AN OPTIMIZED METHOD FOR SEGMENTATION AND CLASSIFICATION OF APPLE DISEASES BASED ON CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Agriculture is a major part of the world economy as it provides food safety. However, in recent years, it has been noted that plants are extensively infected by different diseases. This causes enormous economic losses in the agriculture industry around the world. The manual inspection of fruit diseases is a difficult process which can be minimized by using automated methods for detection of plant diseases at the earlier stage. In this article, a new method is implemented for apple diseases identification and recognition. Three pipeline procedures are followed preprocessing, spot segmentation and classification. In the first step, the apple leaf spots are enhanced by a hybrid method which is the conjunction of 3D box filtering, de-correlation, RGB color model. After that, the lesion spots are segmented by converting the red channel to black and white channel. Finally, the segmented red channel image is classified by CNN Classifier. The experimental results are performed on the Plant Village dataset. The proposed methodology is tested for four types of apple disease classes including healthy leaves, Black rot, Rust, and Scab. The classification results show the improvement of our method on selected apple diseases. Moreover, the good preprocessing step always produced prominent features which later achieved significant classification accuracy.

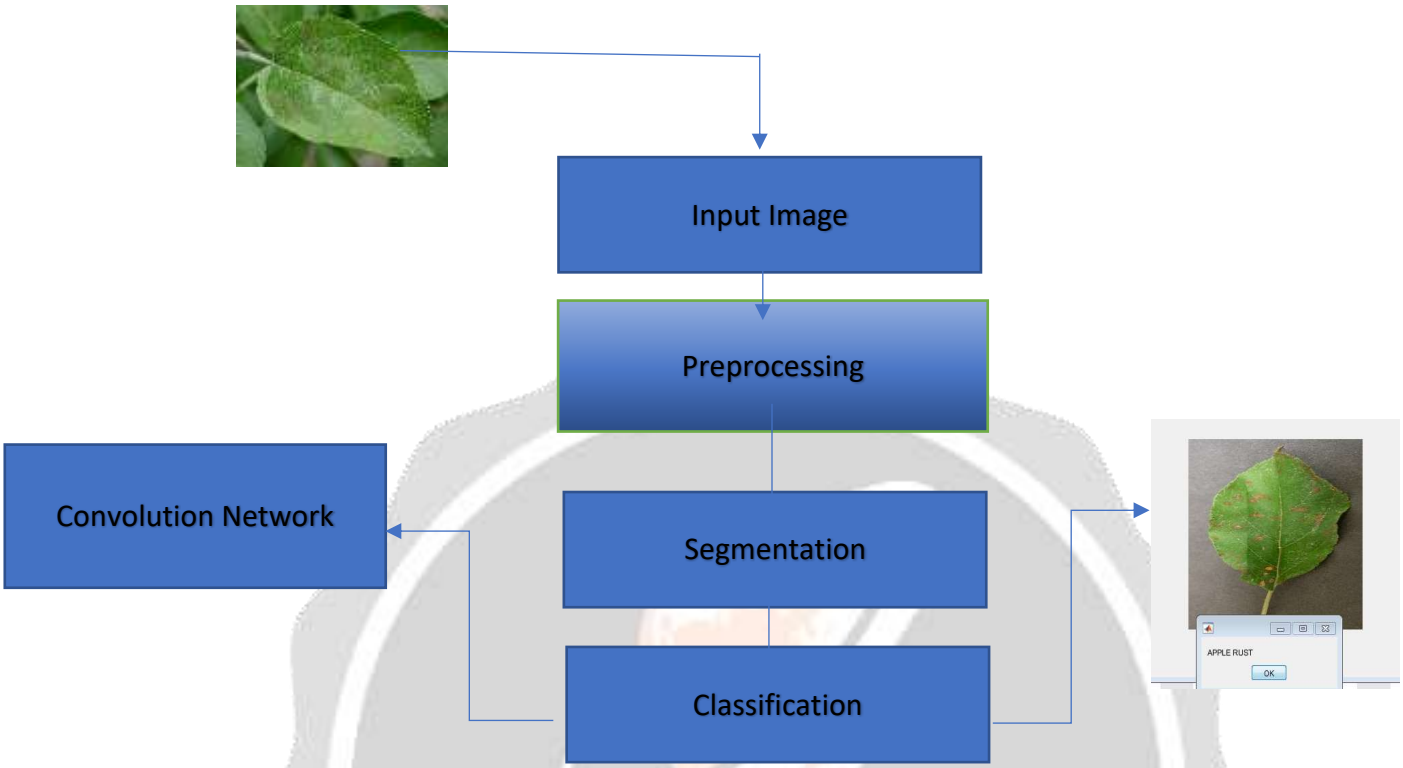
Keywords: *pre - processing, segmentation , convolution neural network,*

