Plant Leaf Disease Detection Using The Preprocessed Data

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***Abstract*— The goal of this Project is to identify plant diseases by employing preprocessed data. Among the preprocessing methods employed were the 'vishushrink' approach for denoising, downsizing images to (256,256), and Contrast Limited Adaptive Histogram Equalisation (CLAHE) for images converted to HSV format. After that, RGB pictures were reconstructed and background noise was removed using U2 segmentation. To resolve dataset imbalance, upsampling was done using image augmentation techniques. Ten distinct disease kinds were taken into consideration while retrieving features such as energy, correlation, and entropy. Several models, including ResNet, MobileNet, and VGG16 with self-attention layers, were implemented. MobileNet only achieved 0.85 accuracy, but ResNet with attention layers achieved 0.99.**

***Index Terms*— Wavelet ('Vishu shrink') , CLAHE , Resnet , VGG16**

I. INTRODUCTION

Crop productivity, food security, and the economy can all be significantly impacted by plant diseases. For plant diseases to be effectively managed and controlled, early and precise detection is essential. The use of subjective and time-consuming traditional disease detection techniques, like visual inspection, may cause treatment delays and a rise in the transmission of the illness.

By identifying various plant disease in initial stage so that we can give medicine to the plants to increase the crop yeild of the plant and to get better food.

Plant disease detection has greatly benefited from the application of cutting-edge technology like computer vision and machine learning. Early disease diagnosis and identification are made possible by these methods' ability to swiftly and reliably analyse enormous amounts of data. By minimising the use of needless chemicals and pesticides, this not only helps to stop the spread of illness but also supports sustainable agricultural practices.

Ensuring food security, safeguarding the environment, and advancing sustainable agricultural methods all depend on the accurate identification of plant diseases. Utilising cutting-edge technologies, we can increase the efficacy and precision of disease detection, which will ultimately result in healthier plants and a more resilient food chain.

To maintain crop health and increase agricultural productivity, plant disease identification is essential. Farmers can prevent crop losses and lessen the need for chemical interventions by detecting infections early on. In this study, we primarily use machine learning and image processing techniques to identify plant diseases. Our dataset consists of pictures of three different plant species, each with three related diseases, for a total of ten classes. To boost model performance, preprocessing methods such image scaling, wavelet denoising for noise reduction, and CLAHE for image enhancement were used. We used image augmentation techniques to apply upsampling approaches in spite of the difficulties presented by an unbalanced dataset. Energy, correlation, and entropy feature extraction approaches were used, along with a number of deep learning models, including VGG16, MobileNet, and We implemented ResNet with layers for self-attention. Finding plant diseases is important because it helps protect agricultural production, lower costs, and encourage sustainable farming methods.

A. Motivation

Our goal is to reduce crop losses—which can have negative effects on the economy and society, particularly in areas where agriculture plays a major role—by creating an effective disease detection system. By this project we can detect the plant disease in early stages and take the preventive care to the crop and by this we can stop spreading of the plant disease and we can increase the crop yield as well as we can avoid the use of pesticides and fertilizer and farmers can go with organic farming.

Early detection also makes it possible to take action promptly, which lessens the need for chemical pesticides and encourages sustainable farming methods. With the use of technological innovations like machine learning and image processing, this initiative aims to give farmers an accessible and affordable tool for crop health monitoring. Our ultimate goals are to alleviate the problem of food insecurity on a global scale and to help millions of farmers around the world support their livelihoods.

B. Objective

The objective of this project is to detect the plant disease using computer vision and deep learning techniques. Through the analysis of images of diseased plants, the system aims to identify the specific disease affecting the plant and provide timely diagnosis to farmers or gardeners. By leveraging advanced image processing algorithms and deep learning models, the project seeks to enhance agricultural practices by enabling early detection of diseases, thus reducing crop losses and improving overall yield . Additionally the project aims to create a user friendly interface so that the farmers can easily upload the photos and can see the whether the plant is affected or not .By this method we can increase the yield of the crop and the farmers can avoid the pesticides .

