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Apple Fruit Disease Identification Using a Novel Gray-Scale Segmentation Algorithm and Sorting Using a Naive Bayesian Classifier

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Abstract

Objectives: Apple fruit classification is crucial in the post-harvest process to ensure quality control. This paper proposes a novel gray-scale segmentation algorithm for accurately identifying diseased regions in apple images. **Methods:** The algorithm converts color images to grayscale, normalizes the histogram, and applies a threshold based on inter-class frequency summation to segment defective areas. Extracted texture features from segmented images are fed into a Naive Bayesian classifier to distinguish between sound and diseased apples. **Findings:** Experiments show that the algorithm outperforms existing methods like Otsu's and Kapur's regarding visual accuracy and execution speed. The Naive Bayesian classifier achieves a remarkable accuracy of 95%, demonstrating the efficacy of the proposed approach. **Novelty:** This work presents a significant step towards enhancing the accuracy and speed of apple fruit sorting machines.

Keywords: Thresholding Algorithm; Apple Fruit; Segmentation; Classification; Naive Bayesian classifier

1 Introduction

Automating the task of sorting apple fruits with a higher accuracy rate and greater throughput is an important post-harvest process in the apple fruit industry. With a combination of efficient image processing algorithms and hardware components, each apple fruit is scrutinized for diseases/defects before it exits the inspection line in an apple fruit sorter. Machine learning and image processing algorithms are used to enhance the accuracy of the sorting machines to ensure their functional reliability. A subset of computer vision is Image processing. An image is a collection of different pixel values. These pixel values are grouped according to their similar attributes using image segmentation algorithms. The pixel values will be different for the objects and the image's background if there is a sharp contrast between them. A threshold value T can be set and pixel values above and below that threshold value can be used for segmenting the foreground object from its background. A gray-scale image can be converted to a binary image. This type of segmentation is called threshold segmentation. Thus, in this paper, a novel thresholding algorithm has been proposed for classifying sound apple fruits from diseased fruits.

Some of the research works that had been done under the topics of image segmentation and classifications are discussed below; Abd Elaziz et al. [1], have proposed a multi-objective and multi-optimization algorithm for gray-image segmentation and tested it against three other similar optimization methods. It was found that the proposed method showed better segmentation accuracy than the compared methods. Baneh et al. [2] in their work have proposed a machine vision method to identify disease in apple fruits. Results showed the effectiveness of the value of k and Euclidean distances in recognition accuracy. It is found that the 5-nearest neighbor classifier and the Euclidean distance using 80 training samples produced the best accuracy rates, at 100% for stem and 97.5% for calyx. A review of the identification, classification, and grading of fruits using machine learning was done and presented by Behera et al. [3]. Cai et al. [4], in their novel study have proposed a neural network for the classification of skin diseases. They have proposed a novel multimodal Transformer, with encoders for both images and metadata and another decoder to fuse the multimodal information. The proposed model's effectiveness was tested using a private skin disease dataset and the ISIC 2018 dataset. The proposed method showed better performance in skin disease diagnosis. A color image segmentation using an automatic seed region growing algorithm using the Watershed method has been proposed by Garcia Lamont et al. [5]. Gongal et al. [6], used a CCD camera and a time-of-flight light-based 3D camera for estimating the size of an apple in tree canopies. To measure the fruit size, the major axis value was estimated based on (i) the 3D coordinates of pixel values on the apple surfaces, and (ii) the size of the individual pixel values within apple surfaces in 2D space. The distance between pairs of pixels within apple regions was calculated using 3D coordinates. 69.1% was the accuracy rate for estimating the major axis using 3D coordinates. The accuracy of size estimation was 84.8% when the pixel-based method was used. Ireri et al. [7], proposed a tomato grading machine vision system. The proposed system detected calyx and stalk scars at an average accuracy of 95.15% for both defected and healthy tomatoes by histogram thresholding value based on the mean green-red pixel values of the regions of interest. Defective regions were classified by RBF-SVM classifier using the L*a*B* color space pixel values. The model achieved an overall accuracy rate of 98.9% upon validation. An approach for spot segmentation of microarray using a global segmentation method was proposed by Karthik and Manjunath [8] and it was found that the performance of the proposed method was more accurate than Fuzzy C-means and Morphological segmentation. A supervised learning task to classify images and insight into an unsupervised classification was proposed by Lele [9]. Liu et al. [10] have proposed a filter that attempts to restore an ideal value using approximately constant intensities with the help of the image clustering process. They have adopted a mixed probability model on a pre-processed image to generate an estimator of the ideal clustered components. Their results showed considerable improvement in peak signal-to-noise ratio (PSNR) values. The visual results were also found to be good. Sha et al. [11], have proposed a robust 2D Otsu's thresholding method for segmenting color images with a region post-processing method for dealing with the noise in the segmented images (Gaussian noise and salt& pepper noise). Their result showed a good accuracy rate. An innovative training criterion based on the analysis of error backpropagation was proposed by Xin and Wang [12], and their experimental results proved that M 3CE can enhance the performance of cross-entropy. Yang et al. [13], have introduced two steps as a classification process. In the first step, lactating sows were segmented using top-view images using a fully connected convolution network. In the second step, refinement of the image was done using the fully connected neural network and Otsu threshold algorithm that gave a better segmentation result and 96.6% accuracy rate. Yu et al. [14], acquired fish images and fed them as input to a Mask R-CNN for training and it was found that the experimental results showed a good segmentation result in segmenting fish bodies even for pure and complex backgrounded images. Zou et al. [15] have proposed an apple sorting method. In their method, Fuzzy PID and traditional PID algorithms are used to simulate and realize the operation of a brushless DC motor and compare the advantages of brushless DC motor control based on fuzzy PID to ensure the safe and stable operation of the system. Using the machine learning algorithms model for color detection, the Support Vector Machine algorithm model finally achieved the classification of the three types of apple samples with a recognition rate of 96.7%.

