Jinja2, Werkzeug. We can use a Fetch Api that works on the basis of a promise that fetches the response from the client in answer to a request sent by the server. It also gives definitions of relevant concepts like CORS module using which we can host different applications on different ports and facilitate the transfer of data between them.

E. JSON

In our work, we have used the JSON format to send data between the two ports. A JSON format is essentially a format to store or depict data. It consists of pairs formed by coupling of names and values that are divisioned by commas. Curly brackets called for their help in enclosing objects and square brackets are for arrays. The advantage of using JSON format is that any programming language can be used to read and create JSON data. The basic JSON data types are: Number - It is a signed decimal number and might have a fraction part or make use of the E notation (exponential). This data type cannot deal with non-number data type, i.e. NaN. String - It is data type that contains a sequence of Unicode characters. The number of characters should be zero or more. Boolean - It is a data type with only two values, either FALSE or TRUE. Array - It is a data type with a set of zero or more values, irrespective of their data types

4. PROPOSED METHODOLOGY

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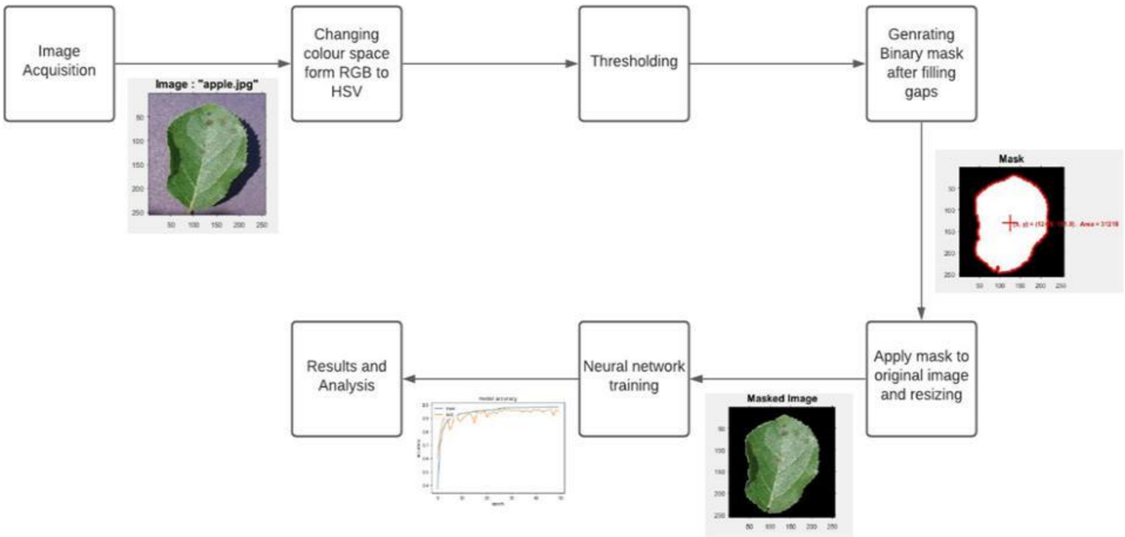

Figure 2: Proposed Model

Pre-processing techniques are used to improve image quality and image features for any field of application. Plant disease detection is no exception. Images in the dataset have background information which is unnecessary for disease detection in leaves of crops. This is overcome by RGB color form image to HSV form, segmenting required portion of image by histogram based thresholding and hole-filling ending into a binary mask image and then masked by dot multiplication on the binary mask, finally resizing it for neural network training. A quick overview is given below in the flowchart and each part is elaborated in the upcoming headings. The below fig.1 has the flow of work simplified through the flowchart.

We can reduce the attack of pests by using proper pesticides and remedies. We can reduce the size of the images by proper size reduction techniques and see to it that the quality is not compromised to a great extent. We can expand the projects of the earlier mentioned authors such that the remedy to the disease is also shown by the system. The main objective is to identify the plant diseases using image processing.

It also, after identification of the disease, suggest the name of pesticide to be used. It also identifies the insects and pests responsible for epidemic. Apart from these parallel objectives, this drone is very time saving. The budget of the model is quite high for low scale farming purposes but will be value for money in large scale farming. It completes each of the process sequentially and hence achieving each of the output. Thus the main objectives are:

1) To design such system that can detect crop disease and pest accurately.
2) Create database of insecticides for respective pest and disease.
3) To provide remedy for the disease that is detected.

In this research work, we focus on creating a solution that would be an easy fix for the leaf disease detection problems. We have collected a large dataset consisting of images of healthy and diseased leaves. We build an iPhone app for the detection of the disease a crop leaf is afflicted with, based on a picture of the leaf. The app will make use of ML algorithms to analyze and predict the disease a leaf has. It will use a model that has been trained on pre-identified diseased leaf images. Based on it, any newly encountered diseased leaf will be identified by its disease. The input image can be either an uploaded one or clicked through the phone camera. The output will be the disease name it has been identified with. Thus, a classification and identification of the disease is enabled. An option to look up remedies for the disease will also be provided. An additional option for a front-end is also made- a Rest Api service that hosts a website to allow entering of a picture name and display its output class.