1.INTODUCTION

Efficient identification and recognition of fruit leaf diseases is a current challenge in computer vision (CV) due to their important applications in agriculture and agro economy. In agriculture, various types of fruit diseases exist which affect the production and quality of fruits. Most of these diseases are judged by the naked eyes of an expert in this area on the basis of their symptoms. However, it is expensive due to the unavailability of experts and higher cost. In this regard, the computing researchers in collaboration with agriculture experts have suggested many algorithms for automated detection of diseases in plants and fruits. Leaf symptoms are an important source of information to identify the diseases in several different types of fruit plants. Apple is an important fruit plant and widely famous for its nutrient values. However, its production and quality are damaged by the attack of different diseases like black rot, rust, and blight. Therefore, it is essential to develop an automated computerized system for detection and classification of apple leaf symptoms at an early stage.

The early detection of these symptoms is helpful to improve the fruits quality and production. In the field of computer vision, it is an active research area to find out the lesion spot and recently several methods are introduced for fruit diseases detection through image processing and machine learning algorithms. Normally, the apple lesion spots are examined by their color, texture, and shape, therefore, the features like color, texture, and shape are essential for classification of apple diseases. A lot of segmentation, features extraction, and classification techniques are proposed in literature for fruit diseases segmentation and recognition such as combination of features.

2. ARCHITECTURE DIAGRAM



3.MODULES

Preprocessing

Segmentation

Classification

1.PREPROCESSING:

Data sets can require preprocessing techniques to ensure accurate, efficient, or meaningful analysis. This technique consists of resizing the input image and converting the input image into gray scale image and using filters. After that we are using 3D box filtering**,** de-correlation**,** 3D-Gaussian filter**,** and 3D-Median filter for improving the vision of the disease spot of the input image. Data cleaning refers to methods for finding, removing, and replacing bad or missing data. Detecting local extreme and abrupt changes can help to identify significant data trends. Smoothing and detrending are processes for removing noise and linear trends from data, while scaling changes the bounds of the data. Grouping and binning methods are techniques that identify relationships among the data variables.

2.SEGMENTATION:

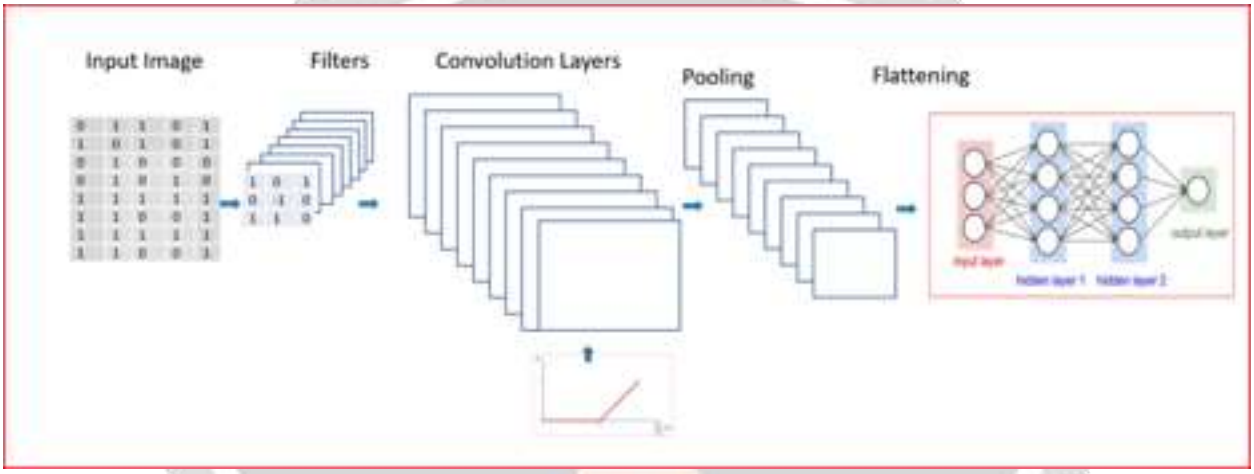
The technique of partitioning the image into segments can be defined as image segmentation. Considering the similar property, segmentation is implemented. This similar property is clustered together; our propounded approach implements the **k**-mean clustering algorithm by introducing a repeated segmentation scheme which explores the centroid of each set in the segment and eventually re-segment the input based on the closest centroid. This technique aids in the extraction of important image characteristics, based on which information can be easily perceived. Then we use different color space conversions like RGB TO HSV color space and different color space conversions for selecting a suitable test image. Then the labels are adjusted with a shape detection method based on