The main objectives for developing this methodology are-

1. to enhance the accuracy of sorting machines in classifying a sound apple from a diseased/defective one and
2. To enhance the speed in classifying the apple fruits post-harvest which in turn will increase production.

So, to achieve the above-mentioned objectives and to overcome some of the drawbacks that exist in the current research works in this field, an image processing method has been suggested in this paper-

1. to extract/segment the region of interest for the feature set to get extracted from an apple fruit image using a novel gray-scale thresholding algorithm
2. to extract texture features using the wavelet transformation coefficients and,
3. to classify apple images the Naive-Bayesian classification model using the extracted feature set. The proposed method can be coded and embedded in the microchip of an apple fruit sorting machine for the classification process.

2 Methodology

2.1 Image Acquisition and Dataset

Using a digital camera, and two LED lights, an image-capturing system was designed, and Apple fruit images were acquired. 15 to 20 images of each apple fruit were acquired. Also, some images were open- sourced from the internet. All acquired images were sent to a computer system. The images of dimensions 235×214, 275×183, 224×224, and 226×223 pixels were used. The sample apple images used were acquired using different apple varieties with diseases like scab, rot, cork spot, worm, powdery mildew, etc., and samples without the disease. 660 apple samples were used for this experiment. Table 1 gives the details of the apple samples used.

Table 1. An Image dataset

Apple type	Diseased/Sound	No. of Samples [660]
Golden Delicious	Diseased	157
	sound	68
Red Delicious	Diseased	110
	sound	33
Granny smith	Diseased	136
	sound	73
Fuji	Diseased	18
	sound	33

2.2 Proposed Method

In the first phase, the acquired apple images were segmented to extract the region of interest (defective/diseased area) using the proposed thresholding algorithm. During the second phase, texture features were extracted using wavelet transformation at levels one and two decompositions using the Haar filter and were given as input to the Naive Bayesian Classifier for classification. The same has been depicted as a flowchart in Figure 1.

One among the important methods for image segmentation is the thresholding method. This method generates uniform regions using threshold criteria "T". Such that, $T = T(x,y), A(x,y), f(x,y)$ where $f(x,y)$ represents the graylevel pixel value at (x,y) and $A(x,y)$ represents the property of the acquired image. As the proposed algorithm depends on the grayscale pixel values, it is a global thresholding algorithm.

