Detection of diseases in fruits using Image Processing Techniques

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Abstract: ***India is one of the leading producers of fresh fruits in the world but its contribution to the global market in terms of exports is very little. One of the reasons for this huge difference is the significantly high wastage of the produce due to the unavailability of systems for the detection of diseases in fruits efficiently, during the harvest and in the post-harvest period. In this paper, two approaches have been applied for the detection of disease in Apple, namely, Multi Support Vector Machine and Convolutional Neural Networks. A comparative analysis has been carried out on the results obtained using the aforementioned approaches. In the Multi Support Vector Machine (Multi SVM) approach, K-means clustering has been used for segmentation and Gray Level Co-Occurrence Matrix (GLCM) has been used for Feature Extraction whereas in the Convolutional Neural Network approach, transfer learning using ResNet-50 has been used for the detection of diseases in Apples. The results obtained from the two approaches can be summarized as 86.3% average classification accuracy in the Multi SVM approach and 95.79% accuracy in the CNN approach.***

Keywords: CNN; GLCM; K-Means; Multi SVM; ResNet-50; Transfer Learning.

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1. Introduction

India is a large producer of fresh fruits. The diverse climatic conditions across the country promote the growth of many varieties of fruits. India holds the 2nd position in the production of fruits and vegetables globally. It exports 8.23 lakh million tons of fruits worth Rs. 5,638 crores annually which is negligible when compared to the world trade of fruits and vegetables which stands at US$ 208 billion. Despite being the second largest producer of fruits in the world, India has an export ranking of only 23rd. One of the primary factors behind this huge disparity in the production and export of fruits is the wastage of fruits due to various diseases. In India, the wastage of fresh fruits constitutes about 30-35% of the aggregate production. Farmers and fruit vendors face tremendous losses of income due to the absence of suitable techniques for disease detection in the early stages. The utilization of technologies like image processing can reduce such wastage and losses by considerable amounts.

The approach that currently exists for the detection of fruit diseases in our country is based on observations by the naked eye. The recognition of the type of fruit diseases is difficult through manual inspection due to the presence of different types of diseases at the same time. At present, no image processing systems are used for fruit health detection on a large scale.

The proposed approach aims to tackle the following major problem areas in fruit disease detection:

(i) *Reducing the time for examining the harvest and detecting infected fruits*: Since the process is automated, the time for inspection is highly reduced.

(ii) *Increasing the efficiency of detecting the disease type*: Although identification of the diseased fruits can be done manually to some extent, detecting the type of disease is not efficient manually due to the simultaneous presence of different types of diseases.

(iii) *Detection and containment of diseases at an early stage to minimize losses*: Accurately detecting the type of disease is important so that control measures for minimizing the identified disease can be employed in subsequent harvests.

2. Literature Survey

Recently, a lot of research has been conducted for detecting fruit and vegetable diseases using image processing and machine learning. In [1], image processing was used for the detection of healthy passion fruits and two types of passion fruit diseases, namely passion fruit scab and woodiness. K-means clustering was used for segmentation. Images were clustered according to k values, such as 2, 4, 6, and 8. Before the segmentation, images were converted to RGB, L*a*b, HSV, and Grey color models to find out the most suitable fruit diseases, namely passion fruit scab, and woodiness. K-means clustering was used for segmentation. Images were clustered according to k values, such as 2, 4, 6, and 8. Before the segmentation, images were converted to RGB, L*a*b, HSV, and Grey color models to find out the most suitable color model for this approach. Local Binary Pattern was used for feature extraction and Support Vector Machine was used for creating the model. According to this approach, passion fruit diseases can be identified with an average accuracy of 79% and their stage can be identified with an average accuracy of 66%.

In [2], an image processing-based solution is proposed and evaluated in this paper for the detection and classification of fruit diseases. The proposed approach is composed of three steps. In the first step image segmentation is performed using the K-means clustering technique. In the second step features are extracted. In the third step training and classification are performed on a SVM.

In [3], the image processing-based approach is composed of the following steps. In the first step, segmentation techniques are used to enhance the image using K-means segmentation, in the second step segmented images are used further for extracting the features using feature extraction by template matching and finally the images are classified.

