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Fusion of Color-Texture Features based Classification of Fruits using Digital and Thermal Images: A Step towards Improvement

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***Abstract*—Now a day's people are very much concerned about quality and safety of food products. So this concern leads to the opportunities in the research to classify infected or non-infected fruits. The research aims to implement an approach to improve the classification accuracy for RGB and thermal image fruit database. The large scope of the field demands a proper choice of data collection and feature representation approach. Here, for the purpose of classification eleven categories of fruits have been considered. In this paper, different feature extraction techniques like color (Color Moments and Color Coherence Vector) and texture (GLCM) have been executed. To achieve better classification accuracy of different fruit images, the fusion of features like color-texture has been carried to classify the images using RF and KNN classifier (algorithm). The results revealed that color features give 100% accuracy with RF and KNN classifier for RGB images whereas fusion of GLCM, Color Moments and Color Coherence Vector gives highest accuracy of 93.4% with RF classifier for thermal images.**

***Index Terms*— Color moments, color coherence vector, GLCM, thermal Images, feature extraction and classification.**

I. INTRODUCTION

The demand of quality fruits has increased vividly due to large number of opportunities available in the import and export market. Fruits play crucial role in our everyday life and are considered as healthy food. The precise grading of fruits plays important role in agricultural and food industry to increase the profitability and to boost competitiveness. The major challenge in classifying the fruits using their RGB and thermal images is their characteristic features which creates confusion as different class images may have some features in common and some of the features within the class may exhibit unique and even weird. These limitations lead a requirement of multiclass automatic fruit classification system. Computer vision [1] is booming for the qualitative evaluation of fruits with a variety of applications ranging from complex vision guided robotic control to customized inspection. The growth of computer vision systems for grading, sorting and quality assessment for assorted raw and processed food is due to the advancement in hardware and software for image processing.
The variety of different imaging techniques like RGB, hyper spectral, thermal, x-ray etc. [9, 18] have been used to deal with such problems. Thermal imaging has been just employed in the various fields like bruise detection in

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plants, estimation of crop maturity, chilling etc. which harms to the fruit quality in storage space. The advantage of the thermal imaging system is that we can detect infected part of the fruit from inner as well as outer side. The objects having more than 0 Kelvin temperature throw out some radiation, which are function of the emissivity and the outside temperature. Fruits have extra ability to absorb the heat as compared to leaves and background scenes, which can be utilized as attribute for classification. To get better the potential of thermal imaging as the valuable tool for fruit classification by automated system that turn out unfailing analysis using non-intrusive methodology.

A. Literature Review

A machine vision using GLCM and color moments features are proposed in [2] for training SVM and system proves beneficial to detect papaya diseases with accuracy of 90.15%. Ref. [4], features like color (color moments) and texture (GLCM) are extracted and further classified using SVM. The accuracy achieved by using color, texture and fusion of color and texture was 32.29, 69.79 and 83.33% respectively. Tomato fruit [7] is taken into consideration for evaluating deformities and ripeness with GLCM and color moments features and classified by leave one out classifier with accuracy 96.47%. To classify the fruits, fusion of features like color coherence vector, Global Color Histogram and Unser descriptor were analysed with SVM and LDA [14]. The classified result of grape fruit peel [15] revealed that classification with only texture features gives less accuracy compared to fusion of color-texture features i.e. 81.7 and 96.7% respectively. Ref. [3], to recognize bruised blueberries pulsed thermographic imaging system was utilized. To select features, RELIEFF algorithm has been used and for classification LDA, SVM, RF, logistic regression and KNN classifiers are considered. The average accuracy accomplished was 83.5%. To forecast maturity of mango, L*a*b color space with mean intensity algorithm has been used and the accuracy for the same with fuzzy classifier was 89% [5]. Ref. [6], k-means clustering, color and texture features like color moments and GLCM respectively have been used with SVM classifier to detect bruises in apple with the assessment of quality automatically. Ref. [10], for the extraction of defected fruit surface, its area and degree has been calculated and shows the temperature variation between normal and defected part to give the position and degree of defected tissue. The on-line apple bruise detection system was developed by analysing its thermal properties and observed the recognition rate for sound, defective and sound apple with calyx as 83.3%, 90% and 100% respectively [13].

