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Research paper

Automated carrot disease recognition: a computer vision approach

Anup Majumder[1]*, Md. Tarek Habib[2], Papiya Hossain Lima[2], Saifuddin Sourav[2], Rabindra Nath Nandi[3]

[1]Institute of Information Technology, Noakhali Science and Technology University, Noakhali- 3814, Bangladesh
[2]Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh
[3]Department of Computer Science and Engineering, Khulna University of Engineering and Technology, Bangladesh
**Corresponding author E-mail:anupju.cse20@gmail.com*

Abstract

To ensure the freshness of fruits and vegetables modern image processing tools can help a lot. Experts can detect the defected fruits and vegetables by watching them with their eyes but the process is too long and not suitable for all the stores, farms, supermarkets or the exporters all around. There comes the blessings of new computer vision technologies with image processing techniques that can do a lot of works in a second. In this paper an automated approach is developed to detect defects of fruits and vegetables and recognize diseases by using machine vision based image processing techniques. There are many algorithms that can detect defects of fruits and vegetables hence, we separated the defected parts of the carrots using k-means clustering and then classified it with Multiclass Support Vector Machine. Here, a supervised machine learning concept is implemented to recognize various carrot diseases. As the domain of this research model, carrot diseases are classified and 96% of accuracy is achieved which can certainly help in our agricultural science along with proper maintenance.

Keywords:*Carrot Disease; Agro-Medical Expert System; Computer Vision; k-means Clustering; Support Vector Machine; Performance Metric.*

1. Introduction

Agriculture is the key income source of people living here in Bangladesh which is the 8th most densely populated country in the world [1]. A major part of the national GDP about 15% comes from agriculture which provides a vast amount of employment which is about 60-70% of the population [2]. Here people mainly producing many kinds of agricultural products to get to survive. But it is pathetic that our country is not fully digitalized in this most important sector although so many features and techniques are available provided by the modern technologies that can make a great change in agricultural sector. There are a lot of noble and prominent research possibilities and opportunities are available in our agricultural science that are not being risen properly. Most of the farmers of this country are illiterate and not properly concerned about the causes of unexpected loss of their harvest which can be a matter of devastating fluctuation in our targeted GDP and also affects the livelihood of the farmers. To avoid this type of trouble a proper maintained system should be there which can help the farmers to detect the diseases before it is too late to take steps for the entire harvest or for the further harvesting. As well, in this research an automated system is developed which can certainly help farmers to detect disease affected fruits or vegetables and also recognize which type of disease attacked the analyzed object from captured image. To demonstrate the expertise system various type of carrot diseases are chosen which is a very popular vegetable in Bangladesh, cultivated widely in croplands, also carrots have a great productivity globally. Manual visual system is used in Bangladesh to define if the carrots are fresh or disease affected which is very slow and time consuming process.

A very common disease of carrot is Root Fly. Experts say [3] if this disease attacks the crops then the affected plants should be collected and removed from the crops so the entire harvest does not get affected. Also the land should not be harvested repeatedly for carrots. Farmers need to know these information in a short and easy way.

Normally Bangladeshi farmers go to the experts physically to know about the problems or have to wait for very long for the experts which can turn the whole harvest in a vain. If they have this discussed agro-medical automated system in their hand it can help them gratefully to recognize the diseases and thus make sure about the methods they need to follow for further harvesting.

In this paper, the proposed automated system is developed based on machine vision concept. An image is captured through a mobile device or any type of camera then it is send to the system and analyzed for further processing. Features are extracted using some image processing techniques and the extracted features is given to our proposed model to predict which type of disease the captured carrot image is having. Our proposed model based on Multiclass SVM which give a fruitful result of this work that can solve the traditional problems of the farmers of this country as well as reduce the risks of unorganized cultivation of crops.

2. Literature review

Many image processing techniques were developed through many years of research for object detection and use of classifiers as well. But, a small number of approaches have been applied for detection of fruits and vegetables particularly focused on carrots.M.T. Habib and et al. [4] proposed a machine vision based approach for papaya disease classification. However they have used k-means clustering for segmenting the attacked region and perform the classification using SVM and have used 10 feature set. But in this approach it returns the accuracy of 90.15% where the data size is 126. Howarth et al. [5] have used size measurement, average slope difference, first derivative of the diam. profile, and connected component algorithms with computer vision concept to detect the defected areas. This method is proposed for only grading of carrots.

Howarth et al. in [6] developed a quantitative method to estimate tip shape for classification of carrots which uses curvature profile based on Freeman-chain code. A parameter estimation technique Levenberg-marquardt method is used to extract several critical features of the carrots and its shapes. Finally a Bayes decision classifier is used to classify the tip shapes. Using this classifier 86% of the data were successfully classified. This work only classified the shapes of carrots of grading.

Tao, Y.; Morrow et al. [7] have used rule-supervised inspection control scheme for automated potatoes grading that inspected potatoes. Multivariate discrimination techniques used to classify from the color and the shape separation is done by Fourier domain. The developed method used a combined approach of statistical and structural texture analysis for bruise, disease, injury and russeting scab. The multivariate discriminant technique gave an accuracy of 90% for greening potato.

