Detection of various categories of fruits and vegetables through various descriptors using machine learning techniques

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Abstract: An accurate and efficient recognition system for fruits and vegetables is one major challenge. To solve this challenge, we have examined various feature descriptors based on colour and texture such as RGB, CMH, CCV, CDH, LBP, CSLBP and SEH. All process of proposed framework consists three phase: 1) background subtraction; 2) feature extraction; 3) training and classification. In this paper, Otsu's thresholding is used for background subtraction. Further all segmented image is used in the feature extraction phase. Finally, C4.5 and KNN is used for training and classification. The various performances metric such as CA, precision, recall, F-measure, MCC, PRC and FPR are used to evaluate the proposed system for recognition problem. We also analysed the performance accuracy of both classifiers. In that C4.5 and KNN classifier produce CA values of 94.63% and 90.25%, respectively.

Keywords: detection; fruits; vegetables; descriptor; performance metric; C4.5; k-nearest neighbour; KNN; SVM.

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1 Introduction

India has the ability to produce a variety of horticulture product. This is due to its versatility of environment. Fruits and vegetables hold a 90 percent share of the total horticulture product. The other categories of horticulture product are flower, aromatic plantation, crop, spices etc. The production of fruits and vegetables is 314.65 million tonnes among all horticulture product (Saxena and Rathore, 2017). State Uttar Pradesh positions first in the production of vegetables with 26.4 million tonnes, trailed by state West Bengal with 25.5 million tonnes, which is 30% of the generation of vegetables contrasted with the different state of India. In the fruits product production, state Andhra Pradesh produces 120.98 lakh tones pursued by state Maharashtra 103.78 lakh tones which are as one 24 percentage of natural product creation contrasted with rest the province of India. India export fruits and vegetable worth value of 161 USD million. It secured 14th rank across the word in fruits and vegetables export (http://agriexchange.apeda.gov.in/product_profile/exp_f_india.aspx?categorycode=0102). USA hold 1st rank, followed by Netherland, France, Germany and china are top five country in export of fruits and vegetables.

Agriculture is the backbone of Indian economy. In India, more than 70% of human resources directly or indirectly are employed in agriculture. Indian agriculture has a remarkable contribution to the total GDP. On an average the contribution of agriculture in GDP is 18%. In comparison with the total manpower employed in agriculture, the GDP contribution by agriculture is very less. To increase the contribution of agriculture towards total GDP it will helpful if the modern tool and techniques are used. The fruits and vegetables yield in agriculture is very significant. However, automated recognition system of fruits and vegetables by an automatic process is not focused.

The crucial characteristic of fruits and vegetables is its appearance. This impacts the market value of fruits and vegetables along with consumer's preference. The market prices of fruits and vegetables are usually determined by manual inspections. Traditionally, such a manual inspection for quality assessment is done by experienced persons. This manual method is inconsistent, resulting in effect the selection of fruits and vegetables for the consumer market. Today is the day digital platform. Many customers are buying fruit and vegetables by using the digital platform. Many supermarkets has implemented the recognition system by using some hardware components and bar code. One major limitation of such system is that it is in static form. Bar code based system is fail to recognise the quality of fruits and vegetables. That why, an effective and automated recognition system will help increase in accuracy of the system and consumer market. It will result in revenue generation for manpower include in production of fruits and vegetables. Such an automated recognition system if supported by machine learning system, it may improve the performance of the system.

The fruits and vegetables image recognition mainly depend in set of colour, texture, shape, size. The proposed framework of recognition system utilises the colour such as

RGB, CMH, CCV, CDH and texture such as LBP, CSLBP and SEH to classify the image fruits and vegetables in different class of image. There are many descriptors available to extract the feature of the image. These features are classifying by C4.5 and k-nearest neighbour (KNN) in the experiment. All classify results are evaluated based on various performance matrix such as CA, recall, precision, MCC, PRC and FPR.

The overall objective of this paper is to recognise and classify the fruits and vegetables with different pose, variability on number of image and last with cropping partial occultation effect. The specific objective is mainly cover in five phases.

1. To proposed the framework for recognition of different categories of fruit and vegetables.
2. Collect the various class of image of fruits and vegetable.
3. Under the variety of available segmentation techniques, perform the background separation of fruits and vegetables using Otsu's thresholding method.
4. Choose the effective and appropriate colour and texture techniques to extract the feature vector of image.
5. Finally, by using C4.5 and KNN classifier perform training and classification using various performance metric.

Development of such framework needs to address some challenge. one major challenge is lack of data-set to evaluate the system. The other challenge is selection of optimal techniques to identify the different category of fruits and vegetables. Many researchers have used different descriptor but all are having complex system to extract the feature of the image. So identifying the suitable descriptor to feature extraction of fruits and vegetables is one other major challenge. Some other major challenges are classification of fruits and vegetables based on different performance. The extensive literature surveys of previous carried work by many researches are discussed in Section 2. Section 3 present the framework used to recognition of different categories of fruit and vegetables based on colour and texture descriptor. Section 4 shows the experimental results and discuss. Comparative analysis of results is discussed in Section 5. Finally, the conclusion is presented in Section 6.

2 Related works

In this section, we will try to focus on an extensive literature survey of previous carried work by many researches in the area of image recognition and classification. The first attempt on image recognition and classification is done by many authors (Stehling et al., 2002; Pass et al., 2004). The fruits and vegetables image recognition and classification is presented by (Zhang and Wu, 2012). They have used the colour and texture descriptor to extract the feature of the image. All the feature is used in training and classification based on KNN classifier. The proposed system produces 95% accuracy rate. One limitation is dataset has been used for the experiment purpose is very old. Due to that system may not be able to take advantage of recent development in dataset of fruits and vegetables.

Rocha et al. (2010) present a novel approach for recognition of fruits and vegetables. In their work many feature is fused with classifier. The supermarket dataset has 15 different classes of fruits and vegetables used for experiments. The feature descriptor is broadly related to colour and texture. The results show that proposed system reduces the classification error up to 15%. They have also combine the feature descriptor for more complex image having variability in number, illumination, different pose etc. In this, one drawback is that in case of combination of weak feature with high accuracy classifier may not able to produce good accuracy rate.

Same data set has been utilising by Dubey and Jalal (2013) for the experiment. They have first subtracted the background of fruits and vegetables using K-means techniques. Further segmented image is used in feature extracted phase. They have extracted the feature vector of image by colour descriptor such as GCH, CCV, CDH, while texture descriptor feature is SEH, LBP and CSLBP. Further, these all feature used for training and classification by multi-class support vector machine. In other paper carried by Dubey and Jalal (2015) on same experimental dataset, they have analysed the mean (μ) and derivation (σ) of all class of fruits and vegetables. In this, CCV + LTP fused descriptor produce highest mean accuracy rate with value 90.6%, Where minimum standard rate 3.8% by CCV + CLBP. One drawback system that CDH+SEH produce less mean accuracy rate and CDH + SEH+ CSLBP show highest standard derivation. That indicate both combine method poor performance compare to other method.

Agarwal et al. (2004) and Jurie and Triggs (2005) proposed a framework for recognition of recognition of particular image that belongs to set of image per class. This approach is called bag of feature techniques. Tikkanen et al. (2000) and Marszalek et al. 2010) show promising results for recognition problem. Arivazhagan et al. (2010) also used different category of fruits and vegetables for experiment and they have achieved good accuracy rate with value 86%. The interesting method was proposed by Berg et al. (1910) for shape matching. They have remove the three major constraint for shape matching such as corresponding point for the two shape with similar local descriptor, minimum geometric distortion and last smoothness of the transfer motion.

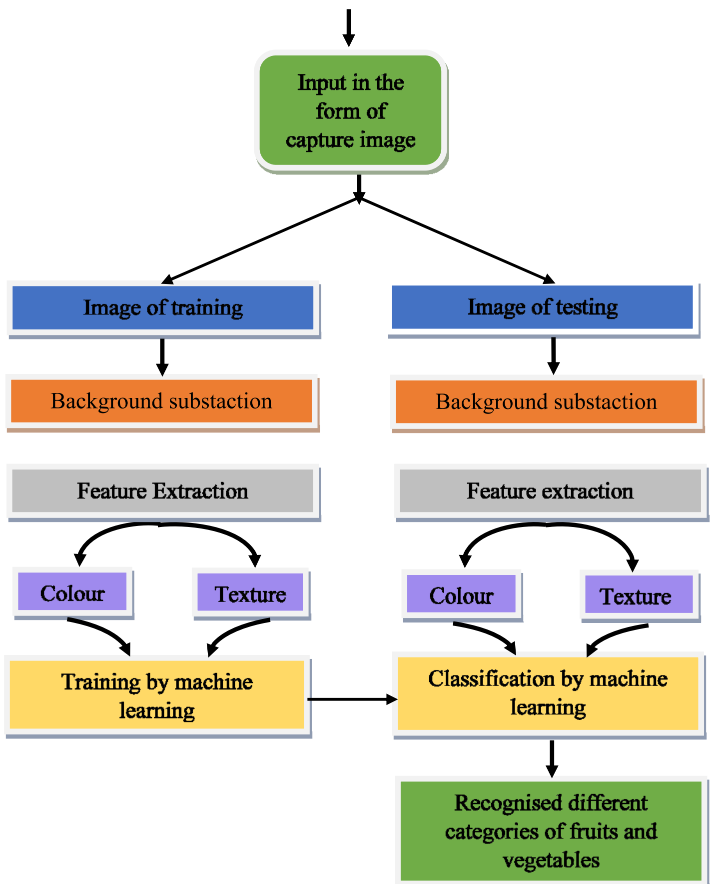
Recently, Moallem et al. (2017) present a framework for apple recognition and classification. In their work they have utilise the SVM, MLP, KNN classifier to classify the apple in to healthy and defected image categorisation. With results, SVM classifier show highest accuracy rate with value of 92.5% and 89.2% for both class, followed by MLP 90.0%, 86.5% recognition rate, finally KNN classifier produce less accuracy rate with value 87.5% and 85.8% respectively.

Al Ohali (2011) has described the feature of date fruits dataset in details. They have classified the feature in to five categories such as Flabbiness, size, shape, intensity and defects. They have implemented the BPNN for training and classification. The results show maximum accuracy rate with value of 80% by model 2 in classifies the grade 2 fruits. One major disadvantage of proposed system is that, it could not able to recognised the Flabbiness feature from date fruits images. An accurate framework for plant identification problem was proposed by Saleem et al. (2019). They have used the public available dataset 'FLAVIA' of leaf image. Different classifier such as KNN, naïve Bayes, MSVM is used for classify the feature vector. The KNN classifier produces best performance among other classifier with value 97.6% and 98.8% for precision and recall respectively. Now days, machine learning based techniques is popular and getting more attention in agriculture machine vision system. Many authors (Liming and Yanchao, 2010; Mahendran et al., 2012; Sofu et al., 2016; Kamilaris and Prenafeta-Boldú, 2018; Rehman et al., 2019) have presented the review the application and role of the machine learning, deep learning in agriculture fields.

3 Proposed framework for recognition of fruits and vegetables

The proposed framework for recognition of fruit and vegetables, are shown in Figure 1. This proposed framework includes two phase such as training and classification. Background subtraction, Feature extraction and feature selection based on colour and texture descriptor require in the both training and classification phase.