5. TESTING AND TESTING RESULT

5.1: TESTING:

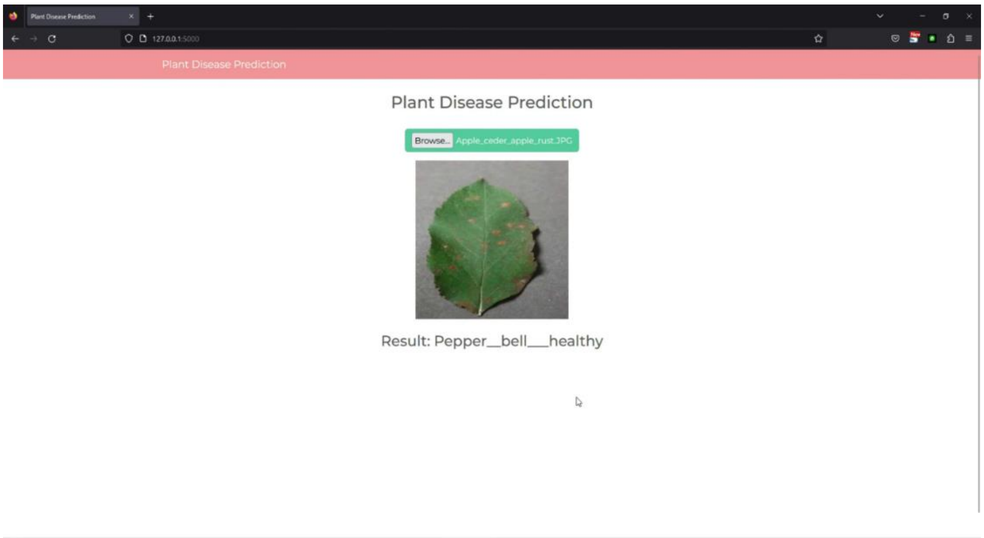

Figure 3: Testing Result

5.2 RESULTS

Confusion matrix:

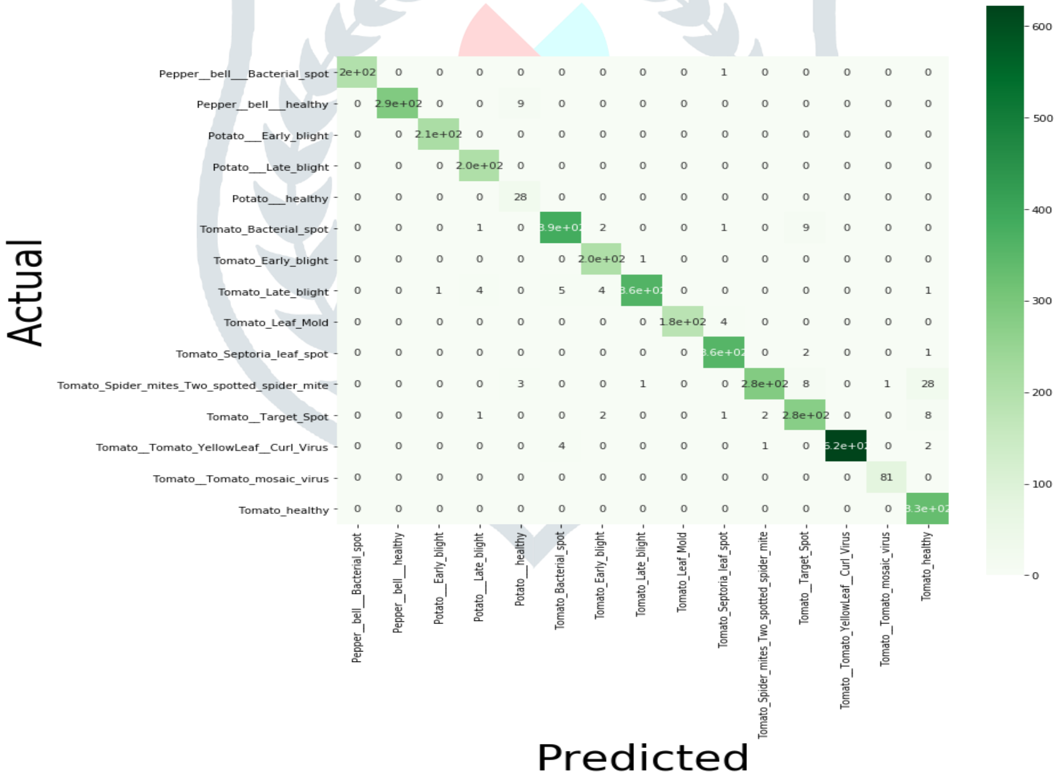

Figure 4: Confusion Matrix

above shows the confusion matrix generated to show the statistical values for the

performance of the neural network. The model has been trained ideal result i.e. to have a diagonal matrix plotted between the actual and the predicted results. The false predicted images are seen more in the tomato crop region, than compared to the rest