F. López-García and G. Andreu-García [8] proposed a Multivariate Image Analysis strategy to develop an automatic detection of citrus fruit defects where T2 statistics – an applied statistics field is used to detect defective parts of citrus peel.In their work it was divided into detection of defects and classification of damaged or sound samples from the method. This unsupervised method is based on Principal Component Analysis (PCA) that uses color and texture features together extracting Eigenspace from unfolding color and spatial data.The correct detection of individual fruit defects is 91.5% and damaged/sound samples classification ratio of 94.2% is achieved from this experiment.

B. J. Samajpati and Sheshang D. Degadwala [9] employ some Color features (CCV, GCH, CLBP, LBP, LTP, Gabor features) and Texture features after conversion of the images from RGB to L*a*b* color space, then k-means clustering is done. After that, authors applied Random forest classifier on segmented image to classify the diseases of apples. Fruit disease is shown after classification by tagging every pixels by using this method. Finally feature level fusion by fusing more than two texture and color features are performed to improve accuracy of the proposed system. But the total accuracy of the proposed system ranges from 60-100% that is not specific.

A. S. Jalal and Shiv Ram Dubey [10] described an image processing technique for Apple fruit disease detection. Apple Bloch, Apple Rot and Apple Scab are used for fruit disease identification and the features used are global Color Histogram, Local Binary Pattern, Color Coherence Vector and Complete Local Binary Pattern. k-means Clustering in L*a*b* space is used for defect segmentation. Multi-class SVM Classifier was used to train and test images. The accuracy the system was 93% and in total 431 sample images were used to demonstrate their work.

M. Barnes et al. [11] designed a machine vision based approach to detect blemish potatoes using an adaptive boosting algorithm (AdaBoost algorithm) to select best features formed with color and texture information of blemish and non-blemish potatoes. A pixel wise classifier is trained and Minimalist classifier is used to select the most useful features which includes the statistical summaries of the whole potato along with the local regions. They have trained images for two categories and the as a result, an accuracy of 89.6% for white potato and 89.5% for red potato is gained.

Leemans et al. [12] tested four different algorithms to identify the diseases with various combination of Golden Delicious apples images using color information. The Mahalanobis distance between each pixel and both medians is computed and compared with the global model which is used next to enhance and filter images. Various defects of apples such as Bruises, russet, scab, fungi or wounds of apples were detected using four kinds of techniques. 80 images were tested in this research work but the accuracy of the system was not mentioned. Shiv Ram Dubey et al.[13] proposed a framework for the defect segmentation of fruits using an unsupervised learning method evaluated using k-means clustering technique. Apple is used in the experiment to detect defected area of the fruit part along with the stem and calyx using k-means. In that system three or four clusters are considered as observation to detect the defects in fruits by clustering from color and spatial features. In this system only defected part was detected but no recognition of the diseases were evaluated.

M. Jhuria et al. [14] provided an approach detecting disease on fruit. Grapes, Apple and mangoes are selected as the domain to experiment the algorithms. Morphology, color and texture feature vectors are chosen for feature extraction. Some image processing techniques were used to detect fruit defect detection on the experiment. . Back propagation is used for weight adjustment of images that are stored in learning database. In that case, morphology feature gives 90% accurate results which was the highest accuracy gained than other feature vectors.

M. Bhange and H.A. Hingoliwala [15] proposed a web based tool that helps to detect pomegranate diseases using image processing techniques. The system contained trained dataset of pomegranate fruits. In first step, feature extracting with color, morphology and CCV is done then clustered by k-means. Next, SVM classifier is used to classify the disease. The proposed system has acquired an accuracy of 82% to identify pomegranate diseases.

To detect and identify defects on fresh peach from markets a machine vision system was developed in the laboratory by B. K. Miller and M. J. Delwich [16]. Scar, cuts, bruise, scale, wormhole, and brown rot were identified by segmenting the images of defected region with a hybrid classifier which described the region as a specific type. The experimental result acquired a performance of the classifier having 31% error rate for the near-infrared system and 40% for the color system.

3. System design

In this research methodology an image is captured through a mobile phone or any kind of camera and then the test image is preprocessed for further processing. Fig. 1 shows the system architecture of our proposed methodology. At first, an image is sent to the trained system for evaluation through a few steps. After analyzing of the image and comparison with the trained dataset it detected if the image object is having any kind of defect or not. If it is disease affected then the system recognize the disease type and finally the output of the system is shown as the predicted disease name in the screen.

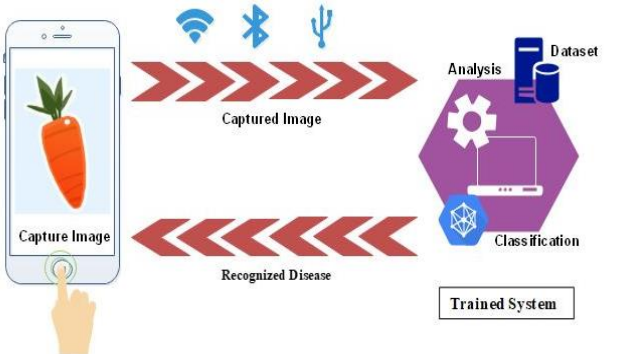


Fig. 1: The System Architecture of Proposed Disease Recognition System.