Figure 1 Proposed system for detection of various categories of fruit and vegetable (see online version for colours)



Source: Tripathi and Maktedar (2020)

In the proposed approach, there is mainly three step involve in recognition of different categories of Fruit and vegetables. In the first method Background of fruits and vegetables are subtracted present by Tripathi and Maktedar (2018). In next phase, based on colour and texture descriptor feature are extracted from the segmented image. In third step, Image of different category of fruits and vegetables are classified based on KNN and C4.5 classifiers. Finally, the accuracy of proposed system is calculated by various performance metrics such as accuracy, precision, recall, F-measure, MCC, precision recall curve, false positive rate.

3.1 Background subtraction

An accurate method for segmentation of culmination and vegetables image is crucial and predominant demanding situations in computer imaginative and prescient. numerous segmentation strategies are available in processing. on this paper, we introduce a framework for end result and veggies background subtraction using Otsu's algorithm. This technique is widely utilised in diverse segmentation process. The Otsu's strategies beneficial in subtraction of historical past below the partial effect of occlusion, cropping, noisy and blurred pictures. Our proposed approach turned into experimented by means of employing fruit and vegetable pictures obtained regionally. Our experimental outcomes verify that, Otsu's threshold based technique is capable of extract fruit and vegetable items with correct accuracy. To evaluate the performance of proposed method, we have used a dataset with 20 different categories of fruits and vegetables apple (169), bitter melon (128), brinjal (158), chilli (118), cabbage (103), fig (178), khira (187), kundru (128), kiwi (130), onion (160), orange (175), pepper green (171), pepper red (115), pomegranate (180), tomato green (180), tomato red (161), sapodilla (181), sponge gourd (153), strawberry (120) and watermelon (148).

3.1.1 Algorithm for Background subtraction based on Otsu's threshold method

1 Collect the original image of fruits and vegetables in R, G, B. The original size of image is reducing by cropping operation to speed up the process.

2 From input colour image, one luminance Y and two chrominance channels Cb, Cr are extracted.

3 Perform morphological operation such as open and close on Y channel.

4 Y channel are segmented by using Otsu's thresholding method by selecting the threshold value.

5 In this step, perform the Invert operation on segmented image received from step 4.

6 R, G, B channel is extracted from Inverted image.

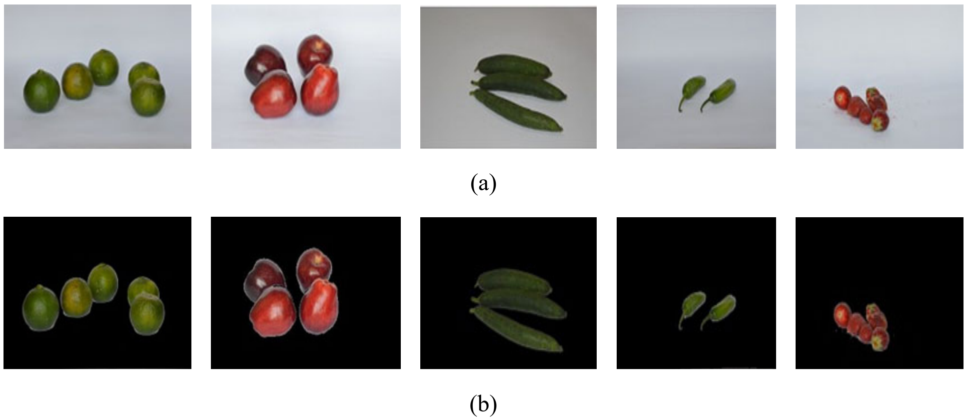
7 Perform concatenated operation between inverted image with respective three channels Y, Cb, Cr. Let us assume that, the results of this operation is denoted by in intermediate image.

8 Extract R, G, B channel from intermediate image that are in form of Y, Cb, Cr.

9 Finally, R, G, B channel are concatenated with inverted image and obtain results are in form of background subtracted image.

We have used Otsu's thresholding background separation method among various available segmentation techniques. Extraction region of interest from image are shown in Figure 2. Figure 3 show background subtraction image under partial occlusion and cropping effects. Under noisy and blurring effect are shown in Figure 4. Note that, our proposed algorithm for background separation will extract the background, it does not separate the various combination of objects in a single image object. It is because in collection of data set, we have considered only one class of fruits and vegetables with different orientation and variety in number. In this dataset, we have not considered background separation for mix collection of fruits and vegetables.

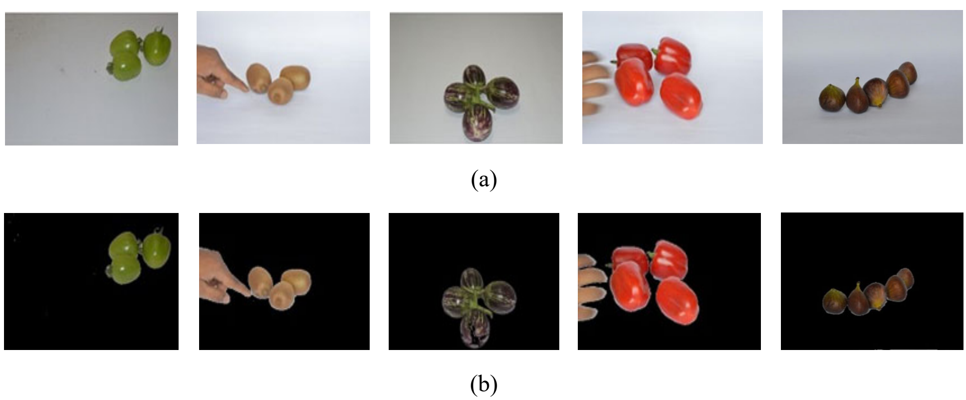
Figure 2 Background subtraction from the images, (a) before subtraction (b) after subtraction (see online version for colours)



(a)

(b)

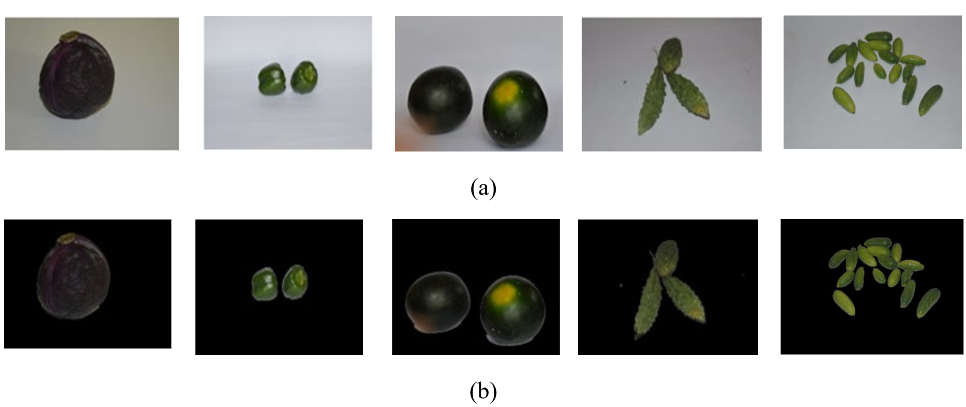
Figure 3 Background subtraction effects below partial occlusions and cropping impact, (a) before extraction (b) after extraction (see online version for colours)



(a)

(b)

Figure 4 Background subtraction results under noisy and blurring impact, (a) before extraction (b) after extraction (see online version for colours)



(a)

(b)

3.2 Feature extraction

Previous studies showed that there is no clear guideline to choose a single extraction method, however, even descriptors selection strategies are still application subordinate and an open research issue. On this sub-segment, we extract some capabilities that have shown promising results inside the fruits and vegetables categorisation issues. We have used a few colour and texture functions to validate the accuracy and performance of the proposed approach. The colour features used for the fruit and vegetable recognition problem are red green blue (RGB), colour coherence vector (CCV), and colour difference histogram (CDH), colour moment histogram (CMH), while the texture features used are local binary pattern (LBP), centre-symmetric local binary pattern(CSLBP) and structure element histogram (SEH).

3.2.1 RGB histogram

The RGB histogram is a mixture of three 1D histograms based totally on the R, G, and B channels of the RGB colouration area. within the normalised RGB colour model, the chromaticity additives r and g describe the colouration information in the image (The sum of r, g, b will usually identical one, r +g+ b=1).

$$r = \frac{R}{R+G+B} \tag{1}$$

$$g = \frac{G}{R+G+B} \tag{2}$$

$$b = \frac{b}{R+G+B} \tag{3}$$

3.2.2 Colour moment histogram

The colour moments of an image are an easy but powerful function for colour-primarily based images retrieval (Vailaya and Jain, 1993; Ghosal and Mehrotra, 1997). From the possibility idea, it is discovered that an opportunity distribution is uniquely characterised by way of its moments. as a result, if we interpret the shade distribution of an image as a probability distribution, then the shade distribution can be characterised thru its moments as properly. moreover, as most of the colour distribution statistics can be captured by using the low-order moments, using only the first three moments: propose, variance and skewness, it is determined that the ones moments deliver an notable approximation and were showed to be inexperienced and powerful in representing the shade distribution of image (Malakar and Mukherjee, 2013). These first three moments are defined as:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{4}$$

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{j=1}^{N}\left(p_{ij} - \mu_i\right)^2} \tag{5}$$

$$S_i = \left(\frac{1}{N} \sum_{j=1}^{N} \left(P_{ij} - \mu_i \right)^3 \right)^{1/3} \tag{6}$$

where p_{ij} is the value of the i^{th} colouration channel of the j^{th} image pixel. Only 3 × 3 (three moments for each colour component) matrices to symbolise the colour content of every image are needed that is a compact illustration as compared to other colouration capabilities.

3.2.3 Colour difference histogram

A feature descriptor called as CDHs is designed with the aid of using colour differences of neighbouring pixels at a positive distance (Liu and Yang, 2013). The particular characteristic of CDH is that it counts the perceptually uniform colour distinction between points beneath distinctive backgrounds with regard to colours and aspect orientations in L*a*b*colour area. It pays greater interest to colouration, area orientation and perceptually uniform colour variations, and encodes colour, orientation and perceptually uniform shade distinction through characteristic representation in a comparable manner to the human visual gadget.

3.2.4 Colour coherence vector

An method to examine image based totally on CCVs are offered by Pass et al. (2004). The define shade coherence as the degree to which picture pixels of that colour are contributors of a huge location with homogeneous colour. those regions are referred as coherent regions. Coherent pixels are belonging to a few big contiguous areas, where as incoherent pixels are not. on the way to compute the CCV the approach blurs and discretises the picture's colouration-area to cast off small versions between neighbouring pixels. Then, it finds the related components inside the image so as to classify the pixels of a given colour bucket is both coherent and incoherent. After classifying the photograph pixels, CCV computes two shade histograms: one for coherent pixels and every other for incoherent pixels.

