Computers and Electronics in Agriculture 187 (2021) 106267

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Analysis of visual features and classifiers for Fruit classification problem

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A R T I C L E I N F O

Keywords:
Neural networks
Supervised learning
Fruit classification
K nearest neighbors classifier
Agricultural automation

A B S T R A C T

Analysis of visual cues for fruit classification and sorting allows to automate the visual inspection and packaging process in agricultural applications that is performed so far by human workers. Challenges for automated multi-class sorting systems are similarity in color and shape of different fruit varieties and variation among the same category of fruit. A major constraint in using well known deep neural networks for fruit classification arises because deep neural networks require large training datasets for achieving high accuracies which are generally not available in case of agricultural products especially various fruits and vegetable varieties. A thorough analysis is required to find an appropriate combination of various handcrafted features that could give precise and accurate classification results for small datasets. This paper investigates the use of various handcrafted visual features for fruit classification using traditional machine learning techniques. Different color, shape and texture features are analyzed by comparing the results obtained from six supervised machine learning techniques including K nearest neighbors, Support Vector Machines, Naïve Bayes, Linear Discriminant Analysis, Decision Trees and Feed forward back propagation neural network. We propose a novel combination of Hue, Color-SIFT, Discrete Wavelet Transform and Haralick features in fruit classification problem that outperforms other hand-crafted visual features. This feature combination is found to be invariant to rotation and illumination effects and works well with intra class variations providing good results for identifying subcategories of fruits along with high classification accuracies obtained for difficult fruit categories that are visually similar. It is found that Color-SIFT features alone work very well for fruit classification problem by outperforming other individual handcrafted features. Our approach is trained and tested on publicly available Fruits 360 dataset. Out of different classifiers best results are obtained using Back Propagation Neural Network, SVM and KNN classifier with classification accuracies between 99% and 100%.

1. Introduction

Automated fruit classification and sorting is an important application in the area of agricultural automation. Automated fruit classification systems can be used during harvest for fruit identification and differentiating between various types of fruits for picking with the help of robotic platforms. These can also be used during post-harvest quality assessment for packaging industry and fruit picking and price identification in supermarkets for fast billing. Efforts have been made to replace manual processes of fruit picking and sorting with automated systems which utilize both machine vision and machine learning techniques to improve fruit quality and productivity.

Since the classification accuracy largely depends on quality of features, several works have focused on comparing different set of features in the domain of various datasets. Many researchers have taken various approaches for fruit classification. Xiong et al. (2018) developed a grape detection algorithm for fruit picking robot under artificial lighting conditions. For segmentation of fruit images, they used Chan-Vese algorithm along with morphological processing techniques. Color features were extracted for both day and night time lighting conditions. After grape detection they used minimum bounding rectangle and Hough Line detection to find the picking point of fruit. The accuracy of their system was 92%. Katarzyna and Pawel performed fruit classification for retail sales systems in supermarkets. They proposed a 9 layered deep neural network to perform classification of six apple varieties. They reported an accuracy of 99.78% (Katarzyna and Paweł, 2019). Kumari and V. Gomathy have used color and texture features for fruit classification. They have performed thresholding in HSV color space to extract region

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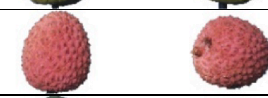
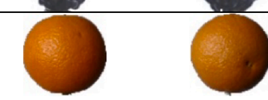
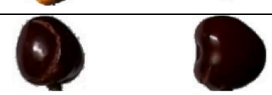
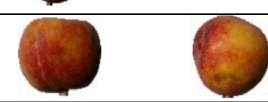
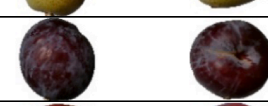
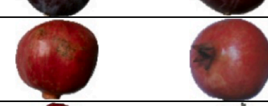
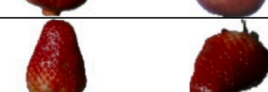
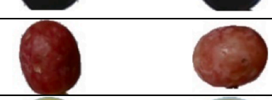
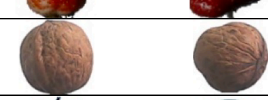
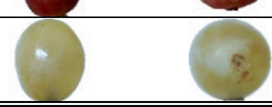
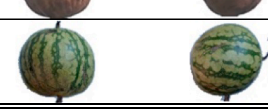
https://doi.org/10.1016/j.compag.2021.106267
Received 4 February 2021; Received in revised form 19 April 2021; Accepted 9 June 2021
Available online 26 June 2021

Table 1
Classes of Fruits with Sample images.