4. Methodology

To get the disease defected fruit and vegetable part accurately, image should be segmented first. Otherwise, the non-affected part of the major area can be a dispersion of this method.

To implement such a machine vision system a machine learning system is required which is described in this research and fig. 2 shows the steps to build the framework for the system.

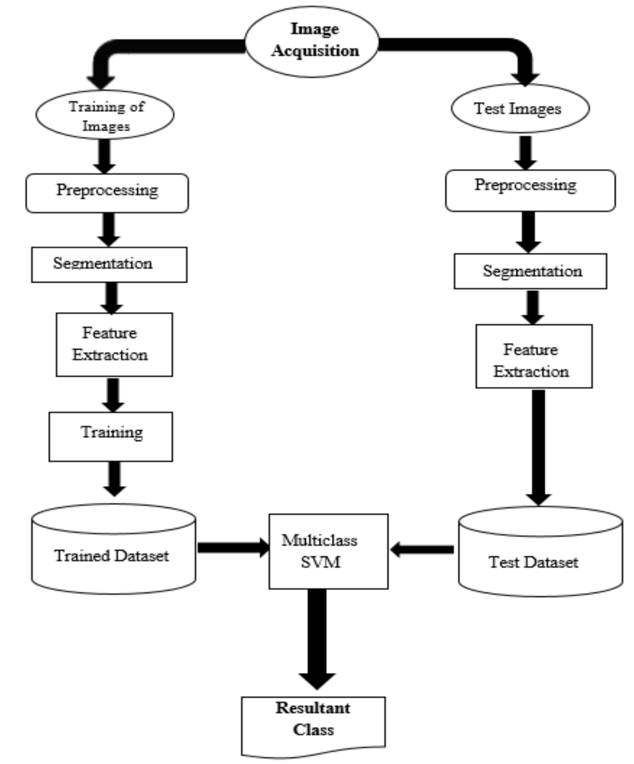


Fig. 2: Work Flow of the Proposed Methodology.

Numerous carrot images are used in this research work which are collected and captured from various places. Used images are formed with RGB (Red, Green, and Blue) color model. The images has differences in quality and formation which needs to be processed to a common form in order to train the dataset.
Before using the image for segmentation, some preprocessing of the images were done like Cropping- for cut-out the unimportant part of the image, Smoothing, enhancement to adjustthe color and contrast, Rotating, Resizing to get all the images in a general form. In this paper, k-means clustering is used to segment the images. Also boundary and spot detection algorithms are used. In boundary detection, the 8-connected pixel algorithm is implemented.
The algorithm for k-means clustering-

1) Convert the image from RGB to L*a*b color model.
2) Identify each pixel in the image to the cluster that minimizes the distance from the center value of cluster.
3) Then segmentation of the image is done.
4) Finally, select the cluster that contains ROI (Region of Interest) only.

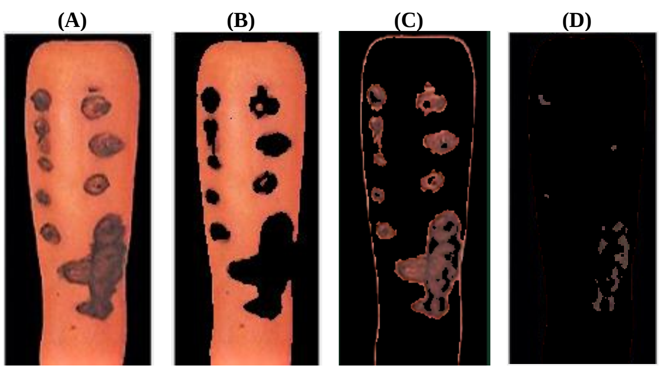


Fig. 3: Image Clustering By k-means (A) Captured Image (B) Cluster 1 (C) Cluster 2 (D) Cluster 3.

In fig. 3 it shows three cluster being produced by k-means. From those clusters one is chosen containing ROI for further processing.

In XYZ color system, Colorimetric distance between the individual colors do not correspond to perceived color differences. The CIE solved this problem in 1976 with the development of the three -dimensional L*a*b color space (or CIELAB color space) [18]. As L*a*b model is a three dimensional model, so it can only be represented accurately in three-dimensional space.
The formula for RGB converting digital images from RGB space to L*a*b are-

$$\begin{bmatrix} L^* = 116\, f\left(\frac{Y}{Yn}\right) - 16 \\ a^* = 500\, [f\left(\frac{X}{Xn}\right) - f\left(\frac{Y}{Yn}\right)] \\ \text{............(i)} \\ b^* = 200\, [f\left(\frac{Y}{Yn}\right) - f\left(\frac{Z}{Zn}\right)] \end{bmatrix} \quad (1)$$

Where X, Xn, Y, Yn, Z, Zn are the coordinates of CIEXYZ color space and where:

$$f\,(\mathrm{t}) = \begin{cases} t^{\frac{1}{3}} & ;\text{If } t > 0.0086; \\ & \text{otherwise} \\ \frac{t}{0.1284} + 0.1379 & \end{cases} \quad (1)$$

The extracted features of the ROI containing cluster is labeled and all the values of eleven features are stored in a m × nmatrix where m is the number of images trained and n is the number of feature that is extracted from the image.
Test image features are extracted to compare with the trained dataset and Multiclass SVM algorithm is applied in the system to classify which class the test image's information belongs to.
Finally the predicted disease name is printed in the screen.
To measure the performance of the system we need to define-
True Positive (TP) = the number of cases correctly identified as actual class.
False Positive (FP) = the number of cases incorrectly identified as actual class.
True negative (TN) = the number of cases correctly identified as negative classes.
False negative (FN) = the number of cases incorrectly identified as negative classes.
The four cases of the classification result can be represented by the following 2 by 2 confusion matrix. Table 1 below gives a contingency table formation for binary class problem.