3.2.5 Local binary pattern

The principle concept of LBP (Timo et al., 2002) is to explain the feel of greyscale pictures by way of extracting their local spatial structure or taking the sign of the difference of the neighbouring pixels with the middle pixel as follows:

$$\begin{aligned} LBP_{N,R} &= \sum_{n=0}^{N-1} s\left(v_n - v_c\right) 2^n \\ s(x) &= \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \end{aligned} \tag{7}$$

Afterwards, A LBP histogram is computed from the LBP code of each pixel of the image to represent the texture feature of the image

$$H(k) = \sum_{i=0}^{I} \sum_{j=0}^{J} f\left(LNP_{N,R}(i, j), k\right) \qquad k \in [0, K] \tag{8}$$

3.2.6 Centre-symmetric local binary pattern

The LBP operator, described in sub-segment 5.3.5, produces lengthy histograms and is therefore tough to use within the context of a vicinity descriptor. To deal with the hassle, we modified the scheme of a way to compare the pixels within the neighbourhood. as opposed to comparing every pixel with the centre pixel, we compare middle-symmetric pairs of pixels. We can see that for 8 neighbour's, LBP produces 256 (28) one of a kind binary patterns, whereas for CS-LBP this range is simplest sixteen (24). Moreover, robustness on flat image regions is acquired by using thresholding the grey stage variations with a small cost T as proposed in (Heikkilä and Pietikäinen, 2006).

$$\begin{gathered} CS - LPB_{R,N,T}(x, y) = \sum_{i=0}^{(N/2)-1} s\left(n_i - n_{i+(N/2)}\right) 2^i \\ s(x) = \begin{cases} 1 & x > T \\ 0 & \text{otherwise} \end{cases} \end{gathered} \tag{9}$$

where n_i and $n_{i+(N/2)}$ correspond to the grey values of centre symmetric pairs of pixels of N equally spaced pixels on a circle of radius R.

3.2.7 Structure element histogram

SEH has been computed, at this time, the pixel number of the image will change when the image is scaled, therefore, the SEH should also change. In other words, images would be dissimilar when the image is scaled. In order to solve this problem better, as a manner to resolve this trouble higher, we discover that the share of pixels is identical whilst the picture is scaled. therefore, the normalisation need to be taken to solve this trouble.

$$e_{ki} = \frac{|E_{ki}|}{\sum_{j=1}^{5} |E_{ji}|} \tag{10}$$

SEH has been normalised, at the moment, the image is comparable while the image is scaled, because the proportion of the SEH is same whilst the image is scaled.

3.3 Training and classification

Much like the method provided in preceding sub-sections which include historical past subtraction, and feature extraction steps are completed for each image of the schooling and type. After feature extraction of schooling image, we learn classifiers specifically C4.5 and KNN. Sooner or later, these trained classifiers are used to categorise the test image into one of the classes of the culmination and veggies on the premise in their function vectors generated using the identical descriptor which is used to generate the feature vectors. special classifiers use specific strategies for the schooling, but essentially carry out the optimisation operations to split the training. It should be noted that the KNN classifiers can be used for continuous value inputs, unlike Decision Trees that is applicable for continuous and categorical inputs.

3.3.1 C4.5 classifier

The decision tree classifies a given facts point beginning at the pinnacle and shifting down to reach a leaf node based totally on approximating discrete valued goal characteristic wherein mastering is primarily based on a choice tree. primarily based at the set of training times given to ID3 set of rules construct, a choice tree is fashioned. these bushes can be carried out as a set of if-then rules to enhance the choice making capability. The top-down method is used to assemble the tree started out with the formation of the root node. At every node, the great classifies attributes decided on as the take a look at attribute based on highest statistics benefit at a node. The information advantage is the discount in entropy which is as a result of splitting the instances primarily based on attribute values. The data benefit for an attribute A at a node is calculated using following formula:

$$\text{Information Gain}(S, A) = \text{Entropy}(S) - \sum_{v \in Value(A)} \left(\frac{|S_v|}{S} \text{Entropy}(S) \right) \tag{11}$$

$$\text{Entropy}(S) = \sum_{i=1}^{numclass} p \log_2 p_i \tag{12}$$

Algorithms of C4.5	
1	Let us assume set of training data set is denoted by S.
2	Also assume all feature sub-set is denoted by A.
3	If all feature sub-set in S are label 1, return to label 1.
4	If all feature sub-set in S are label 0, return to label 0.
5	If A # ϕ ,return to leaf node leaf whose value = majority of label in S.
6	Else, calculate the gain.
	If all feature in S have same label, return a leaf whose value = majority of label in S.
7	Else,
	Let T_1 be the tree returned by ID3, $\{(x, y) \in S: xj = 1\}$
	Let T_2 be the tree returned by ID3, $\{(x, y) \in S: xj = 1\}$
8	Return to node.

3.3.2 KNN classifier

The KNN is a flexible classifier with a wide range of programs from imaginative and prescient to proteins and computation to graphs. The advantage of the usage of KNN is that it makes use of immediate training which means that as quickly as new sample statistics is written on database in short, it gives fast education. It also works on the minimal distance of question times from training points which in addition offers KNN. The KNN classifies facts based totally on the majority of its neighbours having maximum commonplace attributes and also with minimum distance from question object. In KNN classifier, there’s a trouble of selecting the excellent fee of okay. this could be executed by making experiments so as to test distinctive values of okay and pick the value that has the excellent performance.

Algorithms of k -nearest neighbour (KNN)

1. Let us assume set of training data set is denoted by D.
2. We also, assume there are N – Many number of training examples.
3. These training examples are pair as (X1, Y1), (X2, Y2),…….. (Xn, Yn).
4. Choose the value of K.
5. Calculate the Euclidean distance between two point a, b with the help for following expression.

$$d(a, b) = \sum_{d=1}^{D} \left[\left(ad - bd^2 \right) \right]^{1/2} \tag{13}$$

6. Sort the feature based on distance. Those feature having lowest distance put first, followed by second and so on.
7. Finally, label or normalised the classified attribute with the help for following expression.

$$v^1 = \frac{v - \min A}{\min A - \max A} \tag{14}$$

Where,

Min A and max A are minimum and maximum value of attribute A.

4 Experiment and results

In this section, we have discussed the dataset of fruits and vegetables, and applied the proposed system over 20 different categories of fruits and vegetables and evaluate the recognition accuracy. In this, we describe the preparation of the dataset and next by various colour and texture feature descriptor is compared to obtain the recognition accuracy of the fruits and vegetables.

4.1 Dataset

We have collected all the image of fruits and vegetables from the local market at talegaon, Maharashtra. All the images were shown in Figure 5, captured from Nikon digital DSLR camera. We have taken over five months to generate the datasets of fruits and vegetables. The images have collected on different days and condition. We likewise done some operation, for example, cropping and resizing on the collected images. The dataset of fruits and vegetables, consists 20 different categories apple (169), bitter melon (128), brinjal (158), chilli (118), cabbage (103), fig (178), khira (187), kundru (128), kiwi (130), onion (160), orange (175), pepper green (171), pepper red (115), pomegranate (180), tomato green (180), tomato red (161), sapodilla (181), sponge gourd (153), strawberry (120) and watermelon (148).

Figure 5 Dataset used to have 20 different categories of fruits and vegetables (see online version for colours)

Figure 6 represents the illumination difference present in apple, kiwi, cabbage, bitter melon category. Strawberry category with different pose represents in Figure 7. Figure 8 show variability on the number of elements of tomato red category, followed by Figure 9 represents the examples of cropping and partial occlusion. Availability of these attribute create the data set more realistic.

Figure 6 Illumination differences, apple, kiwi, cabbage and bitter melon category (see online version for colours)

Figure 7 Pose differences and strawberry category (see online version for colours)

Figure 8 Variability on the no. of elements and tomato red category (see online version for colours)

Figure 9 Examples of cropping and partial occlusion (see online version for colours)

4.2 Experimental result and discussion

To analysis the recognition accuracy of the proposed system, we examine and compare RGB, CCV, CDH, CMH, LBP, CSLBP, SEH feature descriptor. In the evaluation process, we have used a number of fruits and vegetables image under each category for training. We have also utilised the various performance metrics such as classification accuracy, Precision, Recall, F-measure, MCC, PRC, FPR to evaluate the performance of the proposed system. The details description of matrices is described below.

$$\textbf{CA} = \frac{\begin{array}{c}\text{Total number of fruits / vegetables correctly} \\ \text{classified image used for testing}\end{array}}{\begin{array}{c}\text{Total number of fruits / vegetables} \\ \text{image used for testing}\end{array}} \tag{15}$$

$$\textbf{Precision} = \frac{\text{Total value of true positive}}{\text{total value of combination withtrue positive and false positive}} \tag{16}$$

$$\textbf{Recall} = \frac{\text{total value of true positive}}{\text{total value of combination withtrue positive and false negative}} \tag{17}$$

$$\textbf{F} - \textbf{measure} = \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} * 100 \tag{18}$$

$$\textbf{MCC} = \frac{\text{TP} * \text{TN} - \text{FP} * \text{FN}}{\sqrt{(\text{TP} * \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} * 100 \tag{119}$$

where

TP is number of true positive

TN is number of true negative

FP is number of false positive

FN is number of false negative

PRC = It is calculated by ratio on positive and negative

$$\text{PRC} = \frac{\text{P}}{\text{P} + \text{N}} \tag{20}$$

where

P is positive case

N is negative case

FPR = It is calculated by number of positive in incorrectly anticipated in test class

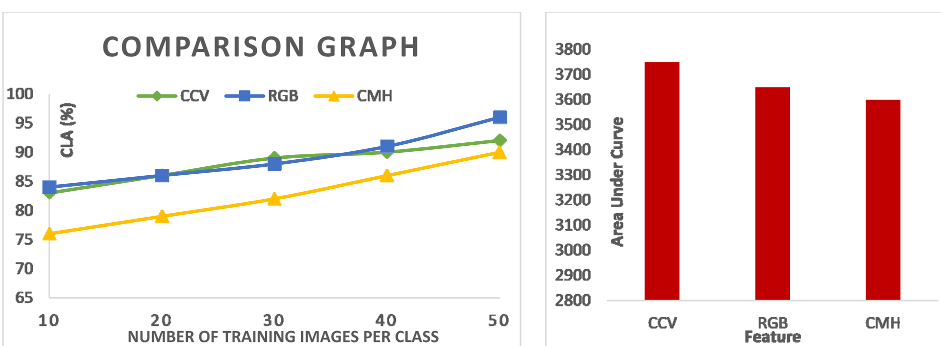
$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} * 100 \tag{21}$$

Figures 10(a to v) show the classification accuracy with an area under the curve (AUC) based on various feature extraction for classification of fruits and vegetables in the testing phase. The results are shown in the graph. In a graph, the x-axis represents the number of training image per class and y-axis represent the classification accuracy in percent. To evaluate the proposed system, we have calculated the average accuracy based on colour and texture descriptor based on C4.5 classifiers.

Figure 10 (a) represents the comparison graph of colour feature between CCV, RGB, CDH and also represent the AUC plot. Among all three colour feature, RGB performs better than other colour with value 96.1% accuracy rate. CDH descriptor produces poor results compared to RGB, CCV. The results with CCV show average performance among others. The performance of other colour feature CCV, RGB, CMH is represented in 10 (b) with AUC. In this, the highest CA is achieved by RGB. CMH show poor accuracy rate and CCV produce average performance among others. Figure 10 (c) represents the comparison graph of colour feature between CCV, CMH, CDH and also represent the AUC plot. Among all three colour feature, CCV performs better than other colour with value 92.05% accuracy rate. CDH descriptor produces poor results compare to CCV, CMH. The results with CMH show average performance among others.