B. Objective

The objective of the present work is to classify infected and healthy fruit automatically. The affected skin of the fruit is determined by texture and color-sometimes texture may influence the color or vice-versa. So it is beneficial to observe both the features separately. Considering these aspects, the proposed system highlights color and texture features as well as fusion of them. The flow of the paper is put forward in following sections: Section II describes detailed techniques adopted for data collection, a description, feature extraction and classification. The result of the classifiers is presented in section III for both RGB and thermal data. The conclusion is given in section IV and deliberates future work.

II. METHODOLOGY ADOPTED

A. Data collection and description

To exhibit the objective of the work, we have used RGB and thermal image dataset. As such no common dataset is used till now for fruit detection and classification, a new fruit dataset with eleven classes is created for the detection of multiclass fruits. The steps for classification process of RGB and thermal fruit images are listed below and presented in Fig. 1.

Step 1. Data Collection: To capture the images, normal digital camera and SEEK thermal camera has been used. The videos of eleven different categories of fruits have been captured and converted into frames to prepare the dataset for the construction of RGB and thermal images which comprises: (i) Apple_Golden-Delicious (ii) Apple_Red (iii) Apple_Washington (iv) Guava (v) Orange_Malta (vi) Orange_Nagpur (vii) Pear (viii) Pomogranate (ix) Papaya (x) Kiwi (xi) Sharda. In total, 1870 images for RGB dataset and 1870 images for thermal dataset with 170 images per category have been used for further processing. The sample RGB and thermal images of each class are presented in Fig. 2 and Fig. 3.

Step 2. Pre-processing: First, the images are resized and then converted into grayscale images.

Step 3. Feature extraction: Color and texture features are used for the extraction of features and then further used for classification.

Step 4. Classification and performance analysis: Classification is done through K-nearest neighbour and random forest classifier and performance is evaluated using accuracy and kappa statistics.