Table 1: Confusion Matrix Formulation

	Predicted Class		
		Positive	Negative
Actual Class	Positive	True	True
	Negative	False	False

From the above table we form all the relevant tables regarding the results of the whole system and finally get the confusion matrix of the outcome of the system. Next we calculate a number of performance metrics, i.e. accuracy, sensitivity, specificity, precision, false positive rate (FPR) and false negative rate (FNR) from the confusion matrix in order to evaluate the performance of the system. To calculate these metrics, the formulas used are given below-

1) Accuracy: The accuracy of this system is its ability to differentiate the actual class and negative classes correctly. To estimate the accuracy mathematically, this can be stated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (3)$$

2) Sensitivity: The sensitivity of this system is its ability to determine the actual classes correctly. . To estimate the sensitivity mathematically, this can be stated as:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \quad (4)$$

3) Specificity: The specificity of this system is its ability to determine the negative cases correctly. To estimate the specificity mathematically, this can be stated as:

$$\text{Specificity} = \frac{TN}{FP+TN} \times 100\% \tag{5}$$

4) Precision: Precision is the number of relevant classes among all the positive cases. To estimate the precision mathematically, this can be stated as:

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \tag{6}$$

5) FPR: FPR of the system is the number of predicted class with which the classifier makes a mistake by classifying normal state as pathological. False Positive Rate can be stated as:

$$\text{FPR} = \frac{FP}{FP+TN} \times 100\% \tag{7}$$

6) FNR: It reflects the frequency with which the classifier makes a mistake by classifying pathological state as normal. False Negative Rate can be stated as:

$$\text{FNR} = \frac{FN}{FN+TP} \times 100\% \tag{8}$$

5. Categories of diseases

In this paper we focused on different types of diseases frequently attacking carrots in this country. Analysis of various types of diseases are very much important in order to identify different features through the vision based image processing techniques. Here we explored 5 types of disease named Black Rot, Growth Crack, Root Fly, Root Knot and Violate Root Rot. Also we have identified the healthy carrots to differentiate from the defected carrots. Various types of diseases are shown in Fig 4. To differentiate among different types of diseases, the dataset need to be trained very thoroughly.

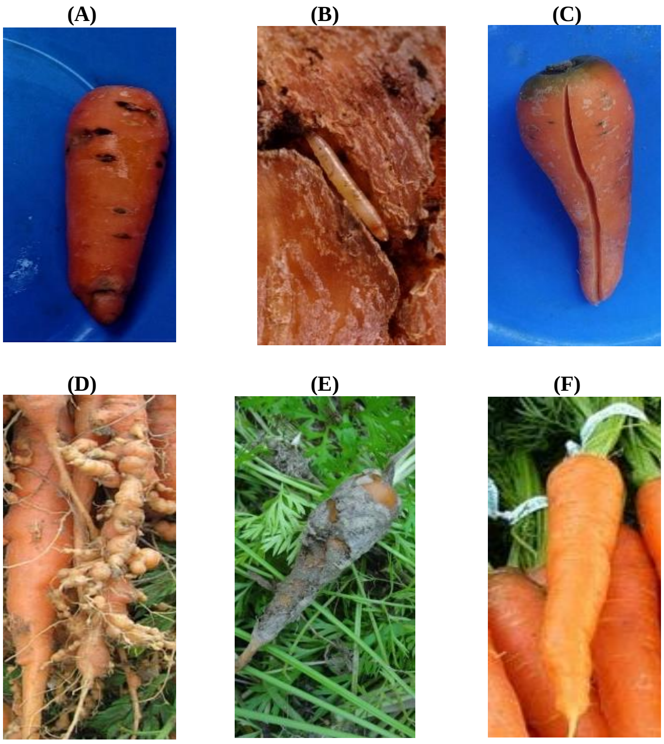


Fig. 4: Different Diseases of Carrots. (A) Black Rot. (B) Growth Crack. (C) Root Fly. (D) Root Knot. (E) Violate Root Rot. (F) Healthy Carrots.

6. Feature set

Feature set selection is the most important part of the methodology here. To distinguish between healthy and defected carrots the right features need to be selected. Spatial gray level Dependence Matrices (SGDM) method is a way of extracting statistical features. And before getting GLCM (Gray Level Co-occurrence Matrix) features first the image need to be converted to gray scale image. Then the statistical features like contrast, correlation, energy and homogeneity can be calculated by the formulas.