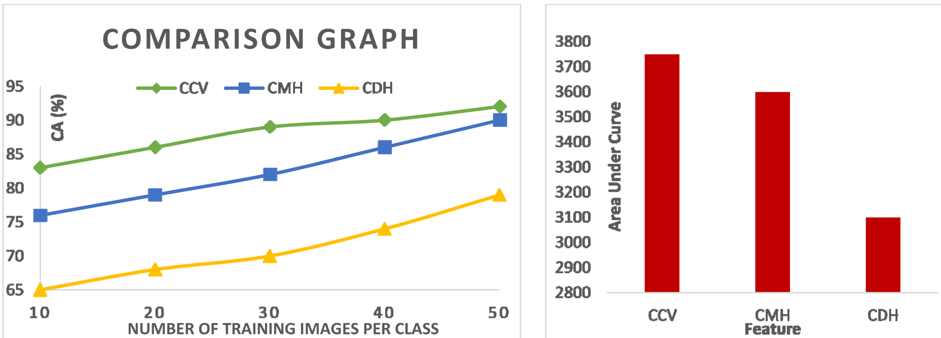
Figure 10 (a) Comparison between CCV, RGB, CDH (colour feature) using C4.5 (b) Comparison between CCV, RGB, CMH (colour feature) using C4.5 (c) Comparison between CCV, CMH, CDH (colour feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)

(a)



(b)

Figure 10 (a) Comparison between CCV, RGB, CDH (colour feature) using C4.5 (b) Comparison between CCV, RGB, CMH (colour feature) using C4.5 (c) Comparison between CCV, CMH, CDH (colour feature) using C4.5 with classification accuracy and AUC plot (continued) (see online version for colours)



s

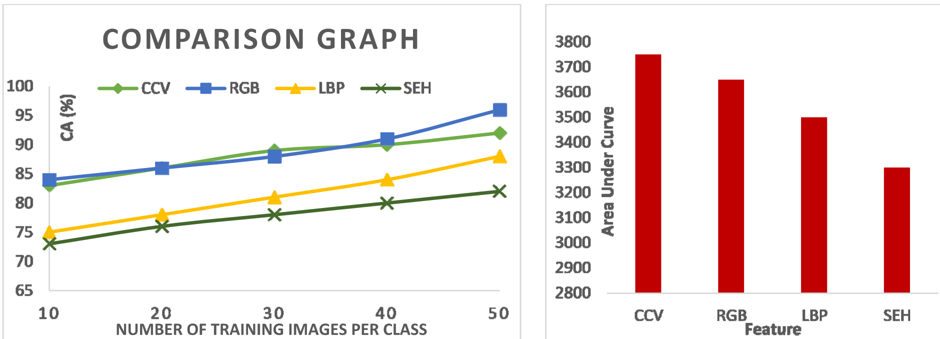
(c)

Figure 10(d) show the comparison graph of texture feature between LBP, SEH, CSLBP and also represent the AUC plot. Among all three texture feature, CSLBP performs better than other texture with value 97.01% accuracy rate. LBP descriptor produces poor results compare to CSLBP, SEH. The results with SEH show average performance among others. Figure 10(e) show the comparison graph of a combination of colour and texture between CCV, RGB, LBP, SEH with AUC plot. In that, with value 96.1 accuracy rate RGB produce better results compared to others. SEH show poor results compare to others. The results CCV, LBP show average performance. In figure 10 (f), The CSLBP show the highest accuracy with value 97.1%. LBP descriptor produces poor results compare to others. The results RGB, CCV show average performance among other descriptors.

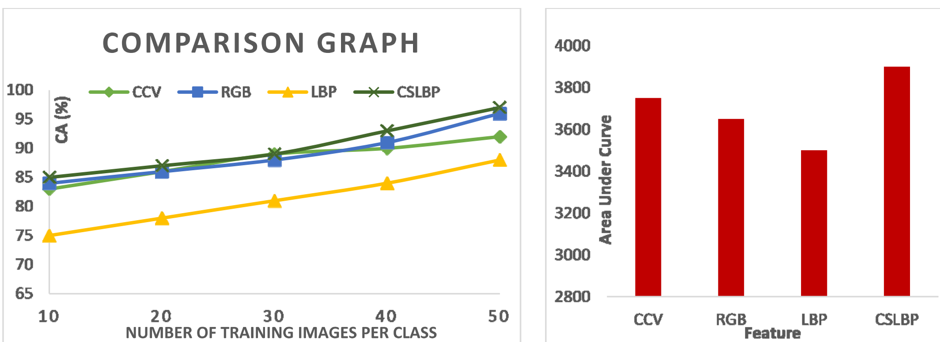
Figure 10 (d) Comparison between LBP, SEH, CSLBP (texture feature) using C4.5 (e) Comparison between CCV, RGB ,LBP, SHE (colour and texture feature) using C4.5 (f) Comparison between CCV, RGB ,LBP, CSLBP (colour and texture feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)

(d)

Figure 10 (d) Comparison between LBP, SEH, CSLBP (texture feature) using C4.5 (e) Comparison between CCV, RGB ,LBP, SHE (colour and texture feature) using C4.5 (f) Comparison between CCV, RGB ,LBP, CSLBP (colour and texture feature) using C4.5 with classification accuracy and AUC plot (continued) (see online version for colours)



(e)

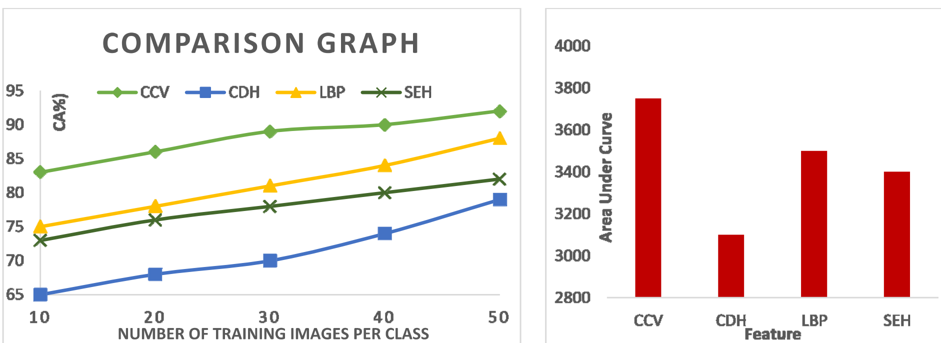


(f)

Figure 10(g) shows the comparison graph combination of colour and texture between CCV, RGB, SEH, CSLBP and also represent the AUC plot. Among all feature, CSLBP performs better than other texture with value 97.01% accuracy rate. SEH descriptor produces poor results compare. The results with RGB and CCV show average performance among others. Figure 10(h) CCV show better performance. The results with CDH show poor performance and LBP, SEH represent average accuracy rate. Figure 10(i) CSLBP descriptor shows the highest accuracy compared to other combination of colour and texture descriptor.

Figure 10 (g) Comparison between CCV, RGB, SEH, CSLBP (texture feature) using C4.5 (h) Comparison between CCV, CDH, LBP, SEH (colour and texture feature) using C4.5 (i) Comparison between CCV, CDH, LBP, CSLBP (Colour and Texture feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)

(g)



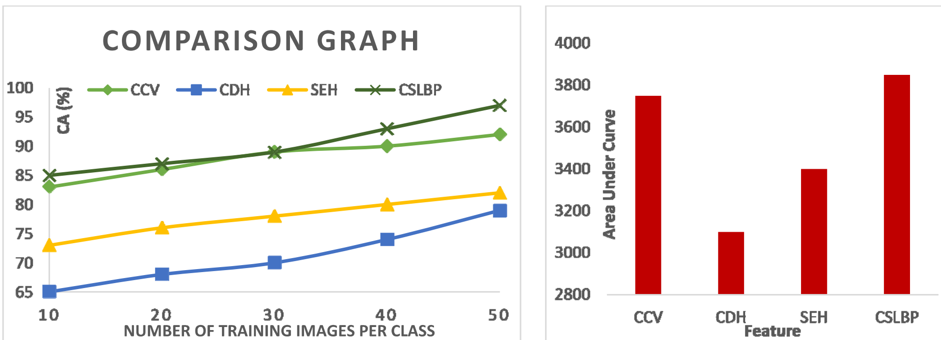
(h)

(i)

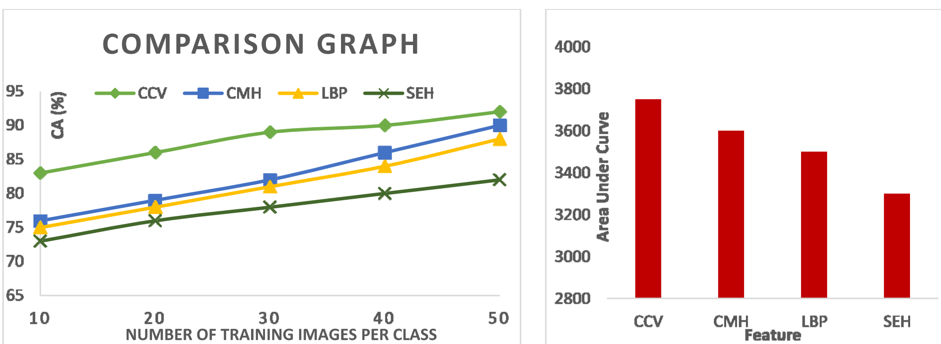
Figure 10(j) show the comparison graph combination of colour and texture between CCV, CDH, SEH, CSLBP and also represent the AUC plot. Among all feature, CSLBP performs better than other texture with value 97.01% accuracy rate. CDH descriptor produces poor results compare. The results with CCV and SEH show average performance among others. Figure 10(k) CCV show better performance. The results with

SEH show poor performance and CMH, LBP represent average accuracy rate. Figure 10(l) CSLBP descriptor shows the highest accuracy compared to CCH, CMH, LBP combination of colour and texture descriptor.