In [4], orange disease detection is done using a convolutional Neural Network. While [5] presents a survey on the automated detection of various diseases associated with crops and also gives a proposed methodology for computing the number of diseases in various crops. Segmentation is done using fuzzy C means. Feature extraction is done using GLCM and classification by Support Vector machines. By using the FCM value, the amount of disease in the infected part is estimated.

For Segmentation, [9] uses Threshold Segmentation, [14] uses fuzzy c-means segmentation, and [9] uses edge detector and morphological operations.

For Feature Extraction, [8,16] uses Global Color Histogram and Color Coherence Vector, [9,12,16,14] uses Gray Level Co-Occurrence Matrix (GLCM) algorithm., [10,13] Blob Analysis, [11,12,16] Local Binary Pattern, Color Coherence vector, Color Histogram [13] SURF (Speed up Robust Feature), Blob Analysis, [15] Histogram of chain code, the density of pixel.

In [17], a convolutional Neural network is used for classification for plant disease detection. In [18,19], it shows the comparison between ResNet50, ResNet 100, VGG-16, and GoogLeNet, where Resnet50 shows the highest accuracy of 96.81% and 98.06% respectively. In [14], different residual networks are being compared, that is, Resnet50, ResNet 101, Resnet18, and Resnet152 whose accuracies are 98%, 98%, 84%, and 98% respectively.

3. Dataset

The dataset consists of 315 images in total. For the purpose, of this study we have taken into consideration three of the most commonly occurring diseases in apples, namely, Apple Rot, Apple Blotch, and Apple Scab. The number of images belonging to each of the three categories of the disease is shown in Table 1.

Table 1: Dataset

Disease	Numbers of Images
Blotch	116
Rot	114
Scab	85
Total	315

4. Diseases in Apples

4.1 Apple Scab

It is a fungal disease that forms pale yellow or olive green spots. It attacks both leaves and fruits. Apples are extremely susceptible to infection from scab during damp or rainy periods. Figure 1 shows an apple infected with Apple Scab disease.

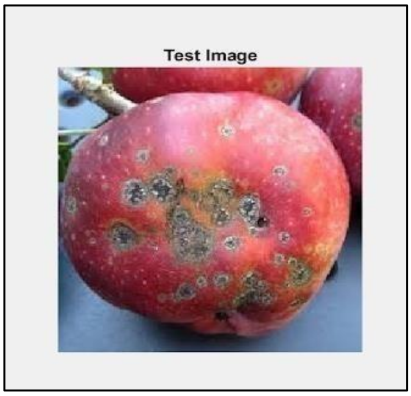

Figure 1: Apple Scab

4.2 Apple Blotch

It is a fungal disease limited to the skin of the apple. The color becomes cloudy or sooty and appears olive green. This disease affects the apple throughout the fruiting season. Figure 2 shows an apple infected with Apple Blotch.

Figure 2: Apple Blotch

4.3 Apple Rot

It is a fungal disease, causing light to dark brown circular spots. As the spots enlarge, the rot progresses towards the core. The fungi survive the winter in dead wood and attack the new season fruits. Figure 3 shows an apple infected with Apple Rot.

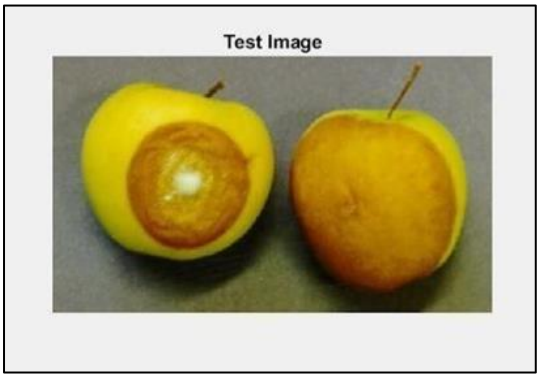

Figure 2: Apple Rot

5. Proposed Methodology

Two approaches have been proposed for the detection of disease in fruits, namely, Multi Support Vector Machine and Convolutional Neural Networks. A comparative analysis is then conducted on the results obtained using the aforementioned approaches.

5.1 Implementation using Multi-Support Vector Machine

The basic steps of this approach are:

a. Loading of the data set
b. Image Pre-Processing
c. Image Segmentation
d. Feature Extraction (GLCM)
e. Training and Testing program using SVM

For this study, we have limited the detection to three commonly occurring apple diseases namely apple scab, apple blotch, and apple rot. equation editor to create the equation. Then select the “Equation” markup style. Press the tab key and write the equation number in parentheses.