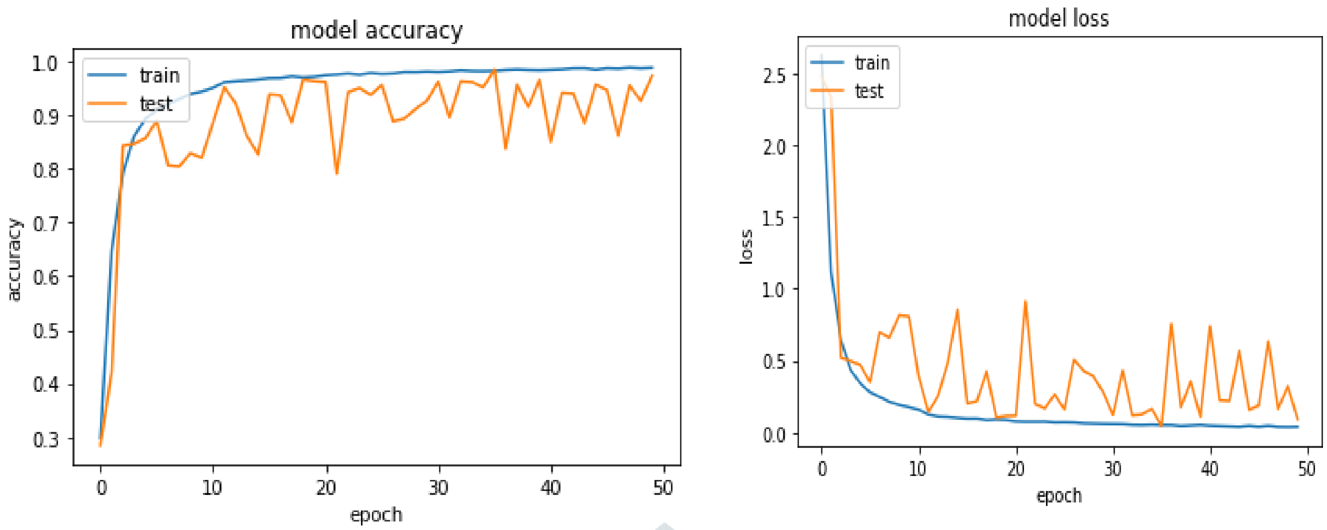

Figure 5: *Shows the relation between number of iteration and average loss during training. Y- axis represents the average a) and loss (b) respectively and X-axis represents the number of epochs. The model is trained up to 21850 iterations with average 94.96 and loss of 0.0634*

6. CONCLUSION & FUTURE SCOPE:

6.1: CONCLUSION

By examining the structural deformation of leaf pictures, crop diseases may be identified. For more effective illness categorization, the background is suppressed and these characteristics are given greater weight. To eliminate background features, we first convert the obtained picture to a different colour and then mask it using thresholding. Plant-Village datasets comprising apple, cherry, maize, grape, bell pepper, potato, and tomato leaf pictures are used to analyse the performance measure of the proposed work using the DCNN model. The suggested work outperformed previously presented state-of-the-art methods with an average accuracy of 98.23% both conceptually and practically (94.96%).

6.2 FUTURE SCOPE

The main goal for the future research work is to develop a complete system comprising a trained model on the server, as well as an application for mobile phones that display recognized diseases in fruits, vegetables, and other plants based on photographs taken from the phone camera. This application will aid farmers by facilitating the recognition and treatment of plant diseases in a timely manner and help them make informed decisions when utilizing chemical pesticides[6]. Also, future work will involve spreading the use of the model across a wider land area by training it to detect plant diseases on aerial photos from orchards and vineyards captured with drones, in addition to convolution neural networks for object detection. Drones and other autonomous vehicles, such as smartphones, to be used for real-time monitoring and dynamic disease detection in large-scale open-field cultivations. A future possibility for agronomists working at remote locations could be the development of an automated pesticide prescription system that would require the approval of an automated disease diagnosis system to allow the farmers to purchase appropriate pesticides. Thus, the uncontrolled acquisition of pesticides could be severely restricted, resulting in their excessive use and misuse, with their potentially catastrophic effects on the environment.

Our model can be extended to classify various other plant diseases like paddy crop, barley, lemon etc. with proper image dataset or can have improved accuracies by expanding the dataset to real-time images. As for the website, we have just established a beta version, this can be improved a lot more by deploying it in real time servers which would, in turn, improve our accuracy of detecting diseases in crops. An app would be a better work than of ours.

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