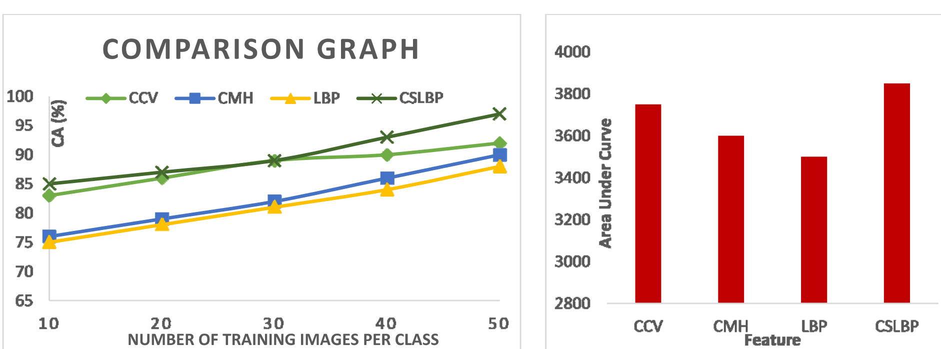
Figure 10 (j) Comparison between CCV, CDH, SEH, CSLBP (texture feature) using C4.5 (k) Comparison between CCV, CMH, LBP, SEH (colour and texture feature) using C4.5 (l) Comparison between CCV, CMH, LBP, CSLBP (colour and Texture feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)



(j)



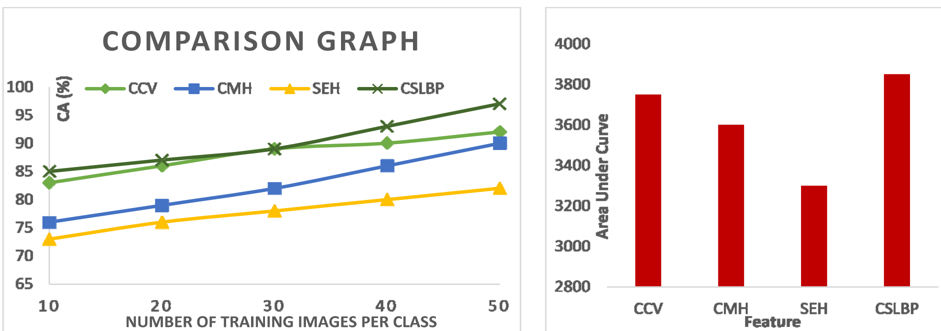
(k)



(l)

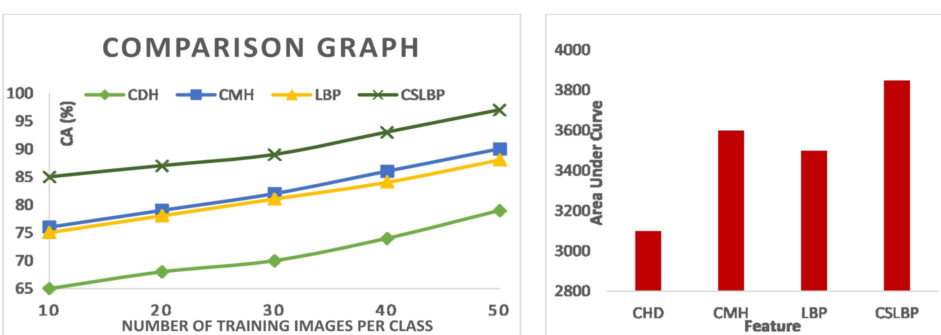
Figure 10(m) shows the comparison graph combination of colour and texture between CCV, CMH, SEH, CSLBP and also represent the AUC plot. Among all feature, CSLBP performs better than other texture with value 97.01% accuracy rate. SEH descriptor produces poor results compare to other descriptors. Figure 10(n) CMH show better performance. The results with CDH show poor performance and LBP, SEH represent average accuracy rate. Figure 10(o) CSLBP descriptor show the highest accuracy compared to CDH, CMH, LBP combination of colour and texture descriptor.

Figure 10 (m) Comparison between CCV, CMH, SEH, CSLBP (texture feature) using C4.5 (n) Comparison between CDH, CMH, LBP, SEH (colour and texture feature) using C4.5 (o) Comparison between CDH, CMH, LBP, CSLBP (colour and texture feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)



(m)

(n)

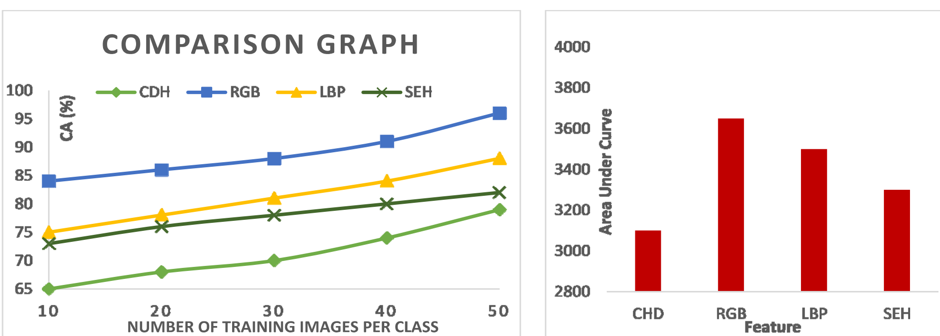


(o)

Figure 10(p) show the comparison graph combination of colour and texture between CDH, CMH, SEH, CSLBP and also represent the AUC plot. Among all feature, CSLBP performs better than other texture with value 97.01% accuracy rate. CDH descriptor produces poor results compare to other descriptors. Figure 10(q) RGB show better performance. The results with CDH show poor performance and LBP, SEH represent average accuracy rate. Figure 10(r) CSLBP descriptor show the highest accuracy compared to CDH, RGB, LBP combination of colour and texture descriptor.

Figure 10 (p) Comparison between CDH, CMH, SEH, CSLBP (texture feature) using C4.5 (q) Comparison between CDH, RGB, LBP, SEH (colour and texture feature) using C4.5 (r) Comparison between CDH, RGB, LBP, CSLBP (colour and texture feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)

(p)

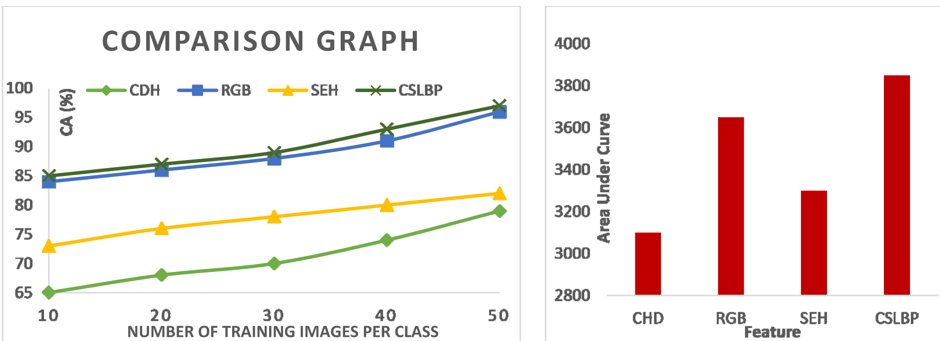


(q)

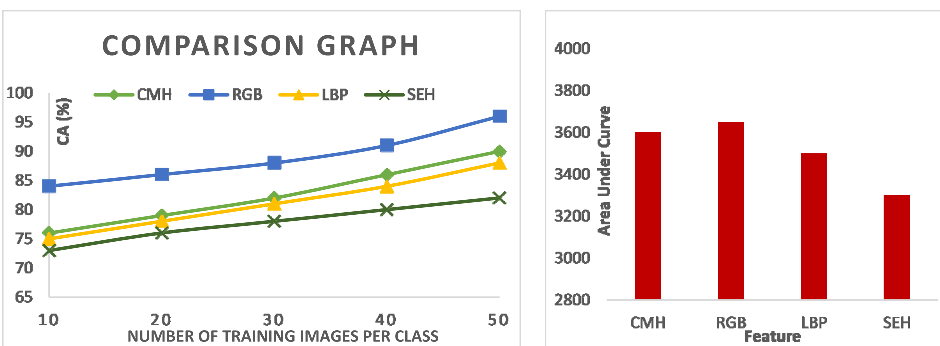
(r)

Figure 10(s) show the comparison graph combination of colour and texture between CDH, RGB, SEH, CSLBP and also represent the AUC plot. Among all feature, CSLBP performs better than other texture. Figure 10 (t) RGB show better performance. The results with SEH show poor performance and CMH, LBP represent average accuracy rate. Figure 10(u) CSLBP descriptor show the highest accuracy compared to CMH, RGB, LBP combination of colour and texture descriptor. Figure 10(v) CSLBP descriptor shows the highest accuracy compared to CMH, RGB, SEH combination of colour and texture descriptor.

Figure 10 (s) Comparison between CDH, RGB, SEH, CSLBP (texture feature) using C4.5 (t) Comparison between CMH, RGB, LBP, SEH (colour and texture feature) using C4.5 (u) Comparison between CMH, RGB, LBP, CSLBP (colour and texture feature) (v) Comparison between CMH, RGB, SEH, CSLBP (colour and texture feature) using C4.5 with classification accuracy and AUC plot (see online version for colours)

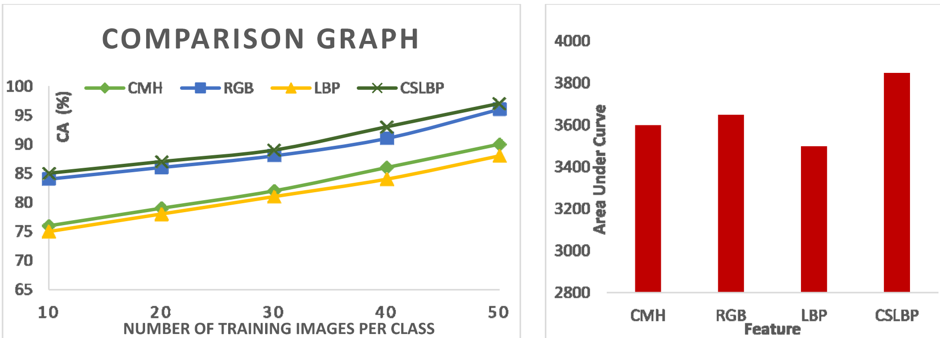


(s)

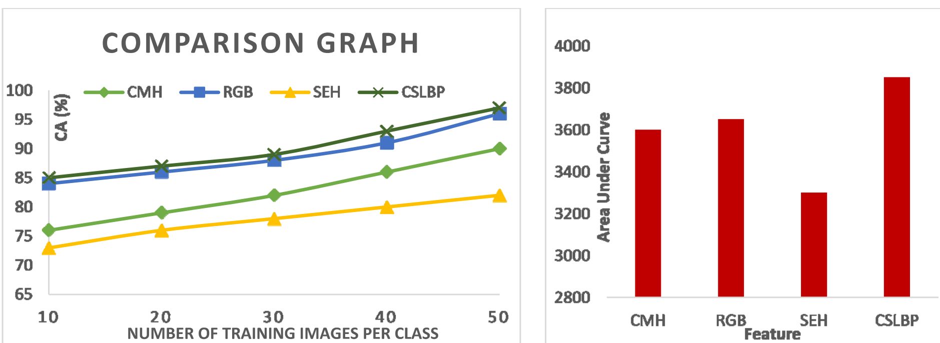


(t)

Figure 10 (s) Comparison between CDH, RGB, SEH, CSLBP (texture feature) using C4.5 (t) Comparison between CMH, RGB, LBP, SEH (colour and texture feature) using C4.5 (u) Comparison between CMH, RGB, LBP, CSLBP (colour and texture feature) (v) Comparison between CMH, RGB, SEH, CSLBP (colour and texture feature) using C4.5 with classification accuracy and AUC plot (continued) (see online version for colours)



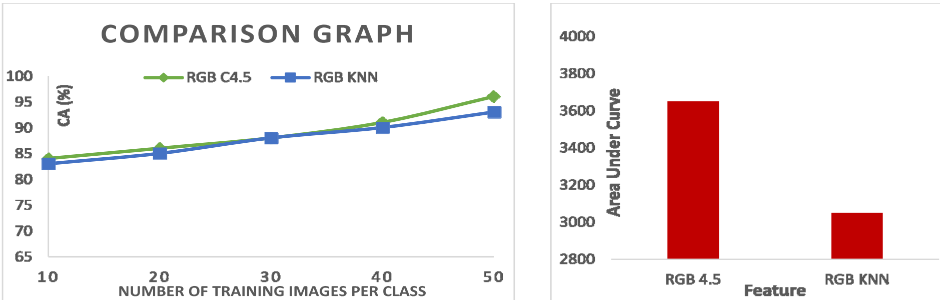
(u)



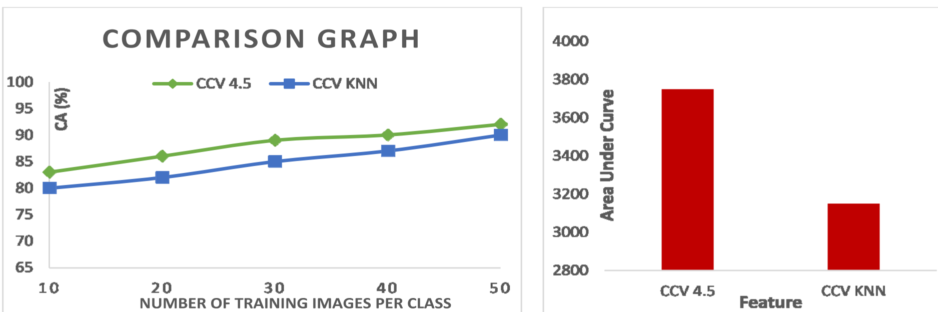
(v)

We have also evaluated RGB, CCV, CDH, CMH, LBP, CSLBP, SEH (colour and texture) using K-nearest neighbour (KNN) classifier. We have not represented the comparison graph and AUC because it fails to deliver better results compare to C4.5 in training and classification. Now, in Figures 11(a to g) show the performance comparison between C4.5 and KNN in training and classification for each colour and texture descriptor along with AUC plot.