The statistical features from GLCM are-

1) Contrast- measures the local variation in the gray-level co-occurrence matrix.

Contrast is 0 for a constant image. The formula for calculating contrast of an image is-

$$\sum_{i,j} |i-j|^2 p(i,j) \tag{9}$$

2) Correlation- measure the joint probability occurrence of the special pixel pairs. The formula for calculating correlation in an image is

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu i)p(i,j)}{\sigma_i \sigma_j} \tag{10}$$

3) Energy- provides the sum of squared elements in the GLCM. Also known as uniformly or the angular second moment. And the formula is

$$\sum_{\mathrm{i,j}} \mathrm{p(i,j)}^2 \tag{11}$$

4) Homogeneity- measure the closeness of the distribution of elements in the GLCM to the GLCM diagonal. The formula for homogeneity calculation is given below

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{12}$$

With these SGDM and GLCM features in total 11 features to detect the disease defected object part from the images. Below another seven features that were selected for the carrot disease recognition are shown.

Another seven SGDM features:

5) Mean: Formula for calculating mean is

$$\mu = \frac{\sum_{i=1}^{N} I_i}{N} \tag{13}$$

Here, N = Total number of faulty pixel

I = Gray-scale color intensity

Now, If there are N pixels in faulty regions, where GS and μ represent gray-scale color intensity of a pixel and mean gray-scale color intensity of all pixels respectively then,

6) Standard deviation: Formula for calculating standard deviation is

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(I_i-\mu)^2}{N}} \tag{14}$$

7) Variance: Formula for calculating standard deviation is

$$\sigma^2 = \frac{\sum_{i=1}^{N}(I_i-\mu)^2}{N} \tag{15}$$

8) Kurtosis: Formula for calculating kurtosis deviation is

$$\kappa = \frac{\frac{1}{N}\sum_{i=1}^{N}(I_i-\mu)^4}{(\frac{1}{N}\sum_{i=1}^{N}(I_i-\mu)^2)^2} \tag{16}$$

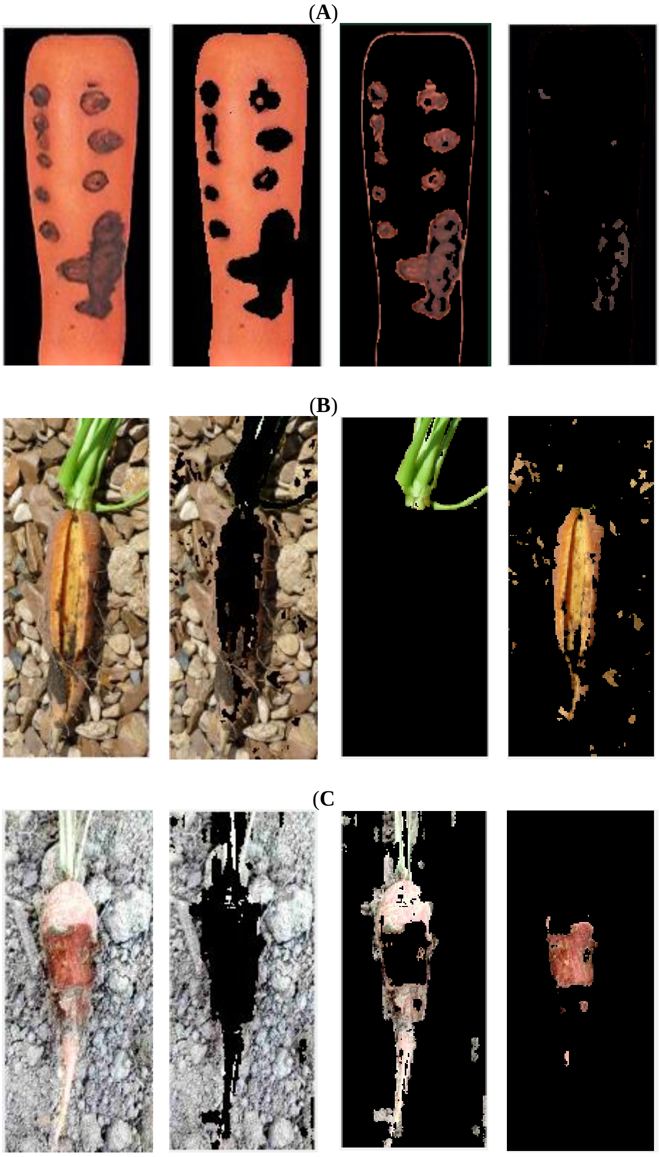
9) Skewness: Formula for calculating Skewness deviation is

$$\gamma = \frac{\mu - Mo}{\sigma} \tag{17}$$

Here, Mo = Gray-scale color intensity of all faulty images.

7. Experimental analysis

In this paper to demonstrate the detection of fruits and vegetables diseases, the used domain is carrot. Five types of diseases of carrot were identified with images collected for six categories including detection of healthy carrots. The diseases are Black Rot (42 images), Growth Crack (28 images), Root Fly (36 images), Root Knot (42 images), Violet Root Rot (20 images) and Healthy Carrots (32 images) in total 202 images are used. After training the dataset, test image is captured and given to the system as input. Image is then segmented with k-means clustering. Predicted class is shown in the output after analyzing the data of that cluster entered containing the Region of Interest (ROI) only. Next, some samples are provided from the experiments of segmentation for Black Rot, Growth Crack, Root fly, Root Knot and Violet root Knot respectively with the clustering process and the calculated affected part or the region of interest. After getting the results the confusion matrix is formed as Table 2. The whole process are implemented in MATLAB, the experimental result is much favorable.