large regional context information to produce meaningful results. From the all above different color spaces we have to choose the best color space that is related to leaf disease classification.

3.CLASSIFICATION:

The technique of partitioning the image into different sections can be defined as image segmentation by the use of CNN. In recent years, with the development of advanced machine learning based detection methods (CNN) have gradually become the mainstream algorithms and achieved the-state-of-the-art results in some aspects. The CNN (CONVOLUTIONAL NEURAL NETWORK based TSD (Traffic Sign Detection) methods are reviewed according to their adopted advanced machine learning labeling methods. Considering the similar property, segmentation is implemented. This technique aids in the extraction of important image characteristics, based on which information can be easily perceived. Then the labels are adjusted with a shape detection method based on large regional context information to produce meaningful results.

4 .STRUCTURE OF CONVOLUTION NEURAL NETWORK



4.1.Image Input Layer

An image InputLayer is where you specify the image size, which, in this case, is 28-by-28-by-1. These numbers correspond to the height, width, and the channel size. The digit data consists of grayscale images, so the channel size (color channel) is 1. For a color image, the channel size is 3, corresponding to the RGB values. You do not need to shuffle the data because train Network, by default, shuffles the data at the beginning of training. train Network can also automatically shuffle the data at the beginning of every epoch during training.

4.2.Convolutional Layer

In the convolutional layer, the first argument is filterSize, which is the height and width of the filters the training function uses while scanning along the images. In this example, the number 3 indicates that the filter size is 3-by-3. You can specify different sizes for the height and width of the filter. The second argument is the number of filters, numFilters, which is the number of neurons that connect to the same region of the input. This parameter determines the number of feature maps. Use the 'Padding' name-value pair to add padding to the input feature map. For a convolutional layer with a default stride of 1, 'same' padding ensures that the spatial output size is the same as the input size. You can also define the stride and learning rates for this layer using name-value pair arguments of convolution2dLayer.

4.3. **Batch Normalization Layer**

Batch normalization layers normalize the activations and gradients propagating through a network, making network training an easier optimization problem. Use batch normalization layers between convolutional layers and

nonlinearities, such as ReLU layers, to speed up network training and reduce the sensitivity to network initialization. Use batchNormalizationLayer to create a batch normalization layer.

4.4. ReLU Layer

The batch normalization layer is followed by a nonlinear activation function. The most common activation function is the rectified linear unit (ReLU). Use reluLayer to create a ReLU layer.

4.5. Max Pooling Layer

Convolutional layers (with activation functions) are sometimes followed by a down-sampling operation that reduces the spatial size of the feature map and removes redundant spatial information. Down-sampling makes it possible to increase the number of filters in deeper convolutional layers without increasing the required amount of computation per layer. One way of down-sampling is using a max pooling, which you create using maxPooling2dLayer. The max pooling layer returns the maximum values of rectangular regions of inputs, specified by the first argument, poolSize. In this example, the size of the rectangular region is [2,2]. The 'Stride' name-value pair argument specifies the step size that the training function takes as it scans along the input.