II. LITERATURE Review

In one paper they have implemented CNN model achieves a training accuracy of 98.01% and a test accuracy of 94.33% and in another paper they have implemented Resent 50 they have got average F1-score of 96% and in some paper they have implemented preprocessing techniques such as contrast limited adaptive histogram equalization (CLAHE) and for balancing the data they have used GAN and they have done modelling using the average classification accuracy of 97.69% only for tomato .

III. Description of the Dataset

The dataset comes from the Kaggle and Which Plant Village dataset, which has 38 classes and 87,900 RGB photos with 512,512 pixels in size. I have only taken ten classes: Apple_healthy , Blueberry_healthy, Cherry_(including_sour)_healthy , Apple_scab , Apple_Black_rot , Apple_Cedar apple rust , Apple_healthy , Cherry Powder (including sour powder) , Maize (corn) Cercospora leaf spot Leaf spot grey,The three plants (apple, cherry, and corn) in Corn_(maize)_common_rust_ and Corn_(maize)_healthy) have a combined total of 24000 images with a size of (512,512). To balance the classes, I have applied image augmentation and I have divided the images into test ,train,validation set.

IV. Data Preprocessesing techniques

A. Image Enhancement

I have removed the noise from the images using the wavelet method and I have used the '**bior6.8**' wavelet for this .The **bior6.8** wavelet belongs to the **Biorthogonal wavelets** have the property that their decomposition and reconstruction filters and making it useful for denoising in the images and here 6 represents the length of decomposition filter and 8 represents the length of the reconstruction filter and these are useful for image processing and Biorthogonal wavelets like 'bior6.8' are particularly well-liked because they provide good localization in both the time (or space) and frequency domains, making them useful for tasks like image denoising, compression, and feature extraction.

Fig. 1. Original image of Apple_Scab

After this we are converting the RGB images into the HSV format .The HSV color format represents the hue, saturation, brightness value . The hue is expressed as an angle around a color wheel and it ranges between 0 to 360 and zero represents red. The saturation represents the intensity or shade of the color .The value represents the brightness of the color.

After this we have used the CLAHE (Contrast limited adaptive histogram equalization) techniques to enhance the contrast of an image by redistributing the pixel intensities . Contrast Limited AHE (CLAHE) is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification. In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function.

After this, I'm using an integrated library to remove the backdrop using U2-net segmentation. A deep learning architecture called U2-Net is specifically made for picture segmentation tasks, with a focus on salient item detection. U2-Net employs a U-shaped network design with skip connections and an encoder-decoder topology.

Fig. 2. Enhanced image of Apple_Scab

Fig. 3. Backaground removal Enhanced image of Apple_Scab

B. Balancing the Dataset

The dataset is unbalanced; in order to correct it, we are employing two methods. 1) Generative Advertial Network (GAN) 2) Augmentation approaches can be employed. Since the GAN method requires a 48 GB GPU, I chose the second method, or image augmentation, and maintained some rotation for all the images. It only takes 2000 images for each class, 20000 images for the train set, 2000 images for the test set, and a some number of images for the validation set.

I have only taken ten classes: Apple_healthy , Blueberry_healthy, Cherry_(including_sour)_healthy , Apple_scab , Apple_Black_rot , Apple_Cedar apple rust , Apple_healthy , Cherry Powder (including sour powder) , Maize (corn) Cercospora leaf spot Leaf spot grey,The three plants (apple, cherry, and corn) in Corn_(maize)_common_rust_ and Corn_(maize)_healthy) have a combined total of 24000 images with a size of (256,256) and these images are preprocessed images.

V. Deep Learning Classifier

I have used some architecture like mobile net , resnet-18 with self-attention layer , VGG16 ,Vision Transformers and I have extracted some features and performed some feature extraction techniques such as From GLCM I have taken some features such as energy, entropy , contrast , dissimilarity , homeginity and from this features I have done some modelling techniques.

I have implemented the mobile net v3 small architecture and MobileNetV3 Small is a convolutional neural network architecture designed for efficient image classification tasks, particularly optimized for mobile and embedded devices. I have trained this model with 50 epochs and I have got the accuracy of 94 percentage for this model.