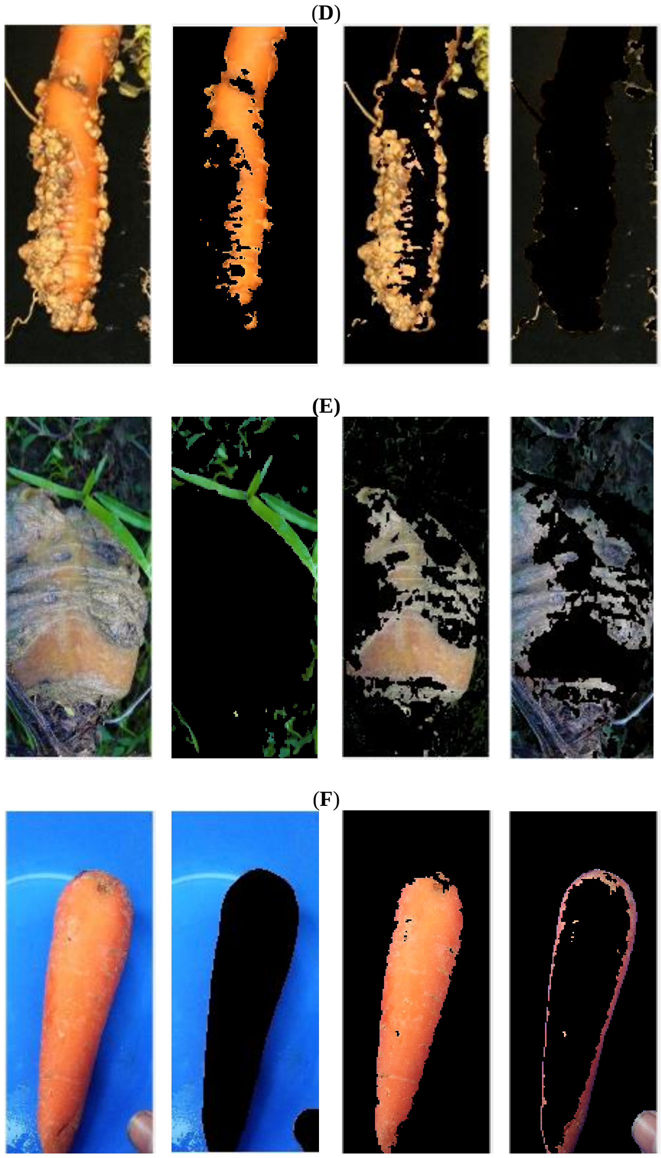


Fig. 5: Segmentation Carrots. (A) Black Rot. (B) Growth Crack. (C) Root Fly. (D) Root Knot. (E) Violate Root Rot. (F) Healthy Carrots.

Table 2: Confusion Matrix for the Proposed Framework

Predicted Class							
		Healthy Carrots	Black Rot	Growth Crack	Root Fly	Root Knot	Violet Root Rot
Actual Class	Healthy Carrots	32	0	0	0	0	0
	Black Rot	0	38	2	0	2	0
	Growth Crack	4	0	22	0	4	0
	Root Fly	0	2	2	30	2	0
	Root Knot	2	2	0	0	38	0
	Violet Root Rot	4	0	0	0	0	16

Accuracy is a very important metric in performance analysis.From the above contingency table, accuracy of the proposed system is 96% is calculated. Accuracy, sensitivity, specificity, precision, FPR and FNR are calculated with the equations (iii), (iv), (v), (vi), (vii) and (viii) respectively. All the calculated results are shown in Table 3.

Table 3: Values of Achieved Performance of the System

Attributes	Percentage
Accuracy	96%
Sensitivity	87.13%
Specificity	97.74%
Precision	88%
FPR	2.27%
FNR	12.8%

Here we can divide the results in two parts. One is positive results, which are accuracy, sensitivity, specificity and precision. Another part gives us the unwanted negative results, which are the false positive rate and false negative rate of the system. We use positive in the sense that higher values result in better performance and lower values result in poorer performance. We use negative in the sense that lower values result in better performance and lower values result in poorer performance.

From fig. 6 we can see that the positive values are much higher than the other negative values which is a strong indication of good quality of the proposed methodology.

In addition, to be clearer about the performance of this work Table 4 and fig. 7 gives the disease wise performance achieved. Here we can see there is no False Positive Rate for Violet Root Rot and Root Fly (0%) and Specificity and Precision is 100% which is a good factor on the performance of this system. Also Violet Root Rot has the highest accuracy value of 98.06% and all the other accuracies are also impressive.