4.6. Fully Connected Layer

The convolutional and down-sampling layers are followed by one or more fully connected layers. As its name suggests, a fully connected layer is a layer in which the neurons connect to all the neurons in the preceding layer. This layer combines all the features learned by the previous layers across the image to identify the larger patterns. The last fully connected layer combines the features to classify the images. Therefore, the OutputSize parameter in the last fully connected layer is equal to the number of classes in the target data. In this example, the output size is 10, corresponding to the 10 classes. Use fullyConnectedLayer to create a fully connected layer.

4.7. Softmax Layer

The softmax activation function normalizes the output of the fully connected layer. The output of the softmax layer consists of positive numbers that sum to one, which can then be used as classification probabilities by the classification layer. Create a softmax layer using the softmaxLayer function after the last fully connected layer.

4.8. Classification Layer

The final layer is the classification layer. This layer uses the probabilities returned by the softmax activation function for each input to assign the input to one of the mutually exclusive classes and compute the loss. To create a classification layer, use classificationLayer.

Advantages:

- Using of different filters we have to increasing the vision of affected parts of leaf diseases and different color spaces we have to choose the best color channel.
- Using of Convolutional Neural Networks we have to identify the appropriate differences between different types of leaf diseases.

Application:

- It is very useful for agricultural industries in order to check the different leaf diseases that give a better solution for the further actions and also reduces the checking process.
- Hence we have to find the better solution for the different types of leaf diseases.

5.ALGORITHM AND TECHINIQUES

5.1Algorithm Explanation:

CNN stands for Convolutional Neural Network is a specialized neural network for processing data that has an input shape like a 2D matrix like images.CNN's are typically used for imagedetectionandclassification. Images are 2D

matrix of pixels on which we run CNN to either recognize the image or to classify the image. Identify if an image is of a human being, or car or just digits on an address.Like Neural Networks, CNN also draws motivation from brain . We use object recognition model proposed by Hubel and Wiesel. A Convolutional Neural Network (ConvNet/**CNN**) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. CCN can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. Each image the CNN processes results in a vote. ... After doing this for every feature pixel in every convolutional layer and every weight in every fully connected layer, the new weights give an answer that **works** slightly better for that image. This is then repeated with each subsequent image in the set of labeled images. Convolutional Neural Networks (CNN or ConvNet) are complex feed forward neural networks. CNNs are used for **i**mage classification and recognition because of its high accuracy.

Convolition:

- Convolution is a mathematical operation where we have an input I, and an argument, kernel K to produce an output that expresses how the shape of one is modified by another.

5.2.Software Description:

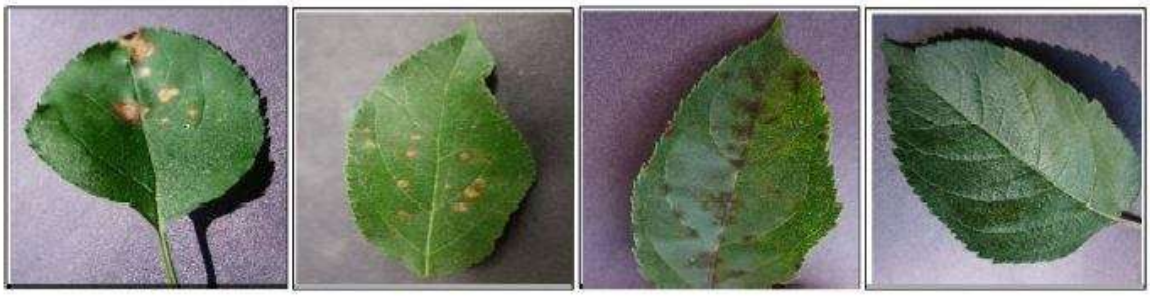
MATLAB is a high-performance language for technical computing integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.

- Data Exploration ,Acquisition ,Analyzing &Visualization
- Engineering drawing and Scientific graphics
- Analyzing of algorithmic designing and development
- Simulating problems prototyping and modeling
- Application development programming using GUI building environment.

Using MATLAB, you can solve technical computing problems faster than with traditional programming languages, such as C, C++, and FORTRAN.