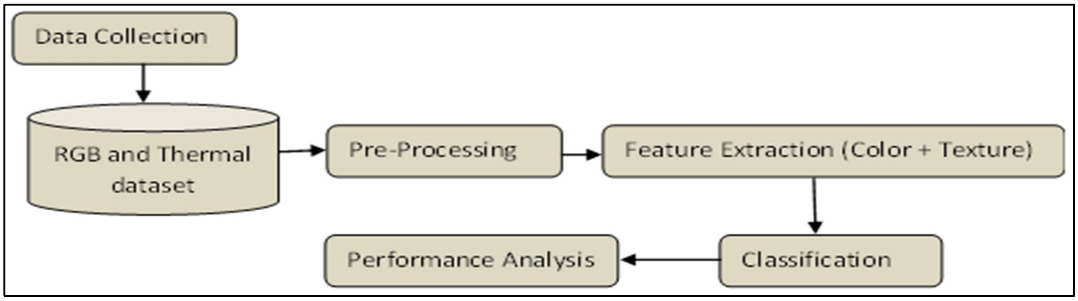

Figure 1.Classification process of RGB and Thermal fruit images

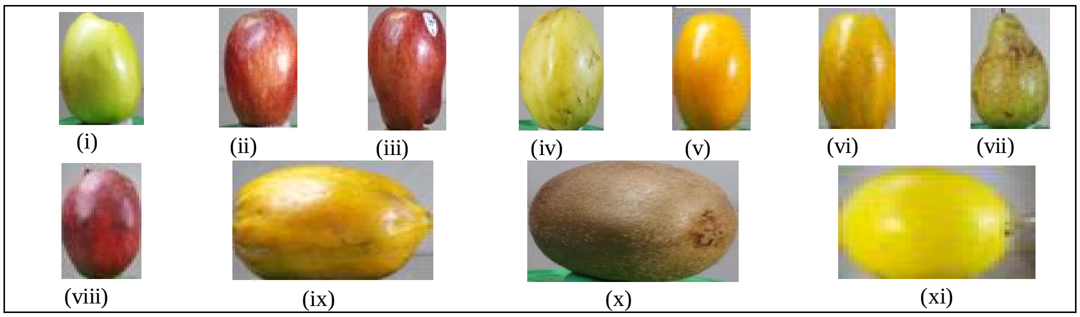

Figure 2. Examples of each class from our RGB image dataset

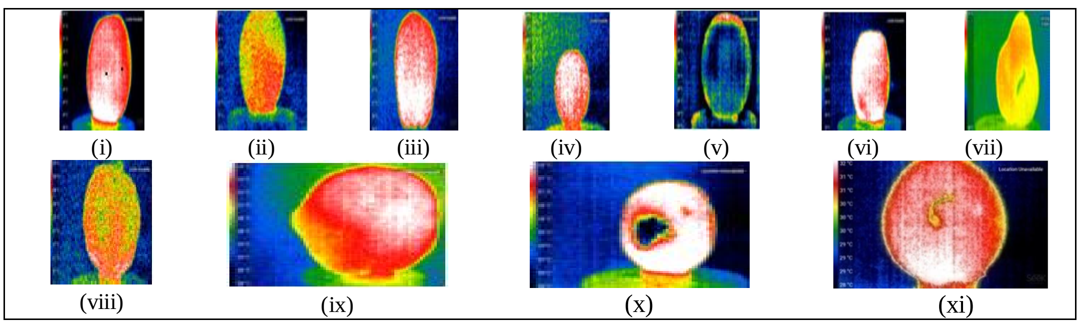

Figure 3. Examples of each class from our Thermal image dataset

B. *Feature extraction*

The performance of any recognition, detection or classification system extremely depends on the extracted features. So the crucial part is to select right feature extraction and classification techniques for better classification accuracy results. In the present work, color and texture based schemes have been used to extract the features of both RGB and thermal images. Color is generally a picture element property whereas texture can be computed from the set of pels. The GLCM based second order texture features and the color features like color moments (CM) and color coherence vector (CCV) have been applied for the extraction of various digital image features.

Texture Feature Extraction

Texture defines degree of smoothness or bumpiness with variant gray level values. It is distinguished by its apparent visual and material properties. The Gray level co-occurrence matrix (GLCM) is most likely used for the extraction of texture based features. The co-occurrence matrix and second order statistical texture features are presented in [8]. In this, first the co-occurrence matrix has been computed and further based on the matrix, texture features have been calculated.

GLCM defines the relation between neighboring and reference pixels with the offset value basically considered as one [21]. The GLCM matrix over the four possible orientations (Φ = 0°, 45°, 90°, and 135°) which determines the position of the pixels for displacement d. The frequency of value of pixel i horizontally adjacent to value of pixel j is specified by every element (i, j) of GLCM. The steps for the extraction of GLCM features are presented in algorithm 1.

Algorithm 1. Grey Level Co-occurrence Matrix (GLCM) feature extraction

Input: RGB Image(R) or Thermal Image (T)

Steps:

(1) a. Resize image into 256 x 256

b. Convert the image into gray scale image

(2) Find the GLCM matrix, $P_{i,j}(d, \Phi)$ defined as follows:

$$P_{i,j}(d,\Phi) = P(i,j\ /d,\Phi), 0 < i,j \leq Z \quad (1)$$

where, Z is the maximum gray level and displacement, $d = 1$ and $\Phi = 0°$

(3) Compute eleven GLCM features using $P_{i,j}(d, \Phi)$

GLCM_FV ← [Angular Second Moment, Inverse Difference Moment, Contrast, Energy, Entropy, Homogeneity, Variance, Correlation, Shade, Prominence, Inertia]

Output: GLCM_RGB_Feature_Vector and GLCM_Thermal_Feature_Vector

Color Feature Extraction

Color is a visual characteristic of the image that results from the light emitted or transmitted or reflected. In the literature numerous color features like color moments, color histogram, color correlogram, color coherence vector etc. have been proposed and adopted [11, 15]. Among them Color features have been extracted with the help of two methods: color moments and color coherence vector.

Color Moments (CM): Stricker and M. Orengo adopted to use the color moments schemes [20]. CM is the statistical color feature extraction technique where mean, standard deviation, skewness and kurtosis features have been extracted. CM has been used to index color images. CM is invariants to rotation and scaling and provides information related to color and shapes.

Mean (μ): Mean is the first order moment and provides average color value of the image.

Standard deviation (σ): Variance (σ^2) is the second order moment and using variance we can find out standard deviation which tells us how many pixels spread out or deviates from the center pixel.

Skewness (μ_3): Skewness is the third order moment and skewness about the mean gives the contribution of every pixel value for the image and tells whether the distribution of the data is left skewed, right skewed or symmetric.

Kurtosis (μ_4): Kurtosis is the fourth order moment and describes the level of outliers in the distribution.