Sr#	Fruit category	Sample image 1	Sample image 2	Sr#	Fruit category	Sample image 1	Sample image 2
1	Apple Braeburn			16	Guava		
2	Apple Golden 1			17	Lemon		
3	Apple Golden 2			18	Lime		
4	Apple Pink Lady			19	Lychee		
5	Apple Red 1			20	Mango		
6	Apricot			21	Mulberry		
7	Banana			22	Orange		
8	Carambula			23	Papaya		
9	Cherry 1			24	Peach		
10	Cocos			25	Pear		
11	Dates			26	Plum		
12	Fig			27	Pomegranate		
13	Grape Blue			28	Strawberry		
14	Grape Pink			29	Walnut		
15	Grape White			30	Watermelon		

of interest. Then they extracted color features from hue and saturation channels and texture features from luminance channel after applying three level discrete wavelet transform. They classified 10 fruit classes from Supermarket produce dataset using SVM classifier. Their system had an accuracy of 95.3% (Kumari and Gomathy, 2018). De Goma et al (2018) extracted color, size, shape and texture features from fruit images of fifteen classes. They compared the performances of four classifiers including KNN, Naïve Bayes, Decision Trees and Bagging classifier. Best results were reported for KNN classifier with 81.9% accuracy. Patel and Chaudhari (2019) also compared various widely used machine learning techniques for fruit classification. Six fruit categories were considered including apple, banana, orange, pear, watermelon and mango. They used thresholding and morphological processing for finding area of interest. Extracted features included area, color, centroid, zone, perimeter, size and roundness. Classifiers used were KNN, SVM, Naïve Bayes, random forest and neural network. Best accuracy reported was 91.67% for SVM classifier which outperformed the other classifiers. A CNN based classifier was developed by Sakib, Ashrafi and Siddique which was able to recognize 25 classes of fruits on Fruits 360 dataset with 100% test and 99.79% train accuracies (Sakib et al., 2019). Nosseir and Ahmed (2019) developed an algorithm to classify four fruit types and to detect rotten fruit from fresh. Fruit type identification was based on color and texture features using KNN classifier. Rotten fruit classification was performed using SVM classifier. Hossain et al. (2019) compared two deep learning architectures including a six layered CNN and a VGG-16 pre-trained deep learning model, on two datasets. Highest accuracy achieved on supermarket produce dataset was 99.75% and 96.75% on self-collected dataset using VGG 16 model. Jana and Parekh (2017) classified seven fruit classes based on shape features in context of auto harvesting. The shape features included fruit area, perimeter, major and

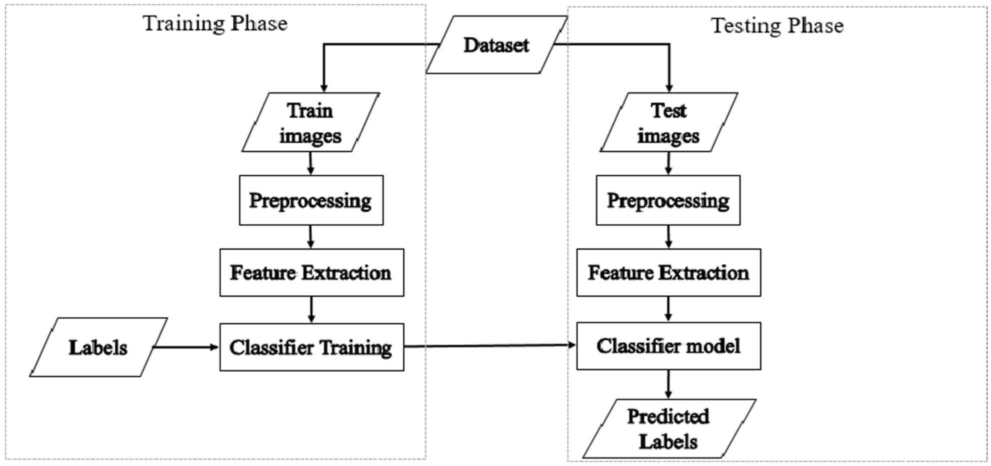


Fig. 1. Flowchart of the generalized framework for classification.

minor axes lengths; distance between the foci of an equivalent ellipse; minimum bounding box width, height and area and perimeter and area of smallest convex polygon. Images were obtained using smart phone camera and from websites. Highest accuracy reported was 95% using Naïve Bayes classifier. Macanhã et al. have classified 15 fruit classes based on two feature descriptor methods. Their dataset composed of images of fruits with white background obtained through the internet. They used zoning and character edge descriptor features combined with Discrete Fourier Transform. MLP and KNN were used as classifiers. Best accuracy achieved was 97.5% (Macanhã et al., 2018). Rojas-Aranda et al classified apples, oranges and banana by adding color based features as input to a CNN along with the input images to improve the accuracy of the classifier. The dataset was collected using the camera of an iPhone device. The CNN architecture used was MobileNetV2. The highest accuracy reported was 95% (Rojas-Aranda et al., 2020).