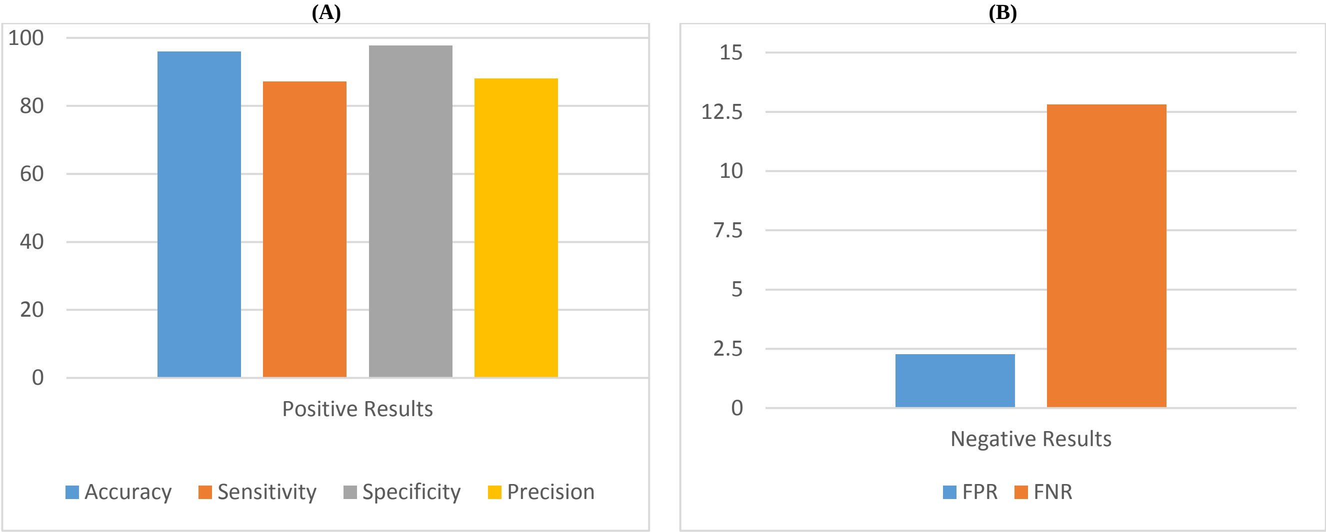


Fig. 6: Values Of Performance Achieved Of The System. (A) Positive Values. (B) Negative Values

Table 4: Disease Wise Values of Performance Achieved

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	FPR (%)	FNR (%)
Black Rot	96.19	90.48	97.62	90.48	2.38	9.52
Growth Crack	94.39	73.33	97.83	78.57	2.17	0.27
Root Fly	97.12	83.33	100	100	0	16.67
Root Knot	95.28	90.48	96.47	86.36	3.53	9.52
Violet Root Rot	98.06	80	100	100	0	20
Healthy Carrot	95.28	100	94.44	76.19	5.55	0

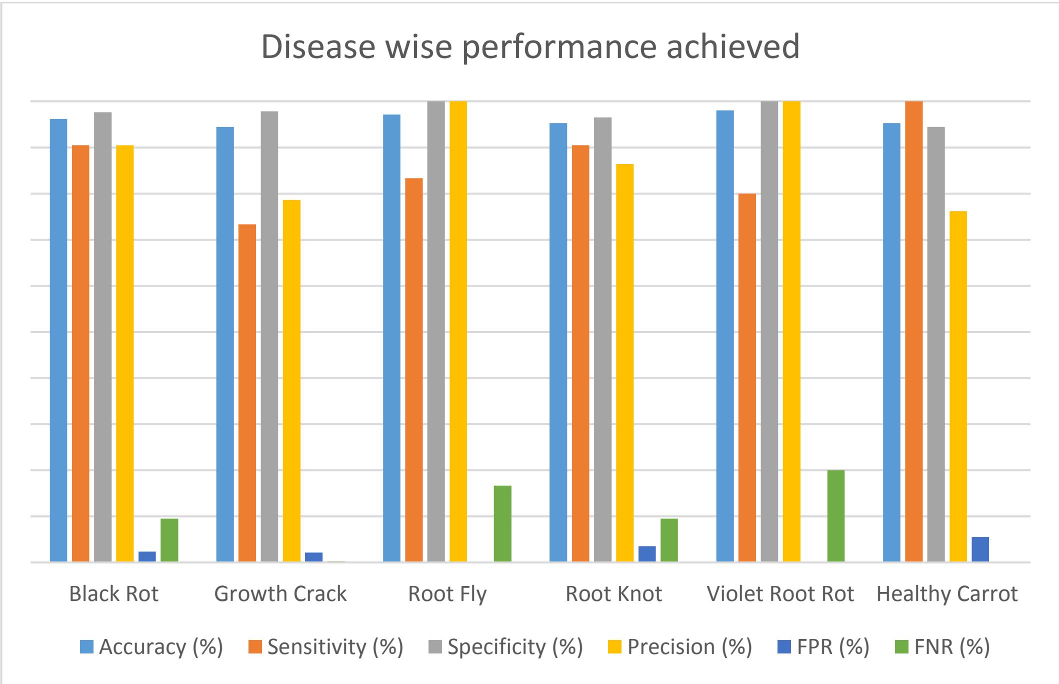


Fig. 7: Comparison of Disease Wise Performance.