Proposed thresholding Algorithm: Let "$Imageset$" be the apple dataset such that $Imageset = [Ima_1, Ima_2, Ima_3 .... Ima_N]$, where '$N$' is the total number of color images in the apple image dataset. For each Ima_i, where $i = i..N$, algorithm 1 is applied to obtain the threshold value. Algorithm 1 specifies the steps involved in calculating the threshold value. As the first step, the acquired apple color image Ima_i was resized to 255×255 pixel-size and converted to a grayscale image Gima. Then, the gray-level histogram is normalized using the square root function for each image histogram [imhist = imagehistogram(Gima)] intensity level. The square root of the individual frequency $[Nhist_i = \sqrt{imhist_i},\ i\ = 1..N]$ was calculated using the transformation technique to generate an effective threshold value 't' $[t = 1, 2, ...255]$ that will segment the region of interest accurately. An Exhaustive search is then done to find the threshold value 't' that brings a difference in the inter-class cumulative sum of the histogram intensity levels between the two threshold classes namely *Class1* and *Class2*. Where it ranges between *Class1 = 1, 2, ...t* and *Class2 = t + 1...255*. The sum of intensity levels is computed from 255 bins of histograms. The inter-class summation is calculated as follows:

$$W0 = \sum_{i=1}^{t} Nhist_i \tag{1}$$

$$W1 = \sum_{i=t+1}^{t255} Nhist_i \tag{2}$$

The first threshold point where W0 becomes greater than *W1* between the threshold classes *Class1* and *Class2* is the optimized threshold value. Using this 't' value segmentation is done to generate a binary image *Bima*, where *i = 1..N* using the rule

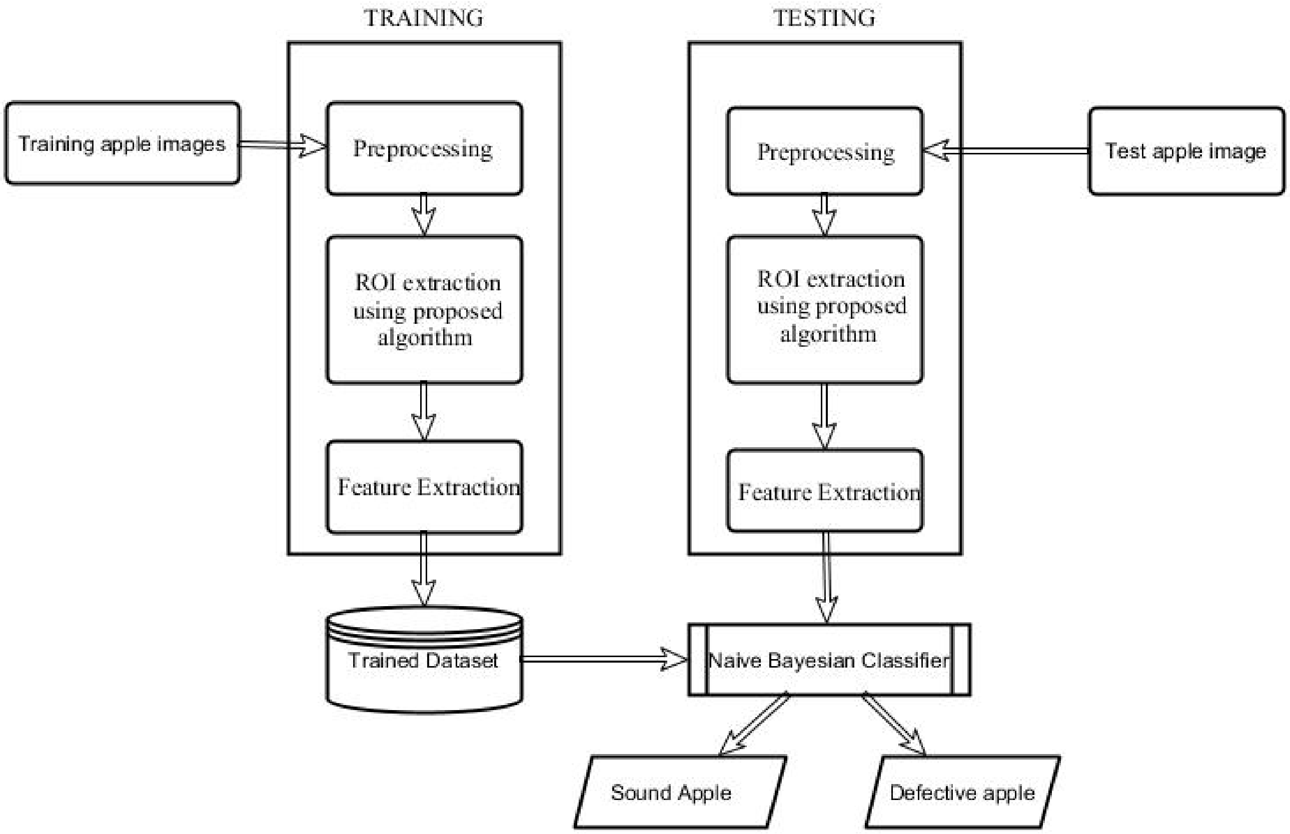

Fig 1. The proposed apple fruit classification method

mentioned below for further processing:

$$\text{Bima} = \left\{ \begin{array}{l} 0,\ if\ Ima(m,n) > t \\ 1,\ if\ Ima(m,n) < t \end{array} \right\}$$

Algorithm 1: Proposed thresholding Algorithm:INPUT : Color RGB image
OUTPUT : Segmented binary image

Step 1 : Load the apple image
Step 2 : Resize the loaded images into 255 x 255
Step 3 : Convert the image into a Gray-scale image
Step 4 : Calculate the gray image histogram intensity level
Step 5 : Normalize each histogram intensity level by finding the square root
Step 6 : For each threshold value ranging from 1 to 255, repeat Steps 7 and 8
Step 7 : Calculate the sum of intensity levels for the classes separated by the threshold values W0 and W1
Step 8 : If (W0 > W1) then T is the corresponding optimal threshold value. Exit
Step 9 : Segment and generate a binary image using the 'T' value

$$\text{Bima} = \left\{ \begin{array}{l} 0,\ if\ Ima(m,n) > t \\ 1,\ if\ Ima(m,n) < t \end{array} \right\}$$

Feature Extraction: In the second phase, features like Energy, Homogeneity, Contrast, and Correlation [**Equations (3)-(6)**] were extracted from the segmented binary image. Texture features were calculated using Discrete Wavelet Transformation coefficients for diagonal, vertical, and horizontal values using the Haar filter. Gray-Level Co-Occurrence Matrix values were calculated as;

$$\text{Energy} = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m} Bima(i,j)^2} \tag{3}$$

$$\text{Homogeneity} = \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{Bima(i,j)}{1+(i-j)^2} \tag{4}$$

$$\text{Contrast} = \sum_{i=1}^{n}\sum_{j=1}^{m} \left[(i-j)^2\,(Bima(i,j))\right] \tag{5}$$

$$\text{Correlation} = \sum_{i,j=1}^{n} Bima(i,j)\frac{(i-\mu)(j-\mu)}{\sigma 2} \tag{6}$$

Classification using Naive Bayesian Classifier: The Naive Bayesian Classifier is a supervised classifier. The following are the steps involved in the classification process:

1. Train the Naive Bayesian Classifier using segmented apple images features with their labels [sound or Defective]
2. Compute P(i) using histogram-based estimation
3. Compute P(i/x)
4. Maximum P(i/x) is found, and the unknown instance is assigned to that class.

3 Results and Discussions

Results obtained after executing the proposed thresholding algorithm and classification process using MatLab software has been discussed in this section.

3.1 Performance comparison of the proposed thresholding algorithm

Figure 2 shows the result of the proposed algorithm of the original image and the segmented image for four different apple sample images. Visual accuracy can be observed to be high in segmenting the defective/diseased part. This helped in classifying the Apple images as sound and defective ones accurately.

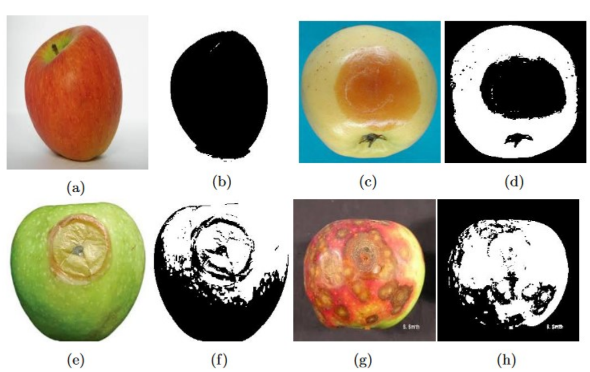

Fig 2. a,c,e,g - Input images ; b,d,f,h - Proposed algorithm segmented images

The proposed threshold algorithm was compared with similar gray-scale thresholding algorithms like Otsu's and Kapur's algorithms. The performance of the proposed was compared for visual accuracy and execution speed. Figure 3 shows the segmented images.