Current study is aimed at designing a robust, efficient, and repeatable system for classifying various categories of fruits from images using handcrafted features. Handcrafted refer to the features that are extracted manually based on data present in the image for example edges, corners, histograms etc. Widely used deep neural networks that utilize automatically learned features face the problem of requiring a huge amount of training data per class to achieve good classification results which, in the case of agricultural products like fruits and vegetables, is usually unavailable. Many research reporting the use of handcrafted features and traditional machine learning techniques in the area of fruit classification still have room for improvement regarding accuracy and repeatability of classification algorithms. It is anticipated that a rightful combination of handcrafted features should give better accuracies for a dataset with less data per class. Another objective is to compare the performances of some widely used supervised learning techniques to find the best performing classifier for fruit classification using handcrafted features. By extracting suitable features and using an efficient classifier, reasonable contributions are intended to be made in the field of automated fruit classification and sorting. After rigorous experimentations and analysis of various color, shape and texture features we propose a novel combination of Hue, CSIFT, Discrete Wavelet Transform and Haralick features that achieves high accuracies in fruit classification problem.

Rest of the paper is arranged as follows: Section 2 describes the proposed methodology in detail. Details of the results are given in Section 3. Section 4 briefly discusses the observations extracted from the results. Finally, conclusions are drawn in Section 5.

2. Materials and methods

The dataset selected for the proposed research is Fruits-360 which is available freely from (Muresan and Oltean). The dataset has 131 fruit and vegetable classes containing total 90,483 images. The images were collected by rotating the fruit/vegetable using a slow speed motor shaft in front of a white paper sheet placed as a background. In the current study, 30 fruit categories that are commonly available in South Asian markets are selected for classification purpose. Table 1 gives details of the fruit classes along with some sample images from the dataset. Flowchart of the generalized image processing-based decision making framework is given in Fig. 1.

2.1. Preprocessing

It is important to extract fruit region from the image using image segmentation techniques so that relevant features can be extracted for classification purpose. Thresholding and Morphological processing are used for image segmentation. Initially, a Gaussian smoothing filter with standard deviation of 0.2 is applied on the images to reduce noise and illumination effects. Then images are converted to grayscale and hard thresholding is applied to convert the gray images to binary.

Erosion is then applied followed with dilation with a disk type structuring element. The size of the disk is determined heuristically. These operations are performed in order to remove stalks and to extract the fruit region of interest.

2.2. Feature extraction

Selecting appropriate features is a very important step in any classification problem since the efficiency of the classifier largely depends on the relevancy of features. As per the literature review, mostly used features for fruit classification are color, size, width & height of fruit, texture and shape features. Out of these, size, width and height of fruit cannot be used for Fruits 360 dataset as the collectors of dataset have not taken images from a constant distance instead, they have moved the camera to fit the fruit in the frame hence a cherry appears to be of same size as a watermelon. Three types of features are analyzed in this study.

2.2.1. Color features

Color of the fruit is a distinguishing feature that has been extensively used by the researchers for classification. In this research, color information is found by extracting two types of color features present in the fruit region.

(a) Dominant Hues: Hue represents the type or more specifically the tone of a color. It ranges from 0° to 359°. In current study, K-means clustering technique is used to find three dominant hues in the color image. Hue value corresponding to the background is ignored while two hue values corresponding to two dominant shades in the fruit area are extracted as features. The formula used for hue calculation is given in equation (1) (Loesdau et al., 2014).

(b) Color SIFT Features: CSIFT (Abdel-Hakim and Farag, 2006) is a color invariant local feature descriptor which is used for describing objects in an image. It combines the color and geometric information of the object as compared to conventional SIFT descriptors which use only geometric information. Color descriptor software created by Koen van de Sande (Van de Sande et al., 2011) is used to extract Color-SIFT features. Dense Sampling with a spacing of 6 pixels and scale of 1.2 is used for computing the SIFT descriptors. The length of standard SIFT descriptor is 128 which in case of Color-SIFT is increased by a factor of 3 so that the length of CSIFT descriptor becomes 384. The feature vector obtained has a dimension of 285 $\times$ 384 for each image which is reduced by taking mean along the columns and then applying Principal Component Analysis (PCA) to obtain a final feature vector of dimension 1 $\times$ 20 per image. The final dimension is selected after experimentation to achieve best classification accuracy.

$$H = \begin{cases} 0 & R = G = B \\ 60^*\left(0 + \dfrac{(G-B)}{max(R,G,B) - min(R,G,B)}\right) & R = max(R,G,B) \\ 60^*\left(2 + \dfrac{(B-R)}{max(R,G,B) - min(R,G,B)}\right) & G = max(R,G,B) \\ 60^*\left(4 + \dfrac{(R-G)}{max(R,G,B) - min(R,G,B)}\right) & B = max(R,G,B) \end{cases} \tag{1}$$

2.2.2. Texture features

Texture features contain information regarding spatial arrangements of intensities in the image. Two types of Texture features are analyzed.

(a) Statistical Texture Features: Gray Level Co-occurrence Matrix is calculated for each image. Then seven Haralick statistical features are extracted including homogeneity, contrast, correlation, variance, sum average, sum variance and information measure of correlation 1. Formulae and further details of Haralick features can be seen from (Löfstedt et al., 2019).