5.1.1 Block Diagram

Figure 4 shows the various stages of the proposed approach using a block diagram. As shown in Figure 4, the first three steps in the training and testing phase are identical.

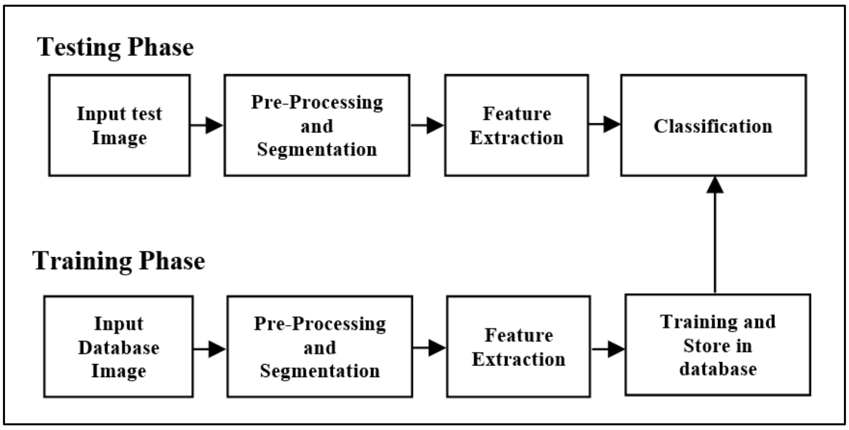

Figure 4: Block Diagram

5.1.2 Image Acquisition

Image acquisition is the first step of digital image processing. In this step, the image is acquired by MATLAB either using a digital camera or by retrieving an image already stored in the device and it is then used for further processing operations.

In this study, images of the apple fruit diseases were retrieved from the dataset created and stored in the device. Figure 5 shows the results for Image Acquisition in the Graphical User Interface

5.1.3 Image Preprocessing

Image pre-processing is done to improve the image data. The input image may contain unwanted distortions that need to be removed or enhancement of certain image features may need to be performed for obtaining better results. Pre-processing encompasses various techniques such as changing image size and shape, filtering noise, and enhancing image, and morphological operations.

Figure 5: Image Acquisition Result

In this study, the following steps in pre-processing were found to produce better results.

i) *Resizing the image*:
The images were resized to the dimensions [250 250] to achieve a faster computation speed for the program.

ii) *Applying the median filter*:
The Median filter is applied to all the images to remove salt and pepper noises.

iii) *Convert RGB color space to l*a*b color space*:
La*b* color space is a color system consisting of 3 axes namely L for lightness and a and b for the color dimensions. The La*b* color space is device-independent. Since all of the color information is in the 2 layers a* and b* as opposed to 3 layers in RGB, computation speed is faster with La*b* images.

Figure 6 shows the enhanced image obtained after Pre-Processing.

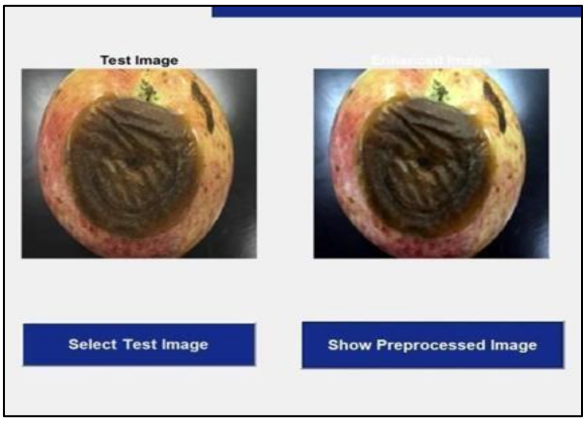

Figure 6: Image Pre-Processing Result

5.1.4 Image Segmentation

Image segmentation is the process of converting a digital image into several segments for easier analysis. In this study, color image segmentation is done by the K-means clustering technique to segment out the defective region for feature extraction. K-means algorithm is an iterative algorithm that tries to partition the dataset into K pre-defined distinct non-overlapping subgroups or clusters where each data point belongs to only one group. It assigns data points to a cluster such that the sum of the squared distance between the data points and the cluster’s centroid is at the minimum. All of the color information is in the 'a*' and 'b*' layers and colors are classified using K-means clustering in the 'a*b*' space.