6.RESULT

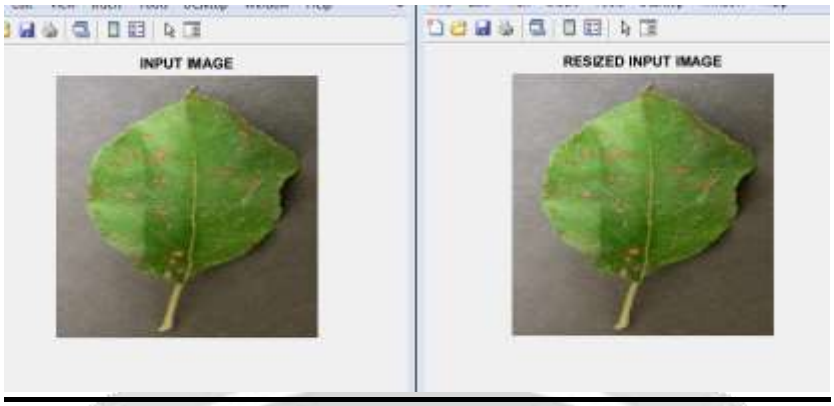
6.1.DATASET IMAGES



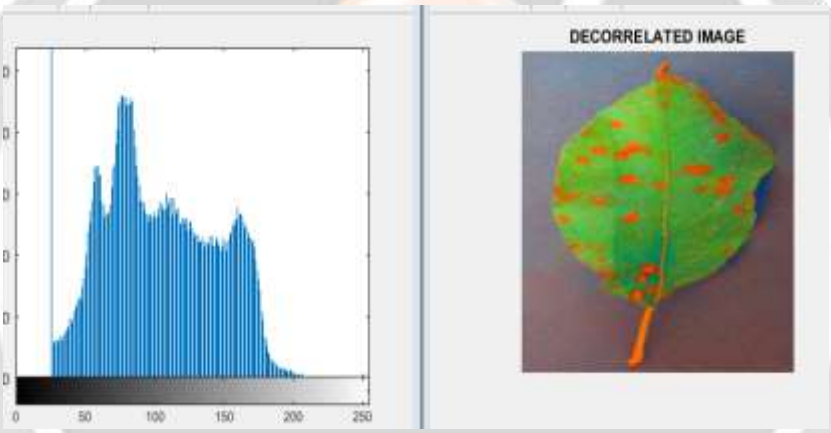
Black rot Apple rust Apple scab Apple healthy

APPLE RUST

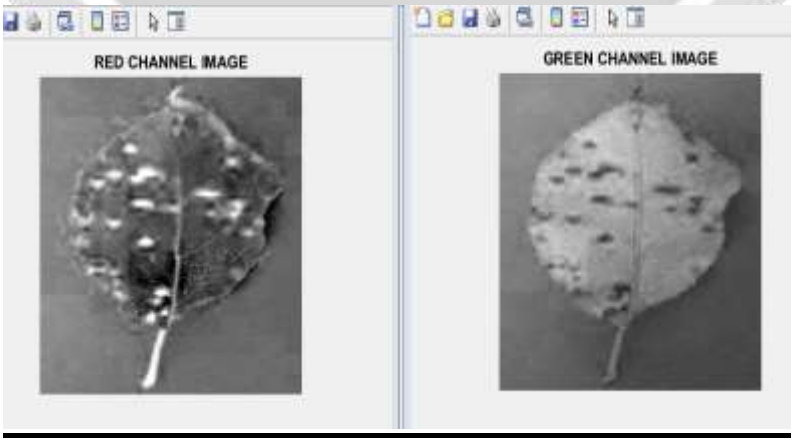
1.INPUT IMAGE& RESIZED IMAGE:



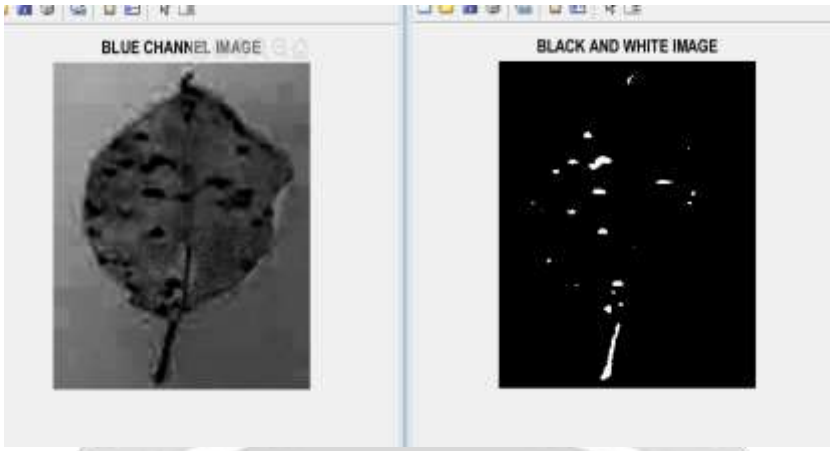
2.HISTOGRAM AND DECORRELATION:



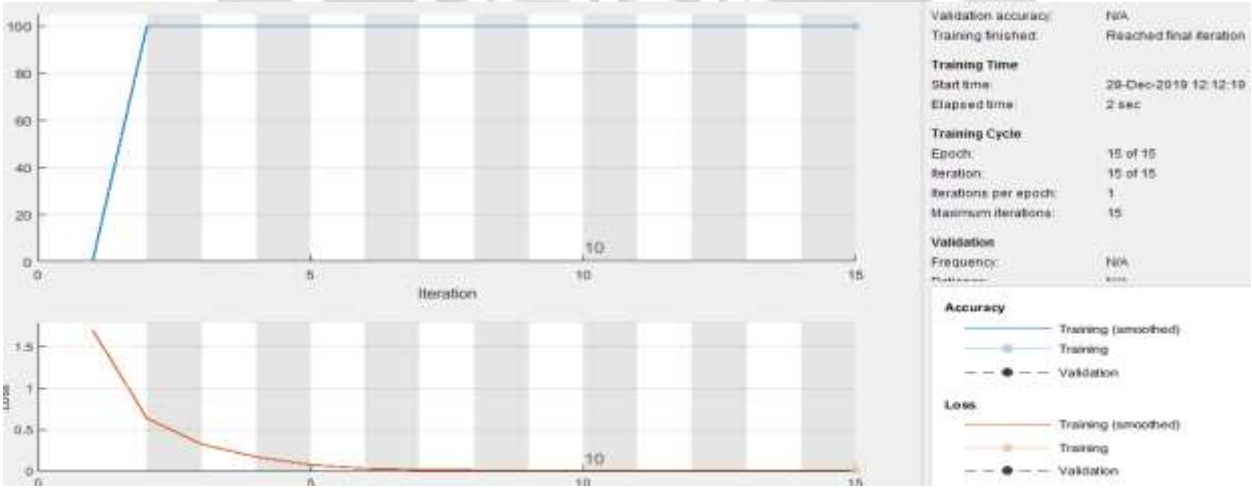
3.RGB COLOR CHANNEL IMAGE:



BLACK AND WHITE CONVERTED RED IMAGE:



SEGMENTED IMAGE



OUTPUT IMAGE:

7.RESULT AND DISCUSSION

The average accuracy of 96.3% for the model is similar to what other researchers have found. The proposed system achieves 98% accuracy compared to existing system which gives 2% increase in performance. This high accuracy can partly be attributed to the similar nature of images in the Plant Village data, images, which are used for both training and validation.

Furthermore, future work will involve spreading the usage of the model by training it for plant disease recognition on wider land areas, combining aerial photos of orchards and vineyards captured by drones and convolution neural networks for object detection. Finally, comparing our results with other methods of detecting diseases from leaves images, it can be said that our method provides better results.

8.CONCLUSION

An optimized automated computer-based method is proposed and validated for recognition of apple diseases. The lesion spot contrast stretching, lesion segmentation, steps are utilized. The contrast of infected spot is enhanced and segmentation is performed by the proposed method. The performance of the proposed method is further optimized by Region Segmentation. Then, the segmented images are classified by the CNN algorithm. The proposed algorithm gives better result with CNN algorithm.

9.FUTURE WORK

In future,with more time and with more comprehensive research the proposed system can be made more accurate and also new leaf detection algorithms can be added so as to give the more accurate result.

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