A. Resnet18 with self attention layer

The Residual Network (Resnet18) that I used has eighteen trainable layers. I eliminated the final two layers, added the self-attention layer, and then put the Dense layer at the end of the network, which represents the number of classes.Self-attention enables neural networks to weight the value of various items in a sequence, such as pixels in a picture, based on their contextual interactions with one another. The Resnet18 design is mostly used for image classification tasks. This is accomplished by calculating attention scores, which gauge how important each element is to each other in the sequence.

I have used the transfer learning for Resnet18 and I have removed the last two layers and added the Self attention layer and I have trained model with train set got an accuracy of 99.4% and I validated model with validation set and I have obtained the accuracy of 99.1% and it is same for test test also.

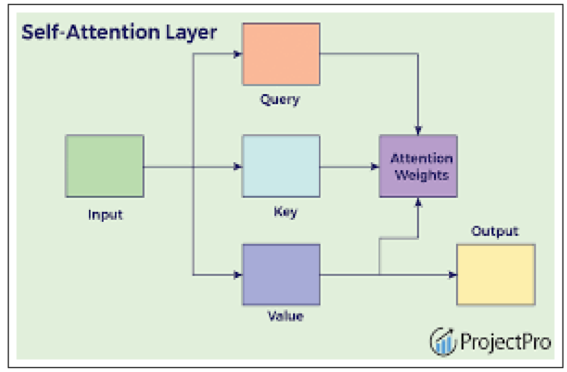

Fig. 4. Architecture inside the self_attention

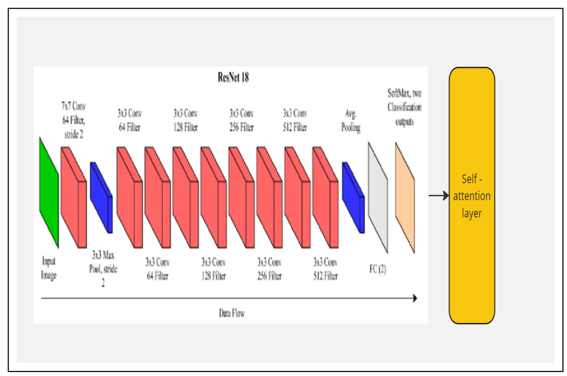

Fig. 5. Resnet with self attention layer architecture

B. Classification using the GLCM features

I have applied GLCM to all image and various statistical measures can be derived from it to characterize the texture and structure of the image. The common features I have extracted was contrast ,Energy ,Dissimilarity,homegenity,entropy.

The contrast Measures the local variations in the image. Th entropy measures the average difference in intensity between neighboring pixels.The Homegenity reflects the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Correlation measures the linear dependency between pixel pairs. The Energy Represents the orderliness or homogeneity of the image.

After this we have applied the ML models such as SVC (applied radial basis kernel) , Random Forest, Adaboost, ANN with SVC . I have got the better accuracy with SVC model of 61.5%.

TABLE I

MODEL COMPARISON

Model	Accuracy
SVC	61.6%
Random Forest	55.5%
AdaBoost with Decision Trees	55.7%
ANN with SVC	0.90

VI. EVALUATION METRICS

In these experiments we have evaluated the accuracy and confusion matrix .The accuracy was evaluated using the TP , TN , FP , FN. The formula for accuracy score is given by:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