(b) Signal Processed Texture Features: Texture features can be extracted after transforming the image into frequency domain using Discrete Wavelet Transform (DWT) (Graps, 1995). Daubechies db1 wavelet is used for calculating single level 2D Discrete Wavelet Transform of the gray level image after segmentation. DWT features include approximation coefficients and diagonal detail coefficients. For an image of size 100 $\times$ 100, the size of approximation and detail coefficients matrices is 50 $\times$ 50 each. Mean vectors of both approximation and detail coefficients are calculated along the columns and combined to form a feature vector of size 1 $\times$ 100. PCA is then applied on this feature vector for dimensionality reduction to get a final DWT feature vector of size 1 $\times$ 7 for one image. New dimension value is selected after performing various experimentations by varying dimensions of the feature vector and by selecting the value for which best accuracy is achieved.

Table 2
Features and Classifiers used for Analysis.

Features	Classifiers
Hue (Loesdau et al., 2014)	SVM (Chamasemani and Singh, 2011)
CSIFT (Abdel-Hakim and Farag, 2006)	KNN (Cunningham and Delany, 2007)
Haralick (Löfstedt et al., 2019)	Naïve Bayes (Kaviani and Dhotre, 2017)
DWT (Graps, 1995)	Decision Trees (Swain and Hauska, 1977)
HOG (Dalal and Triggs, 2005)	LDA (Tharwat et al., 2017)
	BPNN (Sazli, 2006)

2.2.3. Shape features

Histogram of Oriented Gradients (HOG) (Dalal and Triggs, 2005) feature descriptor is used to extract shape based features from the images. 1764 HOG features are extracted for each image using a cell size of 12 $\times$ 12. To reduce the feature vector size, PCA is applied and the number of features is reduced to 50 after experimenting with various dimensions and selecting the one based on the best results achieved.

After calculating all the features, experiments are performed to analyze the effect of features individually and in combination with other features on the classification accuracy.

2.3. Image classification

Classifier selection is an important step because the set of same features may produce different results for different classification techniques. In this study, supervised machine learning techniques are used for the prediction of class of the fruit. Following six classifiers are selected and the performance is compared.

2.3.1. Multiclass Support Vector Machine (SVM)

SVM is a binary classifier that finds an optimal hyperplane using given training data to classify the unseen data. For multiclass problems, approach is to reduce the problem to multiple binary classification problems (Chamasemani and Singh, 2011). Multiclass learning is implemented using one vs one coding design. A linear kernel function is used.

2.3.2. K nearest neighbor (KNN)

KNN classifier assigns a class to the test sample based on majority voting from its k nearest neighbors. Neighbors are found using some distance metric with Euclidean distance being a commonly used distance metric (Cunningham and Delany, 2007). In this research, value of k is set as 1 for classification purpose. The value of k is found by adjusting experimentally until the lowest error is achieved. Euclidean distance is used as the distance metrics to find neighbors.

2.3.3. Naïve Bayes Classifier (NB)

Naïve Bayes classifier is based on Bayes theorem. Learning is greatly simplified by assuming that features are independent of each other (Kaviani and Dhotre, 2017). The probability density of predictors is estimated using normal distribution.

2.3.4. Decision Trees (DT)

Decision tree algorithm (Swain and Hauska, 1977) performs classification by learning simple rules inferred from the features. The data is split at decision nodes while the leaves are the final outcomes. Gini Diversity Index (GDI) is selected as the splitting criteria for DT in this research.

2.3.5. Linear Discriminant Analysis (LDA)

LDA (Tharwat et al., 2017) is a commonly used technique for dimensionality reduction and classification problems. Mean and covariance for a Gaussian distribution is estimated for each class during classifier training. The test sample class is predicted based on lowest error.

2.3.6. Feed Forward Back Propagation Neural Network (BPNN)

In feed forward neural networks, the signals flow from input to output in one direction through hidden layers. When the neural network is trained using a back propagation algorithm it is called feed forward backpropagation neural network (Sazli, 2006). In this study BPNN with 12 hidden layer neurons with sigmoid activation function is used for classification purpose. Number of hidden layer neurons are selected

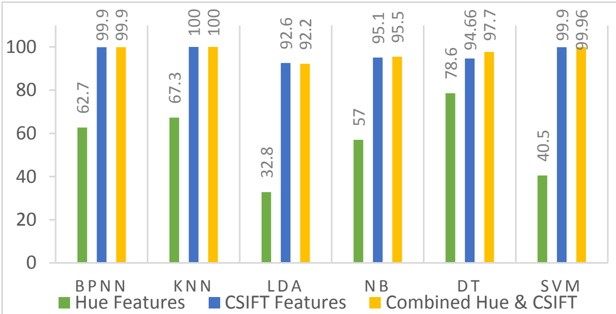


Fig. 2. Comparison of Accuracy for 30 fruit classes using color features.