The steps for the extraction of color moments features are presented in algorithm 2.

Algorithm 2. Color Moments (CM) feature extraction

Input: RGB Image(R) or Thermal Image (T)

Steps:

(1) a. Resize image into 256 x 256

b. Split image into R, G and B channels

(2) Compute four color moments i.e. mean standard deviation, skewness and kurtosis of each channel using eq. (2), (3), (4) and (5) respectively.

$$meanR,G,B\ (\mu) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} R(x,y)}{MN} \quad (2)$$

$$standard\ deviationR,G,B\ (\sigma) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} |R(x,y)-\mu|^2}{MN} \quad (3)$$

$$\text{skewness}R,G,B\ (\mu_3) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} (R(x,y)-\mu)^3}{MN\sigma^3} \quad (4)$$

$$\text{kurtosis}R,G,B\ (\mu_4) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} (R(x,y)-\mu)^4}{MN\sigma^4} \quad (5)$$

(3) In total, extraction of 12 CM features of the image.

CM_FV←[meanR, stdR, skewnessR, kurtosisR, meanG, stdG, skewnessG, kurtosisG, meanB, stdB, skewnessB, kurtosisB]

Output: CM_RGB_Feature_Vector and CM_Thermal_Feature_Vector

Color Coherence Vector (CCV): CCV is the histogram based technique with the added feature that it gives spatial information. For each color, CCV separates out coherent pixels which are the part of maximum number of connected pixels and incoherent pixels otherwise [19]. So, CCV provides only the information related to coherent pixels but not about their position of them. In this work, features are extracted using improved color coherence vector technique which provides information related to location of the coherent pixels. The steps for the extraction of improved color coherence vector features are presented in algorithm 3.

Algorithm 3. Color Coherence Vector (CCV) feature extraction

Input: RGB Image(R) or Thermal Image (T), percentage of the image (PerofImg) size for coherent pixel(default = 1%), number of colors (NumofCol) in the CCV (default = 27 colors)

Steps:

(1) Blur the image by replacing average pixel values using following steps
  a. Create a filter, h, that returns a rotationally symmetric Gaussian lowpass filter
  b. Apply the filter, using imfilter, to the image R or T to create a new image with same Boundary channels

(2) Discretize the colors of image into 'n' colors.
  Here, NumofCol← 4 * NumofCol
  DV ← $\frac{\log_2(NumofCol)^2}{3}$
  DV ← DV^3

(3) Classify coherent (C) and incoherent (IC) vector pixels
  a. Find the neighboring pixels (NP) of each 'n' colors
  b. Find the threshold value
     Here, PerofImg← 1
     T ← $\frac{PerofImg}{100} * image\_size$
  c. If NP ≥ T, then coherent vector pixel (C)
     else incoherent vector pixel (IC)

(4) Then find mid position (midC) of maximum connected coherent region using mean

(5) In total, extraction of 108 CCV features of the image
  CCV_FV ← [(C1, IC1,midC1),..........,(C108, IC108, midC108)]

Output: CCV_RGB_Feature_Vector and CCV_Thermal_Feature_Vector

All these features were calculated for 1870 images of both RGB and thermal images and stored in comma separated files (.csv). The two datasets of RGB and thermal images were created for all the above feature extraction techniques. For texture, feature vector consist of eleven GLCM features and the datasets are represented by GLCM_RGB and GLCM_Thermal. The color moment feature vector includes twelve features and its datasets are represented by CM_RGB and CM_Thermal. Also for the color coherence vector, 108 features were extracted and the datasets are represented by CCV_RGB and CCV_Thermal. To achieve the good classification results, the fusion of the features has been done by using the above color and texture feature vectors. The three feature fusion datasets were created for both RGB and Thermal images were represented by GLCM+CM_RGB, GLCM+CM_Thermal, GLCM+CCV_RGB, GLCM+CCV_Thermal, GLCM+CM+CCV_RGB and GLCM+CM+CCV_Thermal. Here, + sign indicates that the fusion of features. All the image processing techniques like pre-processing, feature extractions have been done in MATLAB R2015a [16].

C. Classification algorithm

The various classification techniques have been utilized to assess the quality of fruits [2, 9]. The classification accuracy results of the classifier is based on the input feature vector and for that two classifiers have been used i.e. Random Forest (RF) and k-Nearest Neighbor (KNN).