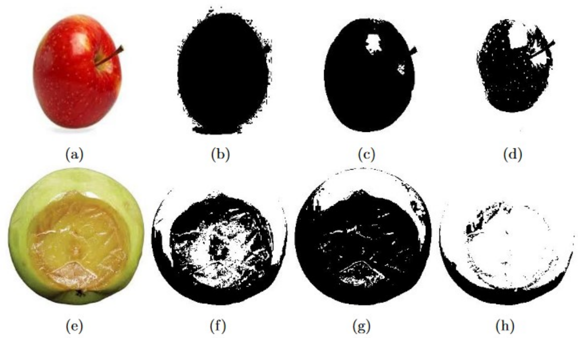

Fig 3. a,e- Images from the dataset; b,f - Proposed algorithm segmented images ; c,g- Otsu's segmented images; d,h-Kapur's segmented images

It can be observed that the visual accuracy in segmenting the region of interest that is the defective/diseased area from an apple image, using the proposed algorithm is high when compared to Otsu's, and Kapur's segmented images. Also, the execution speed of the proposed thresholding algorithm was more when compared to Otsu's and Kapur's algorithms. The execution speed was estimated under the system environment with a configuration of Intel(R) Core(TM) 7200U CPU - 2.50 GHz to 2.70 GHz. Table 2 shows the execution time of all three algorithms in seconds. The same has been statistically proven using the Wilcoxon signed-rank test. To test the significance between the proposed thresholding algorithm and Otsu's algorithm as well as the proposed algorithm and Kapur's algorithm the following hypothesis was framed.

H0: There is no significant difference between the execution times [Proposed Vs Otsu and proposed Vs Kapur]

H1: There is a significant difference between the execution times [proposed Vs Otsu and proposed Vs Kapur]

Figure 4 shows the Wilcoxon signed-rank test result at a 5% level of significance obtained using SPSS software. Both Figure 4a and Figure 4b hypothesis summary shows that the median values between the proposed and Otsu as well as between the proposed and Kapur are equal to zero at a 0.05% significance level. This indicates that it rejects the null hypothesis H0 for both analyses. Thus, it was proved that there was a significant difference between the execution times of proposed and Otsu as well as proposed and Kapur.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The median of differences between Proposed and Kapur equals 0.	Related-Samples Sign Test	.007[1]	Reject the null hypothesis.
2	The median of differences between Proposed and Kapur equals 0.	Related-Samples Wilcoxon Signed Rank Test	.012	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

[1]Exact significance is displayed for this test.

(a)

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The median of differences between Proposed and Otsu equals 0.	Related-Samples Sign Test	.000[1]	Reject the null hypothesis.
2	The median of differences between Proposed and Otsu equals 0.	Related-Samples Wilcoxon Signed Rank Test	.001	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

[1]Exact significance is displayed for this test.

(b)

Fig 4. Wilcoxon signed-rank for the execution time in seconds: a - Proposed Vs Kapur b - Proposed Vs Otsu

3.2 Performance comparison of the Naive Bayesian Classification Model

To test the accuracy of classification using the Naive Bayesian classifier, it was compared with similar supervised classifiers like SVM (Support Vector Machine), KNN (K-Nearest Neighbor), and Logistic regression. The confusion matrix metrics like TP

Table 2. Execution speed in seconds - Proposed, Otsu, Kapur

Comparison of Execution Time			
Samples	Thresholding Methods		
	Proposed	Otsu	Kapur
1	0.0075248	0.02233	0.019777
2	0.0037846	0.018402	0.018247
3	0.004354	0.017829	0.018661
4	0.0051279	0.029959	0.020851
5	0.0039878	0.017707	0.017402
6	0.0046344	0.017572	0.017431
7	0.0110056	0.064207	0.044647
8	0.0039899	0.017383	0.019301
9	0.0051027	0.029247	0.023086
10	0.0158981	0.055322	0.038186
11	0.0045238	0.021901	0.021118
12	0.0043036	0.022927	0.022412
13	0.0092053	0.026104	0.036282
14	0.0038278	0.016841	0.018426
15	0.0041287	0.018312	0.017746

(Defective apple images classified as defective correctly), TN (Sound apple images classified as sound apples), FP (defective apple images classified as sound apple images), FN (Sound apple images classified as defective apple images) values were calculated. Recall/Sensitivity, Precision/Specificity, and F-score, were also calculated. The accuracy rate was also calculated for proposed algorithm segmented images, Otsu's algorithm segmented images and Kapur's algorithm segmented images for comparison with the Naive Bayesian and other classification techniques. The result obtained has been tabulated in Table 3. If it is observed, the accuracy in classifying the 120 test apple images using the proposed algorithm-segmented images using the Naive Bayesian was 95%, Otsu algorithm-segmented images was 73.33%, and Kapur segmented images was 88.33%.