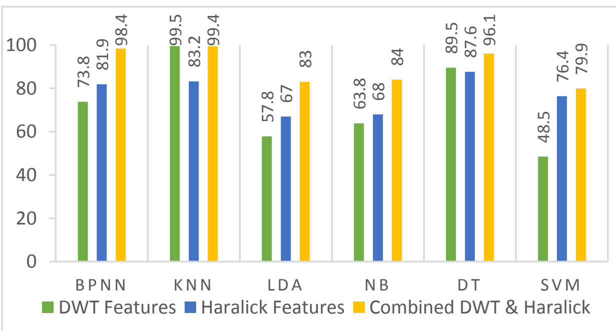


Fig. 3. Comparison of Accuracy for 30 fruit classes using Texture features.

after performing various experimentations by varying the number of hidden layer neurons and by selecting the value for which best accuracy is achieved. The output layer has neurons with softmax function. 50% of the data was used for training, 15% was for validation and 35% for testing purpose.

Table 2 summarizes the features and classifiers analyzed in this study. The two phases of classification problem are:

(1) *The Training phase:* Training feature vector is obtained by combining feature vectors of all the training images. These features are then used to train previously mentioned classifier models one by one.
(2) *The Testing phase:* Feature vectors for the test images are obtained and fed to the classifier model obtained in training phase to get the final prediction of the test image class.

3. Results

Fruit classification is performed using two-fold cross validation and mean accuracy is found. Results for all classifiers are calculated and compared.

3.1. Analysis of color features for fruit classification

Fig. 2 gives a comparison of accuracy with only color features used for classification. It is observed that incase of using Hue features alone for classification, accuracy of all the classifiers remains low while for CSIFT 100% accuracy can be achieved with KNN classifier. SVM and BPNN also give 99.9% results. All the classifiers show good accuracies when both types of color features are combined.

3.2. Analysis of texture features for fruit classification

Fig. 3 gives accuracies obtained for both types of texture features separately as well as after combining. Results show that relatively lesser accuracy values are obtained for all classifiers as compared to color features. Highest accuracy is from KNN classifier.

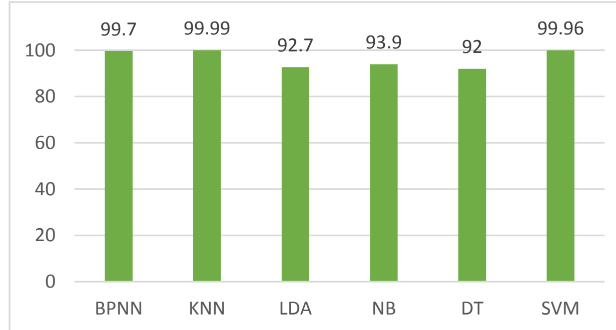


Fig. 4. Comparison of Accuracy for 30 fruit classes using Shape features.

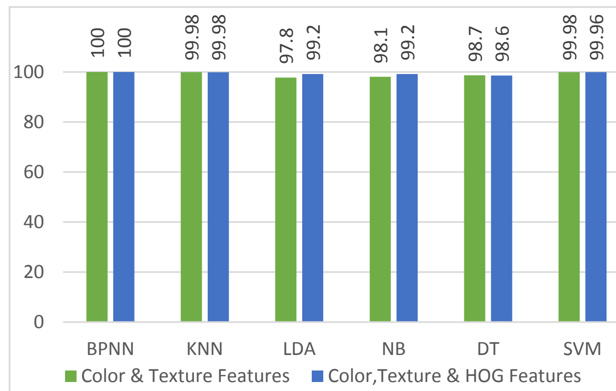


Fig. 5. Comparison of Accuracy for 30 fruit classes using combinations of features.

Table 3
Running Time for various classifiers for both feature combinations.

Classifier	Color & Texture Features	Color, Texture & HOG Features
BPNN	9 s	8 s
KNN	76.8 s	175.4 s
LDA	1.04 s	2.03 s
NB	1.08 s	2.7 s
DT	1.16 s	2.74 s
SVM	20.96 s	27.7 s

3.3. Analysis of shape features for fruit classification

Accuracy of HOG shape features is given in Fig. 4. In this case, BPNN, SVM and KNN give better performance as compared to LDA, NB and Decision Trees.

3.4. Analysis of feature combinations for fruit classification

To analyze the effect of using various combination of features on the accuracies of different classifiers, first color and texture features are combined and tested and then HOG features are also combined with color and texture features. Fig. 5 provides details of accuracies obtained by using both type of feature combinations while table 3 gives the running time for training and testing the classifiers using two-fold cross validation.

BPNN classifies 30 classes of fruits with 100% accuracy for both types of feature combinations. SVM and KNN also reach more than 99.9% for both types of feature combinations. In case of LDA and NB,

Table 4
Percentage (%) Sensitivity values for 30 fruit classes for various feature combinations and classifiers. The empty cells correspond to 100% sensitivity. The values are omitted for better readability and clarity.