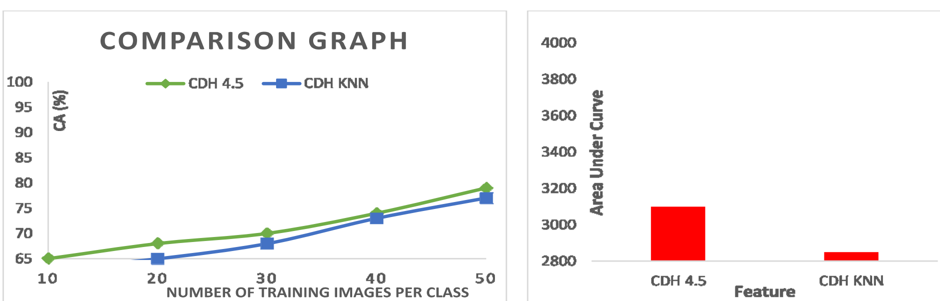
Figure 11 (a to g) Performance comparison between C4.5 and KNN classifier using RGB, CCV, CDH, CMH, LBP, CSLBP, SEH descriptor in the term of classification accuracy and AUC plot (see online version for colours)



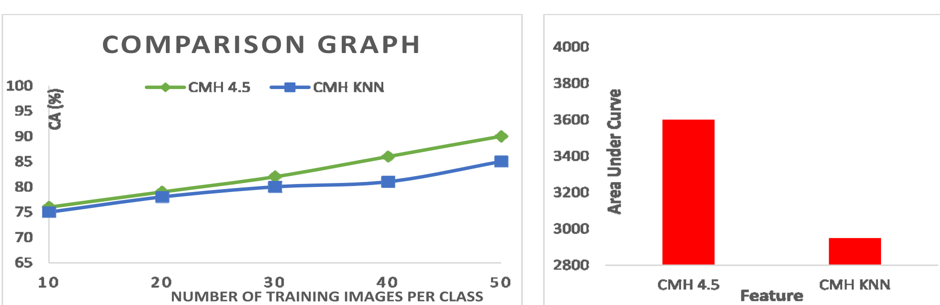
(a)



(b)

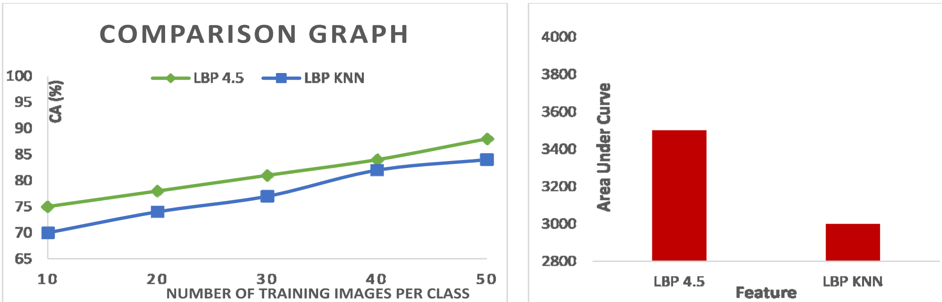


(c)



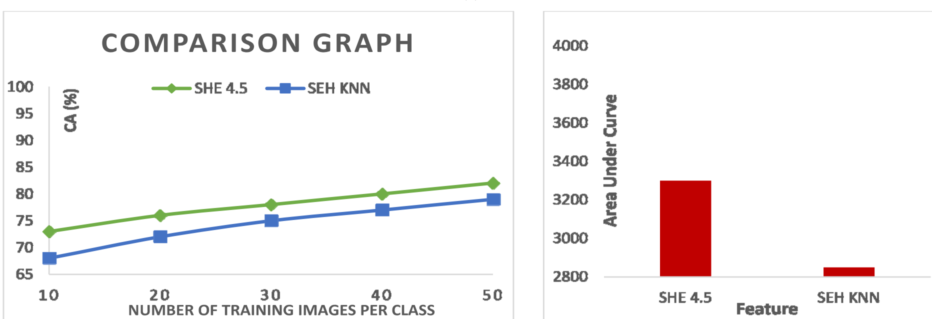
(d)

Figure 11 (a to g) Performance comparison between C4.5 and KNN classifier using RGB, CCV, CDH, CMH, LBP, CSLBP, SEH descriptor in the term of classification accuracy and AUC plot (continued) (see online version for colours)



(e)

(f)



(g)

In Figure 12, we have shown the categorical performance of each descriptor with C4.5 over each category of fruits and vegetables using various performances metric. The average accuracy, average Precision, average Recall, average F-measure, average MCC, average PRC, average FPR are represented by y-axis of Figure 12(a to g) respectively, and x-axis represents the categories of the fruits and vegetables. The fruits and vegetables categories apple, bitter melon, brinjal, chilli, cabbage, fig, khira, kundru, kiwi, onion, orange, pepper green, pepper red, pomegranate, tomato green, tomato red, sapodilla, sponge gourd, strawberry and watermelon are denoted by '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12', '13', '14', '15', '16', '17', '18', '19', '20' at x-axis.

Figure 12 (a) The categorical performance of each descriptor using average accuracy metric for each fruits and vegetables (see online version for colours)

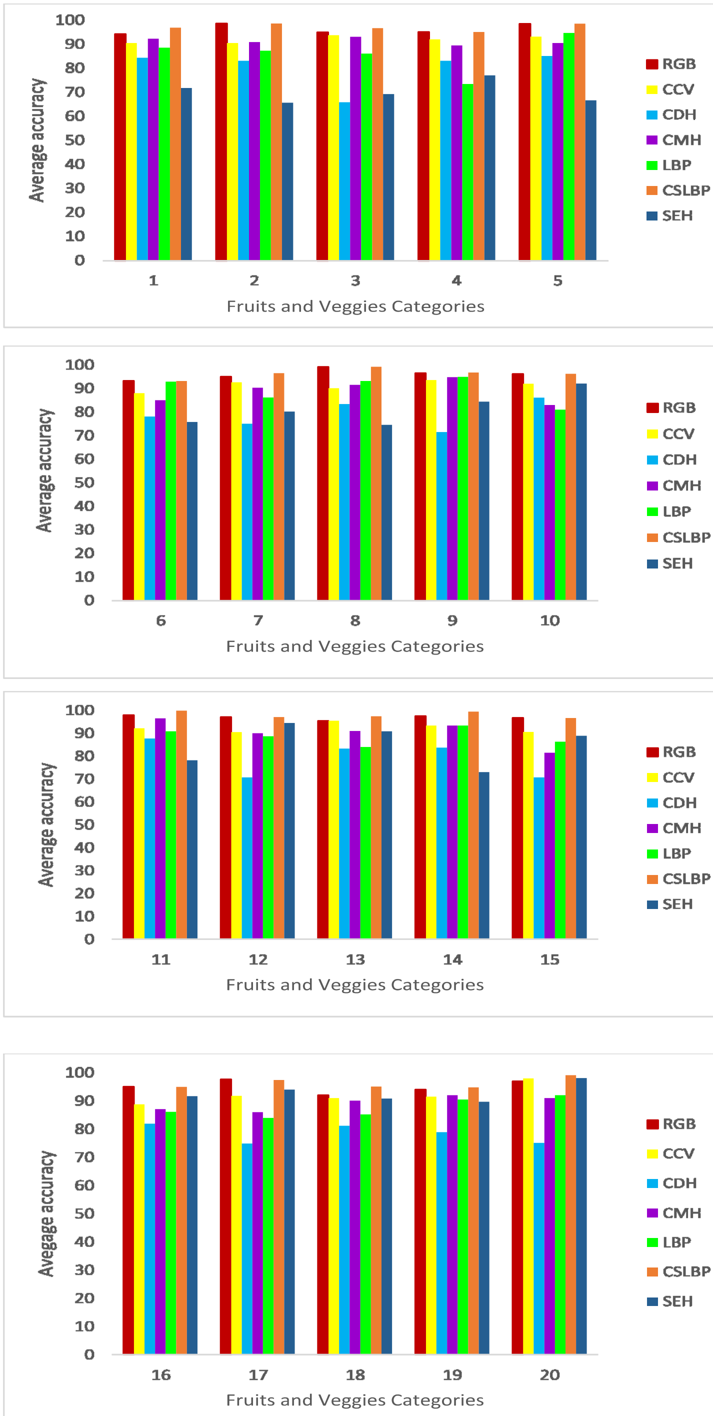


Figure 12 (b) The categorical performance of each descriptor using average precision metric for each fruits and vegetables (see online version for colours)