In this study, the input image is partitioned into 3 clusters for suitable segmentation results. The three clusters obtained are for the background of the image, the non-infected portion of the fruit, and the infected portion of the fruit. Among the three clusters, the cluster produced from the diseased region is selected for training the multi-SVM. Results obtained after segmentation are shown in Figure 7.

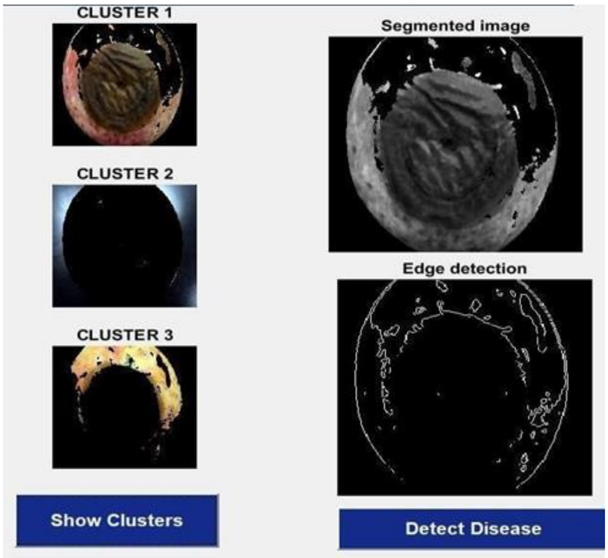

Figure 7: Image Segmentation Result

5.1.5 *Feature Extraction*

In feature extraction, depending on the image data to be processed the most suitable features such as color, texture, morphology, and structure are selected and then extracted to create a feature vector.

In this study, a total of 9 features were used to obtain the best results. The statistical texture features are obtained by using the Gray Level Co-occurrence matrix (GLCM). The GLCM function characterizes the texture of an image by calculating how often pairs of pixels with specific values and in a specified spatial relationship occur in an image, creating a matrix, and then extracting statistical measures from this matrix. The features extracted using GLCM in this study are contrast, correlation, homogeneity, energy, and entropy.

In addition to the above-mentioned texture features, other statistical features that are extracted are root mean square (RMS), standard deviation, skewness, and kurtosis.

5.1.6 *Training and Classification*

In this study, a data set of 315 images was created for the 3 types of apple fruit diseases, namely Apple Blotch, Apple Rot, and Apple Scab, and used for training.

The acquired images are labelled according to the disease and then passed through pre-processing, segmentation, feature extraction, and stored in the database. The model was then trained using the dataset as input and stored. The trained model was then used for classification. For classification, a Multi Support vector machine (SVM) is used.

SVM is a binary classifier, which means the class labels can only take two values ±1. In this study, since there were 3 classes, multi-SVM was used. For multiclass classification, the multiclass problem is broken down into multiple binary classification cases.

5.2 Implantation Using Convolutional Neural Networks

The basic steps involved in this method are:

a. Loading and splitting the dataset
b. Pre-processing dataset images
c. Loading and modifying pre-trained model
d. Train modified model
e. Use the trained model for the classification of fruit diseases

5.2.1 *Block Diagram of CNN Approach*

Figure 8 shows the block diagram for the implementation using Convolutional Neural Networks (CNN).

5.2.2 *Loading and Splitting of Dataset*

The dataset is loaded into the program and then split into two parts- the training set and the validation set. In this study, 70% of the dataset images will be used for training and the rest 30% will be used as a validation set for calculating performance parameters.

5.2.3 *Preprocessing*

The pre-trained convolutional network ResNet-50 takes input images of only a specific dimension and a specific number of color channels, and hence the images in the dataset need to be preprocessed accordingly before using them for training the model. The Resnet-50 takes inputs of the dimensions 224x224x3 where 3 represents the number of color channels i.e., RGB. Hence, the images in the dataset are resized to the dimensions 224 X 224, and the grayscale images are converted to RGB color space.