	Color & Texture Features						Color, Texture & HOG Features					
Fruit category	**BPNN**	**KNN**	**LDA**	**NB**	**DT**	**SVM**	**BPNN**	**KNN**	**LDA**	**NB**	**DT**	**SVM**
Apple Braeburn			92.5	87.2	96.5					98.5	97.3	
Apple Golden 1			99.7	99.7	99.2						99.2	
Apple Golden 2			98.8	99.7		99.8						
Apple Pink Lady			98.4	98.5	98.7						99	
Apple Red 1			96.5	95.4	93.9					94.8	96.7	
Apricot			95.4	93.6	98.9				99	99	98.7	
Banana		99.9	99.9	99.4	98.6				99.1		96.6	
Carambula			95.7	97.8	97.4						97.8	
Cherry 1					99.5		99.8				99.8	
Cocos				99.8	99.5				99.8	98.8	99.5	
Dates			91.2	99.8	98.8				94.3	98.3	99.4	
Fig			99.3		99.7						99.6	
Grape Blue				99.2	99.8					99.9	98.9	
Grape Pink				99.2	97.3					98.8	95.4	
Grape White												
Guava					98.5						98.8	
Lemon					98.8						98.3	
Lime			99.8									
Lychee					99.7							
Mango											99.8	
Mulberry				99.4	97.7					99.7	98.9	
Orange					100						97.7	
Papaya			95.6	98.5	98.6				98	99.1	99	
Peach			92.7	94.4	96.8				95.1		94.5	
Pear			97.6		99.1						97.4	
Plum		99.7		99.7	99	99.7		99.7			99.7	99.7
Pomegranate		99.8	82.8	90.8	96.9	99.8		99.7	92.1	92.7	96.5	99.7
Strawberry			97.4	91	97.9				98.6	98	99.4	
Walnut					99.9						99.5	
Watermelon											99.5	

Table 5
Percentage (%) Precision Values for Color and Texture Feature Combination for various Classifiers. The empty cells correspond to 100% precision. The values are omitted for better readability and clarity.

	Color & Texture Features						Color, Texture & HOG Features					
Fruit category	**BPNN**	**KNN**	**LDA**	**NB**	**DT**	**SVM**	**BPNN**	**KNN**	**LDA**	**NB**	**DT**	**SVM**
Apple Braeburn			87.8	80.8	95.6				94	90.8	96.1	
Apple Golden 1			98.6		99.5						98.5	
Apple Golden 2					99.5						99.7	
Apple Pink Lady					98.7						99	
Apple Red 1			84.2	90.3	95.8				93.8	96.4	93.5	
Apricot				98.4	99.4					98.8	99.4	
Banana					98.9						98.1	
Carambula				99.7	97.4						96.8	
Cherry 1				99.8	99.4						99.2	
Cocos		99.8			98.8						98.2	
Dates				99.4	98.2					99.7	98	
Fig				99.3	99.3					98.9	99.7	
Grape Blue					99.7						99.8	
Grape Pink			93.1	95	98.8				98.2		97.6	
Grape White						99.8						
Guava			99.8								99.9	
Lemon					99.4						99.5	
Lime			99.7								99.5	
Lychee				99.7	99.3						98	
Mango			96.6									
Mulberry					99.2						99	
Orange					98.8						98.6	
Papaya			98.3	91.1	97.9				97.9	98	98	
Peach			89	96.9	96.5				98.9	99.4	95.1	
Pear					97.9						99.4	
Plum			91.2		98.3		99.8	99.8	94.4	99.3	99.5	99.8
Pomegranate		99.7	99	96.9	97.7	99.7		99.7		98.4	98	99.7
Strawberry				98.7	97.3				99.8	98.8	99.3	
Walnut					99.9							
Watermelon		99.8				99.8		99.8				99.8

Table 6
Sample Images for experiment 1.

Fruit Category	Sample Image 1	Sample Image 2
Apple Golden 1		
Apple Pink Lady		
Apple Red 1		
Pear Monster		
Pear Red		
Pear Williams		

addition of HOG features increases the accuracy by 1.4% and 1.1% respectively. While in case of DT, addition of more features does not give any advantage.

It is observed that good classification results can be achieved by using a combination of color and texture features for classifying various fruit categories. By combining the color and texture features, a feature vector of 1×36 features per image is obtained. Addition of HOG features increases the size of feature vector to 1×86 features. It does provide some advantage in terms of classification accuracies, however running time increases especially for KNN, LDA, NB and DT it is almost doubled. Moreover, neural network, k nearest neighbor and support vector machines, all prove to be very efficient for fruit classification by using a combination of color and texture features. It is also observed that Color-SIFT color features individually can provide high accuracies. By adding texture features, accuracies can be further enhanced without much increase in the size of feature vector.

To compare the performance of various classifiers, sensitivity and precision values are also compared. Sensitivity is the true positive rate which gives the ratio of the correctly retrieved instances of a class to the total instances in the given class. Precision also known as positive predictive value is the ratio of relevant instances out of the total retrieved instances for a given class. Formulae are given in equations (2–3).

$$Senstivity = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Tables 4 and 5 give (%) sensitivity and precision values for 30 fruit classes for all the classifiers.