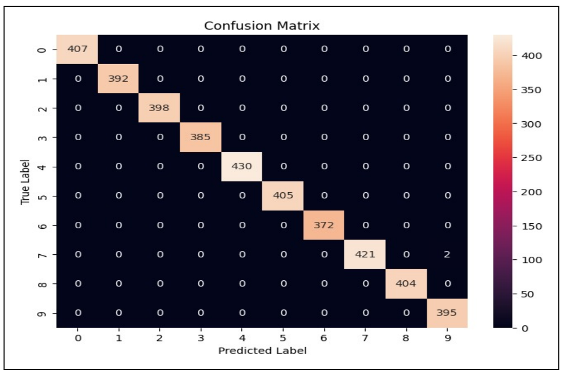

Fig. 6. Confusion matrix for the resnet18 with self-attention layer

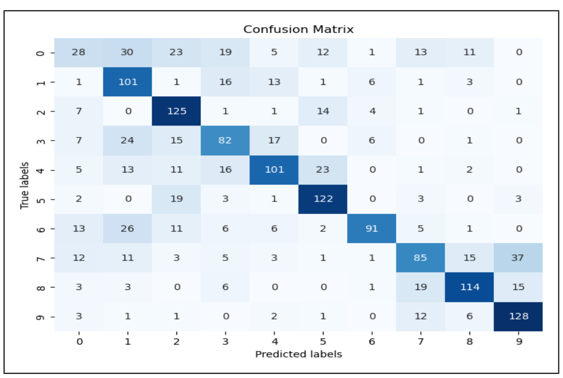

Fig. 7. Confusion matrix for the SVC

VII. RESULTS AND DESCUSSIONS

This section summarized the main results of this study on plant disease classification . The resnet18 with self attention layer has potential to detect the plant disease . For the Resent18 with self attention layer has performed very well when compared with the other models.

The results obtained for the resnet 18 with self attention are shown below

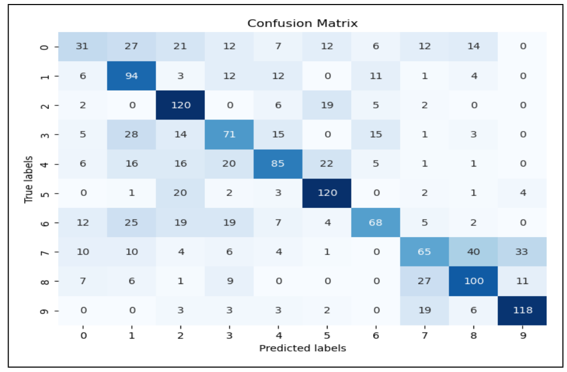

Fig. 8. Confusion matrix for the Random Forest

TABLE II

MODEL COMPARISON

Model	Accuracy
SVC	61.6%
Random Forest	55.5%
Resnet18 with self-attention	99%
mobilenet v3 small	85%

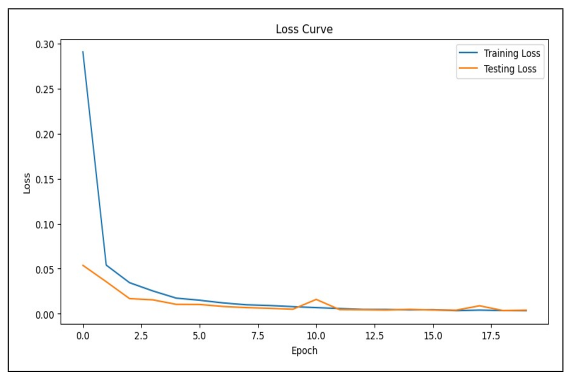

Fig. 9. Loss curve for resnet18 with self attention

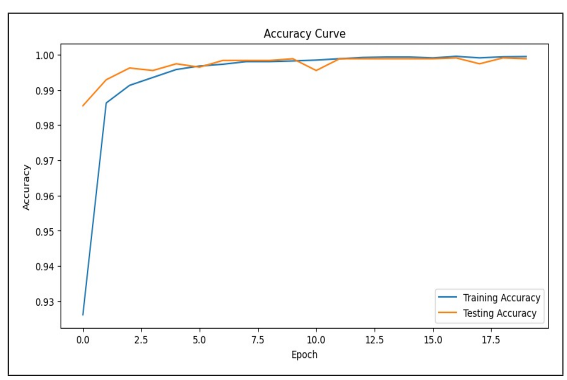

Fig. 10. Accuracy curve for resnet18 with self attention

VIII. Conclusion

From this experiment we can conclude that preprocess-esing of the image data got the better results and after that applying the resnet 18 architecture has got much better results as compared to the other architecture.

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