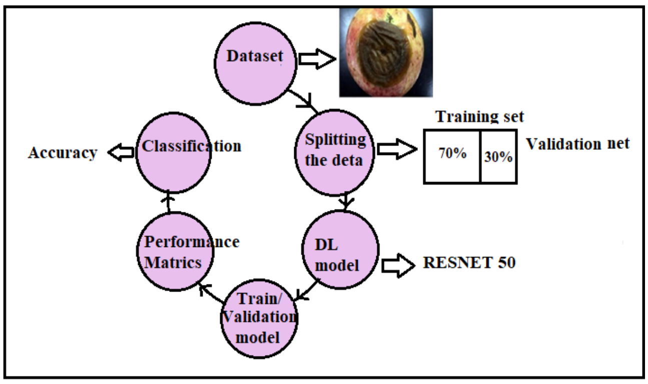

Figure 8: Block Diagram of CNN Implementation [21]

5.2.4 Loading and modifying pre-trained network

The ResNet-50 pre-trained network is then loaded into the program and modified using functions from the Deep Learning Toolbox of MATLAB. The fully connected layer and classification layer of the pre-trained model are replaced with new layers adapted to the dataset. The fully connected layer and classification layer of the pre-trained network are configured for 1000 classes.

In this study, the number of classes is 3 and hence the number of classes needs to be modified. These two layers contain information on how to combine the features that the network extracts into class probabilities, a loss value, and predicted labels.

5.2.5 Training

The modified network is then trained to classify the dataset. After training, the performance of the model is analyzed with the help of the performance parameters obtained by plotting the confusion matrix - validation accuracy, precision, and recall.

5.2.6 Classification

The trained model is then used for classifying the diseases in the validation and input images based on the features extracted by the convolutional layers. The results of the classification of Scab, Rot, and Blotch are shown in Figures 9- 11 respectively.

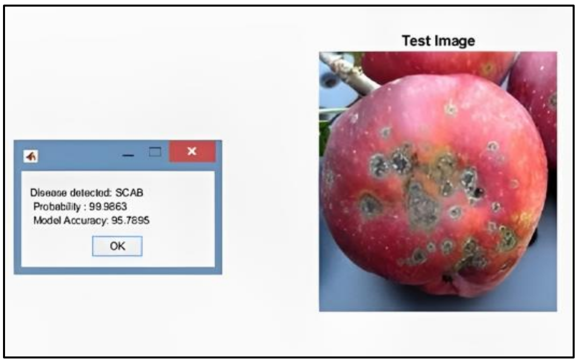

Figure 9: Scab Detection using CNN

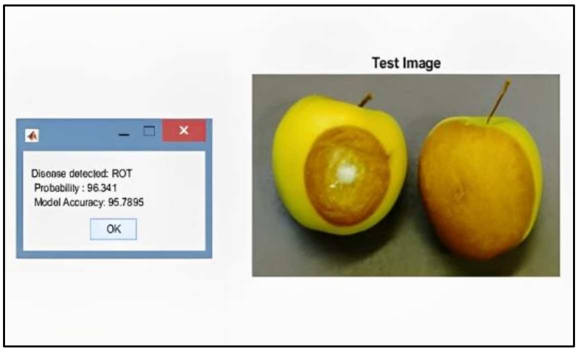

Figure 10: Rot Detection using CNN

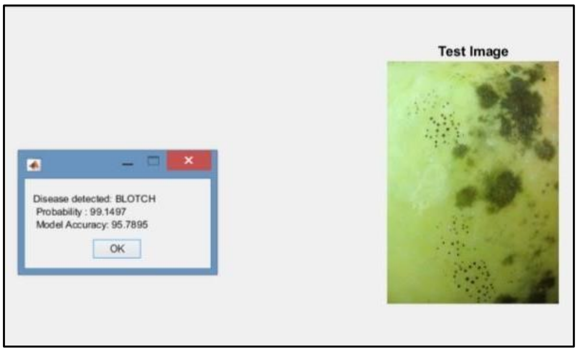

Figure 11: Blotch Detection using CNN

5.3 Graphical User Interface

A graphical user interface as shown in Fig. 12 was also implemented using MATLAB to improve the usability of the program. Graphical user interfaces provide point-and-click control of the software, eliminating the need for commands to run the application. It gives users an easy-to-use interface and visual feedback.