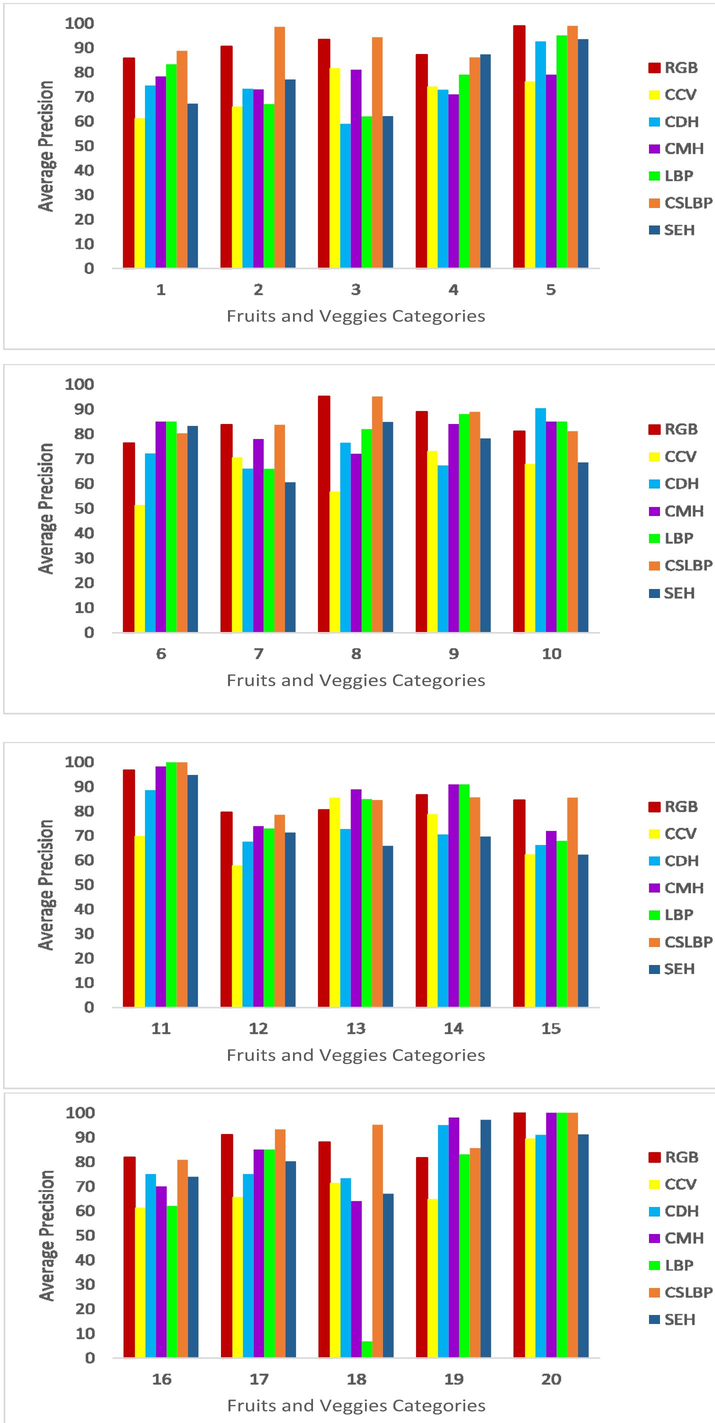


Figure 12 (c) The categorical performance of each descriptor using average recall metric for each fruits and vegetables (see online version for colours)

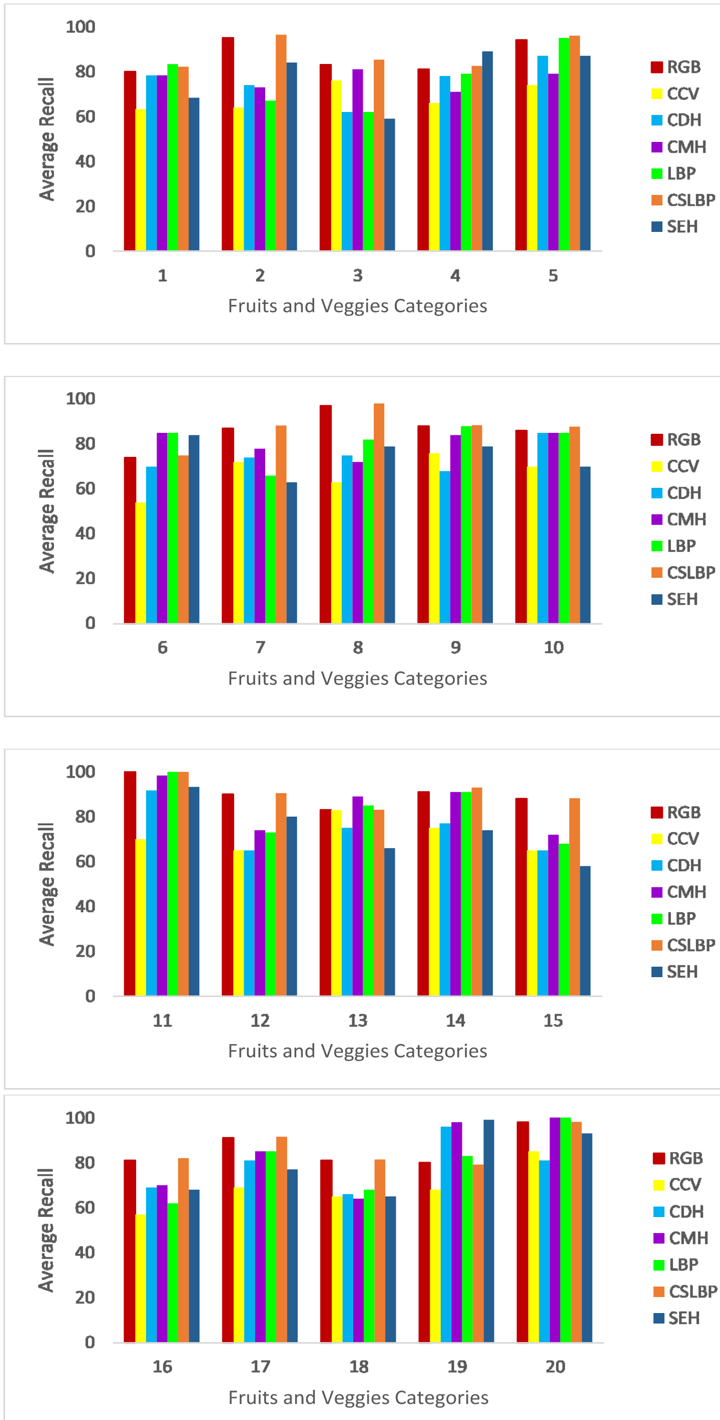
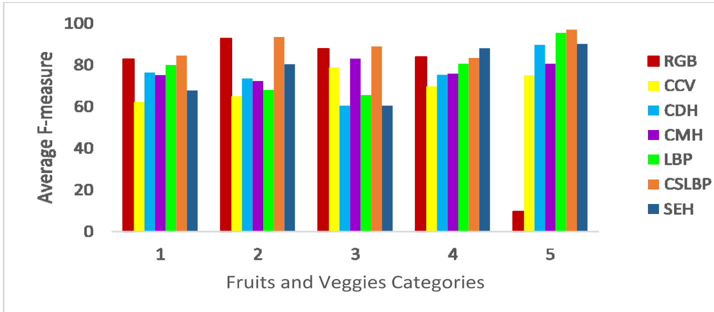
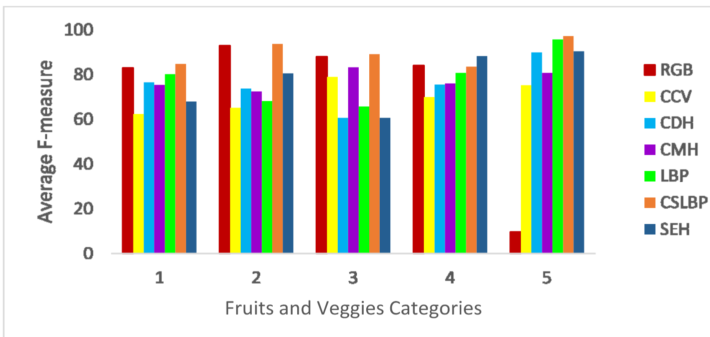
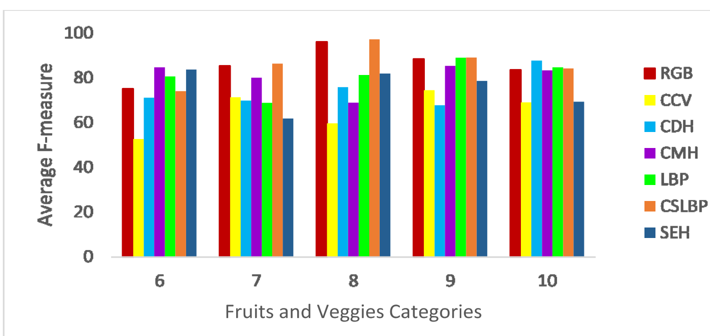


Figure 12 (d) The categorical Performance of each descriptor using average F-measure metric for each fruits and vegetables (see online version for colours)







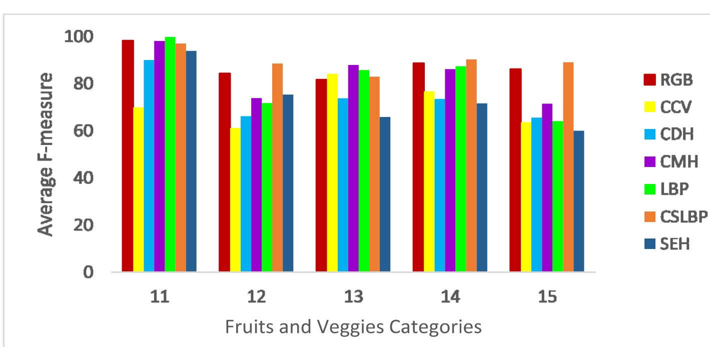


Figure 12 (e) The categorical performance of each descriptor using average Matthews correlation coefficient metric for each fruits and vegetables (see online version for colours)

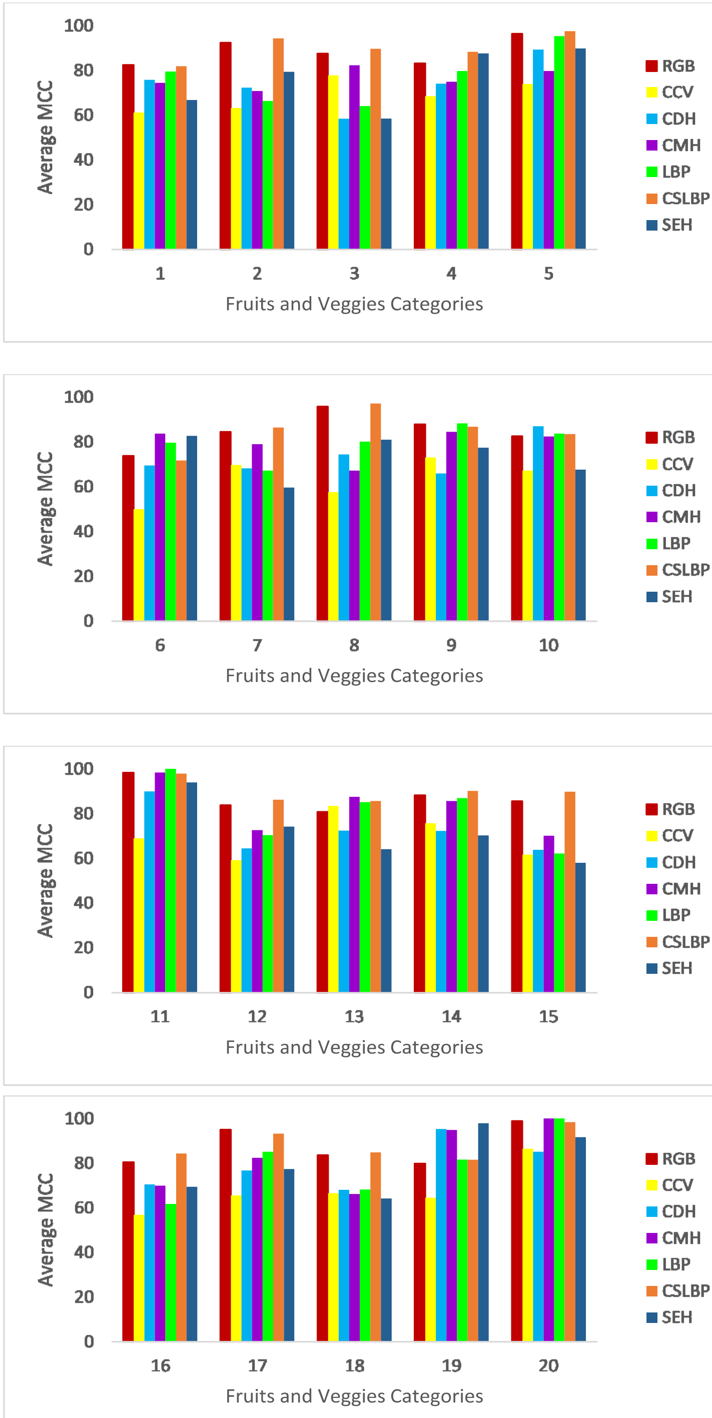


Figure 12 (f) The categorical performance of each descriptor using average precision recall curve metric for each fruits and vegetables (see online version for colours)