To further evaluate the performance of the proposed feature combination and to compare with recent existing methods, two set of experiments are performed. Details of both experiments are as follows:

3.5. Experiment 1

This experiment is performed to compare the results of the proposed methodology with the work done by Naranjo-Torres et al. (2020). They have used Convolutional Neural Networks for classification of three subcategories of apples and pears each from Fruits 360 dataset. Their algorithm had an accuracy of 95.45%. In this experiment same fruit categories are considered to have a fair comparison between the proposed algorithm and the algorithm by Naranjo-Torres et al. Sample images of the fruit categories considered in experiment 1 are given in table 6. The results for both feature combinations are given in Fig. 6 for all classifiers.

It is observed that BPNN, KNN, LDA and SVM classify with 100%

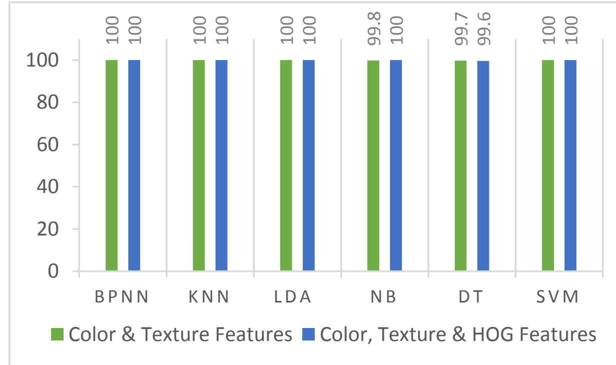
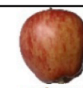
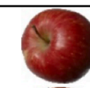
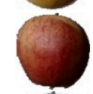
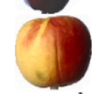
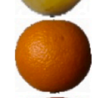
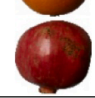
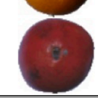


Fig. 6. Comparison of Accuracy for experiment 1.

Table 7
Sample Images for experiment 2.

Fruit Category	Sample Image 1	Sample Image 2
Apple Red 1		
Apple Red 2		
Apple Red 3		
Apple Red Delicious		
Apple Red Yellow 1		
Banana		
Orange		
Pomegranate		

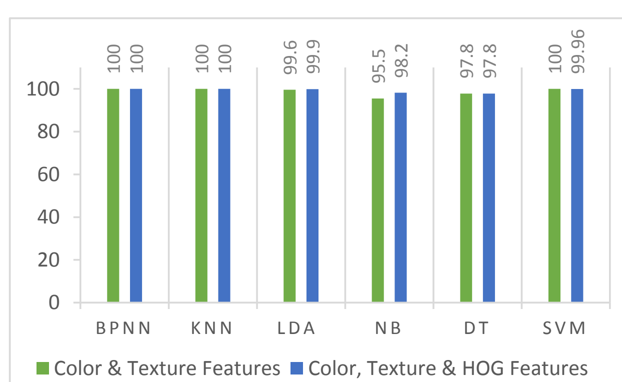


Fig. 7. Comparison of Accuracy for experiment 2.

Table 8
Comparison of fruit classification techniques implemented on Fruits 360 Dataset.

Reference	Technique/Features	Fruit Classes	Classifier	Highest Accuracy
Muresan and Oltean (2018)	TensorFlow library was used for implementation of convolutional neural network	131 (including vegetable classes)	CNN	98.66%
Saranya et al (2019)	RGB Color features, size, width and height of fruit	8	KNN	48.63%
			SVM	60.65%
			CNN	96.49%
Sakib, Ashrafi and Siddique (2019)	Various combinations of hidden layers and epochs were tested and compared	25	CNN	Test accuracy 100% Train accuracy 99.79%
Naranjo-Torres et al (2020)	TensorFlow library was used for implementation of convolutional neural network	6	CNN	95.45%
Fatima and Seshashayee (2020)	LAB Color features, bounding box shape feature and 4 Statistical texture features	12	SVM	100%
Proposed Methodology	Hue and CSIFT Color features, Statistical and Signal Processed texture features	30	BPNN	100%
			KNN	99.98%
			LDA	97.8%
			NB	98.1%
			DT	98.7%
			SVM	99.98%
		6	BPNN	100%
			KNN	100%
			LDA	100%
			NB	99.8%
			DT	99.7%
			SVM	100%
		8	BPNN	100%
			KNN	100%
			LDA	99.6%
			NB	95.5%
			DT	97.8%
			SVM	100%

accuracy for both feature combinations. Naïve Bayes and Decision Tree also classify with an accuracy approaching 100% for both feature combinations. The results show that by using color and texture feature combination, same categories of fruits can be classified with improved accuracy.

3.6. Experiment 2

In this experiment, eight categories of fruits are classified including five subcategories of apples and three other fruit categories. Table 7 shows some example images of the fruits from experiment 2.