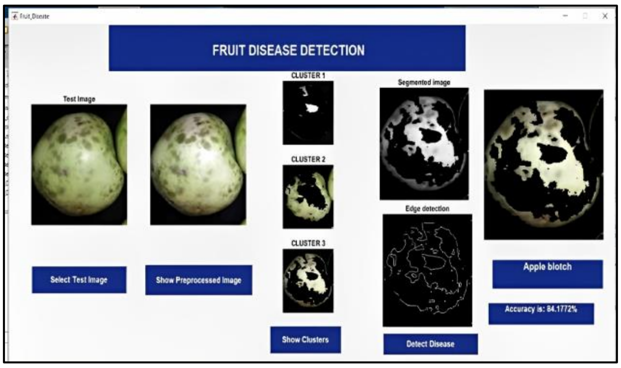

Figure 12: Fruit Disease Detection Graphical User Interface

6. Results

The validation accuracy results obtained for the three categories and the overall accuracy obtained using the two approaches have been analyzed and compared. The possible causes for the deviation from the expected results have also been discussed. It gives the overall accuracy of the model, meaning the fraction of the total samples that were correctly classified by the classifier. As mentioned in [9], the validation accuracy is given by the following equation:

$$\text{Validation Accuracy} = \frac{\text{No. of Correctly Classified Images}}{\text{Total No. of Images}} \times 100\%$$

6.1 Multi-Support Vector Machine Approach

The average accuracies of apple rot, apple scab, and apple blotch on SVM come out to be 88.57%, 85.2%, and 84.6% respectively. The total average accuracy for detecting the diseases by SVM comes out to be 86.3%. Table 2 shows the validation accuracy per class for this approach.

Table 2: Validation Accuracy of Multi-SVM

Disease	No. of Images in Validation Set Images	No. of Correctly Classified Images	Validation Accuracy
Blotch	35	31	88.57%
Scab	34	29	85.2%
Rot	26	22	84.6%
Total	95	82	86.3%

6.2 Convolutional Neural Network Approach

The validation accuracy obtained for the CNN approach is 95.79% as shown in Figure 13.

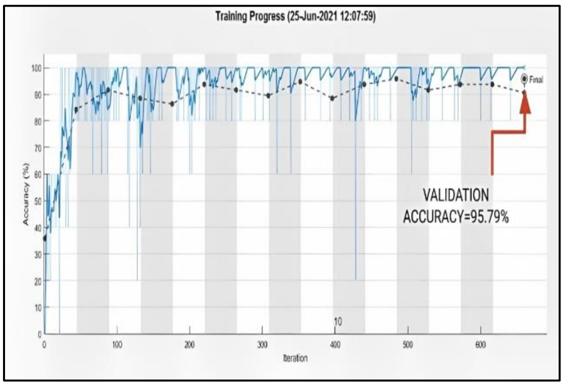

Figure 13: Validation Accuracy of CNN Model

6.3 Confusion Matrix

The Confusion Matrix obtained for CNN gives a measure of the validation accuracy per class as well as the overall accuracy of the trained model. Fig. 14 shows the confusion matrix obtained for the study. It is a 3 × 3 matrix where the rows represent the output or predicted class and the columns represent the actual class.

In Figure 14, the boxes highlighted in green represent the number of correctly classified images whereas those highlighted in Red represent the number of wrongly classified images of each class. The first three columns of the last row represent the validation accuracy per class and the rightmost column of the last row represents the overall model accuracy. Table 3 demonstrates the validation accuracies obtained from the confusion matrix.

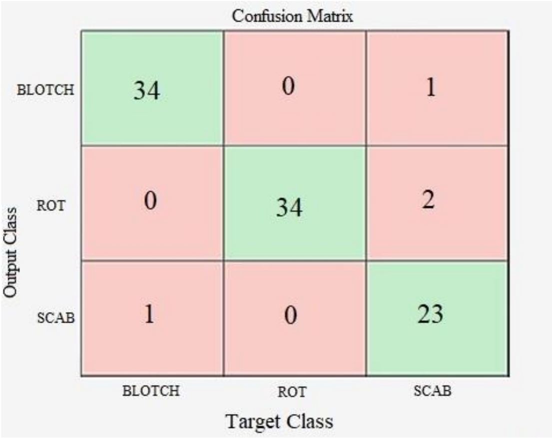

Figure 14: Confusion Matrix for CNN

Table 3: Validation Accuracy of CNN

Actual Class	No. of Images Predicted As			Validation Accuracy
	Blotch	Scab	Rot	
Blotch	34	1	0	97.1%
Rot	0	0	34	100%
Scab	1	23	2	88.5%

6.4 Result Analysis

Figure 15 gives a comparison of the overall accuracy and accuracy per class using the two approaches, namely, Multi SVM and CNN. Table 4 demonstrates these results in tabular form.