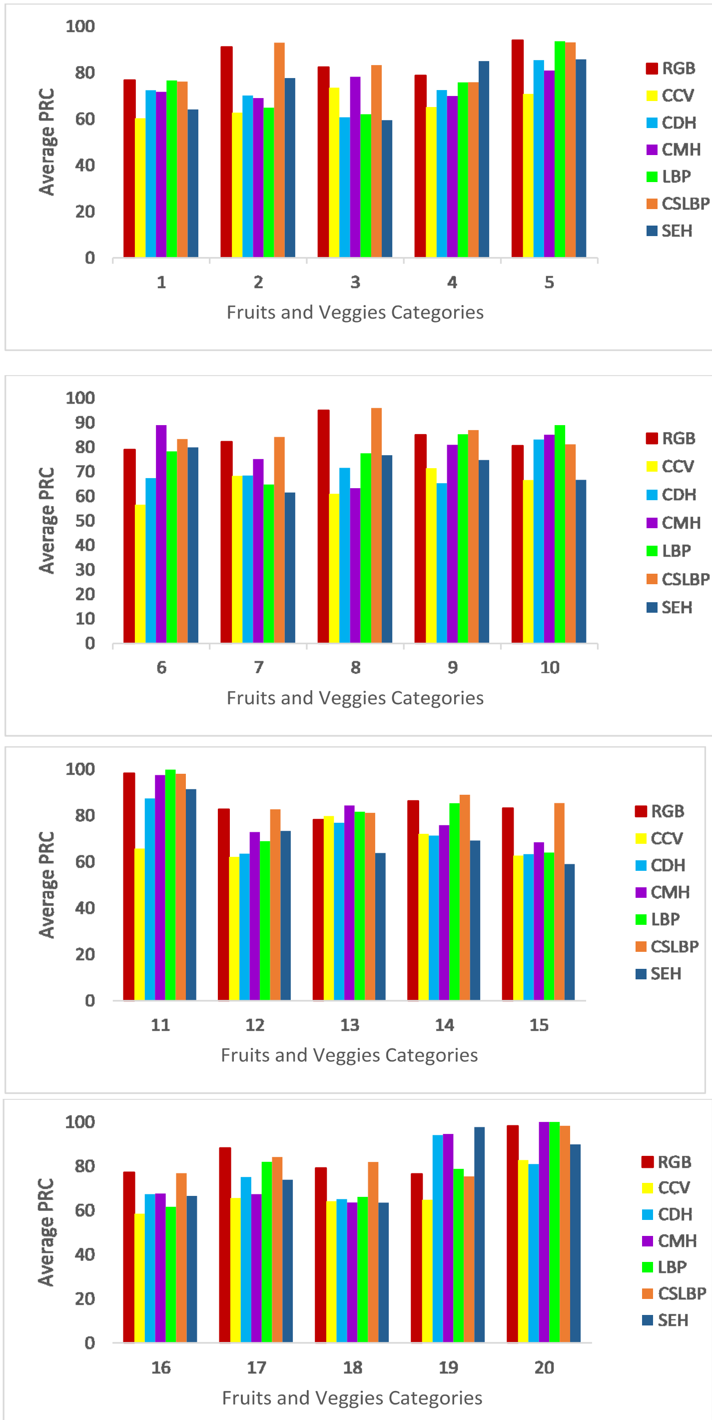
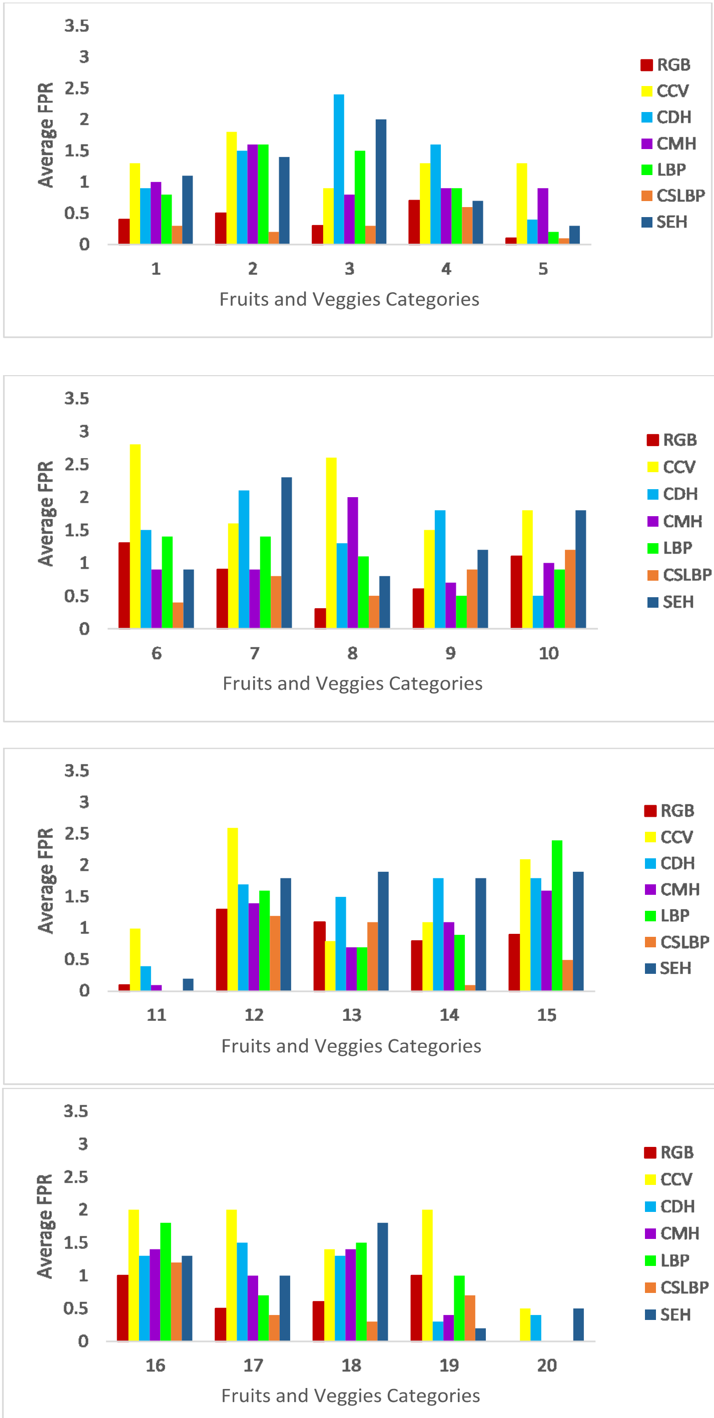


Figure 12 (g) The categorical performance of each descriptor using average false positive rate metric for each fruits and vegetables (see online version for colours)



Also, Table 1 and Table 2 show the metric wise performance over C4.5 and KNN classifiers. With both classifiers the accuracy rate is 96.62% and 90.25%. It means that system has achieved good enough recognition rate. Recall rate in both cases is 79.54%, 68.85% that means the rate of recognising fault-free samples is not so high. False positive rate in both case is low with value 2.49% and 4.63% respectively, which means it is good. Precision is 79.63% and 69.13% respectively; that means fault-free sample recognition rate is not so high. Comparison with existing fruit and vegetables recognition system based on performance accuracy rate is presented by Table 3.

Table 1 Results of metric wise performance over C4.5

Metric	*Value (%)*
Accuracy	94.63
Recall	79.5
Precision	79.63
F-measure	78.01
MCC	75.66
PRC	76.64
FPR	2.49

Table 2 Results of metric wise performance over KNN

Metric	*Value (%)*
Accuracy	90.25
Recall	68.86
Precision	69.12
F-measure	68.57
MCC	69.6
PRC	61.8
FPR	4.63

5 Comparative analysis of results

From the presented detailed experimental results of classification methods to solve the recognition of fruits and vegetables problem based on various descriptor. The following key point are drawn:

- CSLBP texture based descriptor has been shown better performance for the stated problem in both case, i.e., C4.5 and KNN.
- Colour based descriptor RGB, CCV, CDH, CMH has been shown better performance with C4.5 classifiers.
- With both C4.5 and KNN, for categories apple, brinjal, cabbage, khira, onion, pepper green, pepper red, strawberry, tomato green, tomato red, watermelon produces good accuracy rate, whereas better melon, kiwi, kundru, was unable to produce good recognition accuracy rate.

- Overall C4.5 classifiers are more suitable for training and classification of fruits and vegetables compare to KNN classifier.
- Lower dimension feature descriptor is generally more time efficient as compare to feature description with higher dimension.

Table 3 Comparison with existing fruit and vegetables recognition system based on performance accuracy rate

Year	*Dataset*	*Pre-processing*	*Classifiers*	*Accuracy rate*	*Ref.*
2019	20 category of fruits and vegetables	Otsu's based thresholding	C4.5	94.63%	Proposed
2018	5 different category of fruits	-	Linear SVM	92.71	Tu et al. (2018)
2017	Apple	Calyx detection	SVM	92.5%	Moallem et al. (2017)
2015	15 category of fruits and vegetables	K-means	MSVM	93.84%	Dubey and Jalal (2015)
2012	Citrus	Conversion to HSV	Morphological reconstruction using chromatic aberration map and hue map	92.6%	Tu et al. (2018)
2011	date fruit	Binarisation-based threshold	BPNN	80%	Al Ohali (2011)
2010	15 category of fruits and vegetables	Thresholding-based	minimum distance	86%	Rocha et al. (2010)
2009	Seven types of fruits	Manual area segmentation	KNN	90.0%	Zhu et al., (2013)

6 Conclusions

In this paper, we have presented the novel framework of fruits and vegetables recognition problem. One main contribution in this paper is that we have prepared the data set of 20 different categories of fruits and vegetables. The proposed framework consists mainly three phase such as segmentation, feature extraction, training and classification. The background of image is subtracted by using Otsu's based thresholding method. We extracted state of art from segmented images. further, this extracted feature of image is used for training and classification. In this paper, various performances metric is used to evaluate the performance of the proposed framework. We have also compare results of metric wise performance over C4.5 and KNN classifier. The experimental results indicate that C4.5 classifiers are more effective and produce better performance by all performance metric compare to KNN classifiers.

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Abbreviations

AUC	area under the curve	BPNN	back-propagation neural network
CA	classification accuracy	CCV	colour coherence vector
CDH	colour difference vector	CLBP	complete local binary pattern
CSLBP	centre-symmetric local binary pattern	FPR	false positive rate
GCH	global colour histogram	GDP	gross domestic product
KNN	k-nearest neighbours	LBP	global colour histogram
LTP	local ternary patterns	MCC	Matthews correlation coefficient
MLP	multilayer perceptron	MSVM	multi-class support vector machine
PRC	precision recall curve	RGB	red green blue
SEH	structure element histogram	SVM	support vector machine
SSLBP	Scale selective local binary pattern	USD	US dollar