This experiment is performed to compare the proposed methodology with the approach used by Saranya et al (2019). Authors have used three classifiers including KNN, SVM and CNN. Their reported accuracies were 48.63%, 60.65% and 96.49% respectively on the mentioned fruit categories. The features used in their research were color, size, width, and height of fruit.

Results of the proposed methodology for experiment 2 are given in Fig. 7 for all classifiers. 100% accuracy is obtained in the case of BPNN, KNN and SVM. In this case, addition of HOG features improves the accuracy to some extent for LDA and NB while accuracy remains same for DT.

4. Discussion

Section 3 gives details of the results obtained after performing various experiments with color, texture and shape features separately as well as in combination for classifying different fruit categories and sub categories. These results lead to several observations and inferences. In case of 30 classes, it is observed that for individual features tested separately, KNN performs best in case of CSIFT, DWT and HOG features while Decision Trees perform best in case of Hue and Haralick features. For the combinations of Hue and CSIFT features as well as DWT and Haralick features, KNN gives highest accuracy. For combination of all features, KNN, BPNN and SVM achieve highest accuracy. By analysing the results of various features and classifiers, it can be said that KNN remains successful in most of the cases. Neural Network and SVM do not perform well for less number of features, however, the performance of both is greatly enhanced by increasing the number of features. Overall performance of LDA and Naïve Bayes remain relatively low in most cases as compared to the other classifiers even though performance becomes better after using feature combinations for classifying. It is also found that if rest of the features are combined with HOG features, size of feature vector increases by a value of 50 with little advantage regarding final accuracies with an increase in running time. Hence it is finally concluded that by using a combination of hue, CSIFT and texture features good classification results can be achieved.

For 6 and 8 classes, all classifier perform well for both types of feature combinations. Hence outperforming existing methods with better accuracies achieved for classification of same categories of fruits in both the experiments. The results confirm that using a combination of color and texture features can give high accuracies for main fruit categories as well as sub categories.

A summary of all the techniques used in the literature for fruit classification using Fruits 360 dataset is given in table 8 and the results are compared with the results of current study.

Final accuracy of a fruit classification system largely depends on the types of selected classes of fruits. For example if all the classes of fruit have different color, then very good accuracy can be achieved using only color as a feature. In (Fatima and Seshashayee, 2020) all the selected fruit classes had very high variance hence a 100% accuracy was reported. A robust system should be able to detect all the main and subcategories of fruit regardless of high intra class and low interclass variances.

It is observed after all the experimentation that the proposed feature combination works very well for similar fruits like apple, apricot, peach, and pomegranate as well as for sub classes of apples and pears. It is also observed that neural networks, SVM and nearest neighbor classifier achieve better classification results as compared to the other classifiers.

5. Conclusions

Efficiency of fruit classification system depends on many factors including usefulness and relevance of extracted features and selection of an efficient classifier. Moreover, intra-class variations and interclass similarities pose a challenge in achieving high accuracies in such systems. An effort has been made to provide an efficient automated system for fruit classification from images using handcrafted features and supervised machine learning techniques. A detailed and extensive analysis of the performance of different types of features on classification accuracies has been performed aiming on finding best feature combination and an efficient classifier for fruit recognition and classification from images. Color features are found to be very efficient in fruit classification, if combined with texture features, accuracies can be enhanced further without much increase in feature vector size. If HOG features are also combined, classification accuracies improve to some extent with a considerable increase in the feature vector size and consequently, an increase in the running time as well. It is observed that a combination of color and texture features can be used in fruit classification problem using traditional machine learning techniques for smaller datasets with similar imaging conditions as in the Fruits 360 dataset. Our algorithm may find its application in multiple domains including automated fruit packaging, automated identification of various fruit species and their prices in supermarket applications, vision augmentation for people with poor visibility at fresh fruit shops or at home and in autonomous robots for inspection of items in store aisles. The proposed algorithm is able to classify, with compatible accuracies as compared to the existing methods, a variety of similar fruit classes using color and texture features. Six widely known classifiers are used for classification and results compared. It is observed that the best results are achieved with Back Propagation Neural Network, SVM and K nearest neighbors' classifiers. The proposed algorithm is not tested for fruits in cluttered or occluded environment. Our future work will be focused on fruit identification and sorting from images with cluttered background, fruit occlusions and defect detection in context of fruit picking robot.

CRediT authorship contribution statement

Sumaira Ghazal: Conceptualization, Methodology, Software, Writing - original draft. **Waqar S. Qureshi:** Conceptualization, Visualization, Formal analysis. **Umar S. Khan:** Supervision, Resources. **Javaid Iqbal:** Supervision, Funding acquisition. **Nasir Rashid:** Project administration. **Mohsin I. Tiwana:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is funded by the Higher Education Commission of Pakistan under grants titled "Establishment of National Centre of Robotics and Automation (DF-1009-31)".

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