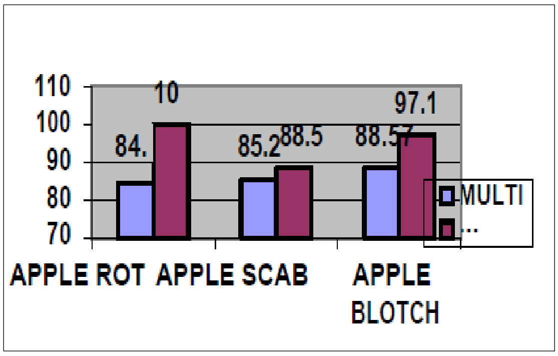

Figure 15: Accuracy Comparison of CNN and Multi SVM

The Y-axis represents the accuracy value and the X-axis represents the class and overall model. The average accuracy of the respective diseases obtained from the program was –

For Multi-SVM:

a. 85.2% for Scab
b. 84.6% for Rot
c. 88.57% for Blotch

For CNN:

a. 88.5% for Scab
b. 100% for Rot
c. 97.1% for Blotch

Table 4: Accuracy Comparison of Multi-SVM and CNN

Disease	Multi-SVM Accuracy (%)	CNN Accuracy (%)
Rot	84.6	100
Scab	85.2	88.5
Blotch	88.57	97.1
Total	**86.3**	**95.79**

7. Observations

It was observed that the diseases Apple Blotch and Apple Rot showed better accuracy than Apple Scab in CNN whereas in SVM, Apple Blotch and Apple Scab show better accuracy than Apple Rot. The possible explanation for this is that neural networks give better results when the dataset is large and since the dataset for Blotch and Scab has around 115 images as compared to Apple Scab which has only 85 images, it gives better accuracy for Blotch and Rot. SVM was seen to depend more on the selection of appropriate features for extraction and the manual selection of clusters than the dataset. It was also observed that CNN showed better accuracy than Multi-SVM.

8. Conclusion

The experimental outcomes show that the proposed solution can significantly improve the time for inspection of diseases by supporting the automatic identification and classification of apple fruit diseases. Based on the experiments performed, the outcome for the classification of apple fruit disease was observed to have achieved 86.3% average classification accuracy in the Multi-SVM approach and 95.79% accuracy in the CNN approach.

In this study, two approaches were proposed for the detection of disease in fruits, namely, Multi Support Vector Machine and Convolutional Neural Networks. A comparative analysis is then conducted on the results obtained using the aforementioned approaches.

In the Multi Support Vector Machine (Multi SVM) approach, K-means clustering has been used for segmentation; Gray Level Co-Occurrence Matrix (GLCM) has been used for Feature Extraction. The images of the fruit under test are first acquired. The image is then pre-processed; the pre-processing step involves resizing the images, enhancing the contrast of the image, removal of salt and pepper noises from the image using a median filter, and segmentation of the image into three clusters. This is followed by feature extraction using the Grey Level Co-Occurrence Matrix (GLCM). The features extracted are then provided as input to the Multi SVM for training and classification. Through the aforementioned approach, the classification of the diseased fruit images into the three types of apple diseases namely blotch, scab, and rot has been performed.

In the Convolutional Neural Network approach, transfer learning has been used for the detection of diseases in fruits. The pre-trained model used in the study for transfer learning is ResNet-50. The images are first acquired and then split into two parts - the test set and the validation set. The dataset images are then pre-processed. Pre-processing includes resizing the images to the input dimensions accepted by the ResNet-50 model i.e. 224x224 and conversion of all grayscale images to RGB color space. The parameters of the fully connected layer and classification layer of the pre-trained model are then modified. The dataset images are then provided as input to the modified ResNet-50 model and then the model is trained. The trained model is then used for classification.

The experimental outcomes show that CNN is a better approach for the problem than Multi-SVM.

9. Future Scope

In this study, we have limited the detection to only three apple diseases namely apple blotch, apple rot, and apple scab, the database can be increased further to include other types of diseases and fruits. As some inconvenience in terms of data storage may arise in the acquisition of images by clicking pictures in the field/storage for detection, real-time scanning can be implemented for better efficiency. The accuracy can be increased with further modification in the program and by increasing the database.

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