Table 3. Comparison of classification accuracy using the Proposed thresholding method segmented images with respect to existing Otsu and Kapur segmented images

Thresholding method	Classification Model	TP	FP	FN	TN	Recall	Precision	F-score	Accuracy
Proposed	Naïve Bayesian	72	2	4	40	0.95	0.95	0.951	95.00
	SVM	70	7	8	35	0.90	0.83	0.864	87.50
	KNN	54	24	6	36	0.90	0.60	0.72	75.00
	Logistic Regression	76	12	22	10	0.78	0.45	0.573	71.67
Otsu	Naive Bayesian	54	4	28	34	0.66	0.89	0.759	73.33
	SVM	72	6	36	6	0.67	0.50	0.571	65.00
	KNN	72	12	30	6	0.71	0.33	0.453	65.00
	Logistic Regression	36	10	64	10	0.36	0.50	0.419	38.33
Kapur	Naive Bayesian	58	6	8	48	0.88	0.89	0.884	88.33
	SVM	60	2	44	14	0.58	0.88	0.695	61.67
	KNN	60	6	10	44	0.86	0.88	0.868	86.67
	Logistic Regression	32	14	60	14	0.35	0.50	0.41	38.33

**SVM : Support Vector Machine, KNN : K-Nearest Neighbor, TP : True Positive, FP : False Positive, FN : False Negative, TN : True Negative

The proposed method got a higher accuracy rate, F-score value, Recall, and Precision percentages than the other classification models. Confusion metrics for 120 test samples were calculated using **Equation 7, Equation 8, Equation 9, Equation 10**, respectively.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{9}$$

$$\text{F}-\text{score} = \frac{2 \times Precision \times Recall}{Precision + recall} \tag{10}$$

Classification accuracy of the Naive Bayesian classifier using the proposed thresholding algorithm, Otsu, and Kapur segmented test images is represented using a bar chart in Figure 5.

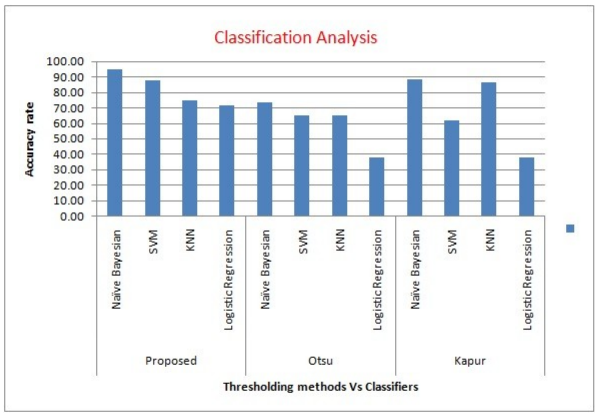

Fig 5. Comparing the accuracy rate of Different classifiers using the proposed, Otsu and Kapur segmented 120 test apple images

4 Conclusion

Segmenting an image is the primary step for all image analysis and classification processes. It helps in the accurate analysis of any image. The proposed thresholding algorithm contributed a lot to identify the region of interest accurately. This accurate segmentation resulted in an accurate classification process. To conclude:

1. A novel thresholding method has been proposed to segment the region of interest (defective/ diseased parts) from an apple image.
2. The segmentation accuracy was evaluated in terms of visual inspection and execution speed. The same was compared with similar gray-scale thresholding algorithms proposed by Otsu and Kapur.
3. The visual accuracy and the execution speed of the proposed algorithm in segmenting the region of interest was higher than Otsu's and Kapur's algorithms.
4. The proposed thresholding algorithm with the Naive Bayesian classifier gave the highest classification accuracy rate of 95.00%.

Thus, the proposed thresholding algorithm of segmentation and Naive Bayesian classification procedure can be embedded in microchips of sorting machines with the required enhancements.

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