8. Comparative analysis of result

Many researches have been working on different types of fruits and vegetables. We will now discuss the various works published at different times for the adulation of our research work.For the sake of our work, samples have been collected from many places considering many useful techniques and work on full Unique Dataset, which is comparatively very perfect and commendable for the system. The methods used by other researchers have influenced our work in many ways, which play an outstanding role in its proper evaluation. Below is a comparative discussion of the works related to carrots or different domain based fruit or vegetables recognition and classification problems. Table 5 shows a comparisons among our work and other related works done by other researchers.

Habib M.T. et al. in their paper [4] developed a method to recognize papaya diseases with k-means clustering and SVM classifier. 126 images of papaya was used on the evaluation and 90.15% accuracy was achieved.

Howarth et al. [5] derived an algorithm for grading of carrots. But disease classification was not performed. After that they have developed a quantitative method in paper [6] to estimate tip shape of carrots which gave 86% accuracy of the problem domain.

López García and Andreu-García [8] used a multivariant image analysis to detect defects on citrus fruit based on PCA achieving individual fruit defects is 91.5% and damaged/sound samples classification ratio of 94.2%. . Bhavini J. Samajpati and Sheshang D. Degadwala [9] proposed a method with color and texture features and Random Forest classifier to detect Apple fruit detection and classification where sample size was not mentioned. Anand Singh Jalal, Shiv Ram Dubey [10] performed detection and classification of Apple fruit diseases with 431 sample image and achieved 93% accuracy on their experiment. Michael Barnes et al. [11] adapted an AdaBoost algorithm which is used to only detect the defected potato with 102 sample image gaining 86.9% of accuracy. Disease detection Pomegranate fruit was done by Manisha Bhange and H.A. Hingoliwala [16] with SVM classifier and accuracy was achieved of 82%. Shiv Ram Dubey [18] performed two types of operations, one is recognition of different type of fruits and vegetables and another is classification of Apple fruit diseases.They got 93.14% of accuracy by k-means clustering with SVM classifier.

As we can see there is only a limited amount of work done on carrots which is limited only in the correct grading and shape selection of the carrots. But there is no system of action to detect the class of the disease which is very important for the farmers of this country. The methods and datasets used in this research paper have been made very systematic way, which makes 96% of accuracy so satisfying. Used Multiclass Support Vector machine combined with k-means segmentation procedure gives a strong methodology to correct recognition of fruits and vegetables disease detection techniques.

9. Conclusion and future work

In this work carrot diseases are recognized through image processing techniques which can be used in different kind of applications to detect any fruit or vegetable diseases which can open a door for helping rural farmers, big markets, super shops, exporter or agricultural farms to grow a highly secured economic development. Machine vision based carrot disease recognition is done.

Table 5: Comparison among Our Work and Other Related Works

Method/Work Done	Object	Problem Domain	Sample Size	Segmentation Algorithm	Classification Performed	Feature Set	Classifier	Accuracy
This work	Carrot (Fruit)	Detection & Classification of diseases	202	k-means	Yes	11	SVM	96%
Habib M. T. et al. [4]	Papaya	Detection & Classification of diseases	129	k-means	Yes	10	SVM	90.15%
Howarth et al. [5]	Carrot (fruit)	Detection	NM	NM	No	NA	NA	NM
Howarth et al. [6]	Carrot (Shape)	Estimation of tip shape	250	NM	Yes	5	Bayesian	86%
F. López-García and G. Andreu-García [8]	Citrus (Orange and mandarins)	Detection and Classification	120	PCA	Yes (damaged/sound sample)	NM	NM	91.5 % (Detection), 94.3% (Classification)
Bhavini J. Samajpati and Sheshang D. Degadwala [9]	Apple	Detection and Classification	80	k-means	Yes	13	Random Forest	60-100%
Anand Singh Jalal and Shiv Ram Dubey [10]	Apple	Detection and Classification	431	k-means	Yes	4	SVM	93%
Michael Barnes et al. [11]	Potato	Detect	102	NM	Yes	399	Ada-Boost/ minimalist	89.6% (white), 89.5% (Red)
Manisha Bhange and H.A. Hingoliwala [15]	Pomegranate	Detect	610	k-means	Yes	3	SVM	82%
Shiv Ram Dubey [17]	Multiple	i) Recognition (15 type) ii) Detection (Apple Disease)	i) 2615, ii) 391	k-means	Yes	6	SVM	93.14%

[1] NM: Not Mentioned.
[2] NA: Not Applicable.

With a supervised learning process. The whole process is done with a 96% of accuracy using collected carrot images which are affected with diseases. Though there were some barriers while working, the background color and poor quality of images can distract the application to give more accurate result. The proposed system shows a new way to involve with the machine learning methods with image processing technique which is able to detect disease affected part of carrots and also recognize the disease automatically.

This approach can be implemented into any kind of mobile based application or web based application to reach the root level farmers easily. Farmers sends the captured image from the land directly and get the output on their hand in a second showing which disease their fruits or vegetables are having so that they can take instant decision of their next step. To prevent immense loss of their profit they were in need of a system like this from the very early period of time. This work can be extended in a new level by experimenting with many other classifiers. This is our plan for the future extension of this work as well.

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