KNN algorithm: KNN is one of the supervised machine learning algorithms. KNN classifier is usually used for its simple of interpretation and fast execution time. KNN considers that training dataset is given, in which the sample class has been determined and indexed and the new samples are predicted by the majority within the training set of k nearest neighbors.

Random Forests (RF) algorithm: It is also a machine learning algorithm and constructs numerous decision trees and fuses them together to acquire correct prediction. Random forest classifier is mostly applied when there is large set of samples [12]. The no. of decision trees used (ntree) and in each tree no. of random variables used (mtry) are the decisive attributes of random forest.

In this work, RGB and thermal dataset of fruits have been utilized for the classification. In RStudio, using Caret package [17], all the datasets were created in section II (A) are divided into training and testing datasets considering 75:25 proportions. As there are 1870 samples in each dataset, training and testing dataset contains 1408 and 462 samples respectively. The training dataset consist of class labels, so transform label as factor. The parameters used for the preprocessing of training dataset of GLCM, CM and GLCM+CM were centered and scaled. But in CCV, GLCM+CCV and GLCM+CM+CCV, predictors could have single unique value; the parameters used for them were center, scale and zv (zero variance). 10-fold cross validation technique repeated with 3 times is utilized to access the statistical relevance of the classifiers. To select the optimum model the accuracy for the k and mtry value in KNN and RF classifier has been used. Then to classify the results, a confusion matrix on the similar test samples was created and two performance measures were evaluated i.e. overall accuracy and kappa value. Kappa statistics considers the accuracy that could be expected due to chance alone. These two parameters were employed for the comparison of classification accuracy in RGB and thermal images for all the above color and texture techniques.

III. RESULTS AND ANALYSIS

The performance measure evaluated for all the datasets viz. six for RGB and six for thermal datasets have been depicted in Table I and Table II respectively. It shows accuracy and kappa value for both RF and KNN classifier in Fig. 4 and Fig. 5.

TABLE I. CLASSIFICATION RESULTS FOR RGB DATASET

RGB Dataset	Total No. of features	Accuracy (%)		Kappa (%)	
		KNN	RF	KNN	RF
GLCM_RGB	11	95.97	97.72	95.57	97.5
CM_RGB	12	100	100	100	100
CCV_RGB	108	100	100	100	100
GLCM+CM_RGB	23	100	100	100	100
GLCM+CCV_RGB	119	100	100	100	100
GLCM+CM+CCV_RGB	131	100	100	100	100

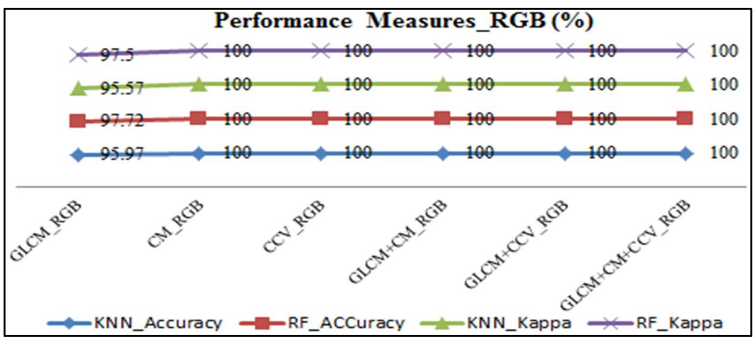

Figure 4. Performance measure of KNN and RF for all RGB dataset

The result in the Fig. 4 shows that the best accuracy i.e. 100% was scored using both KNN and RF classifier for all the RGB datasets except GLCM_RGB dataset which gained accuracy as 97.72% with RF.
The result in the Fig. 5 shows that the accuracy for only texture feature dataset (GLCM_Thermal) was 82.53% and 84.26% for KNN and RF which was less than gained accuracy i.e. 91.17% and 92.95% for only color feature datasets (CM_Thermal and CCV_Thermal) with RF classifier. But with the fusion of color-texture features with GLCM+CM+CCV_Thermal dataset, the overall classification accuracy extends up to 93.4%.

TABLE II. CLASSIFICATION RESULTS FOR THERMAL DATASET

Thermal Dataset	Total No. of features	Accuracy (%)		Kappa (%)	
		KNN	RF	KNN	RF
GLCM_Thermal	11	82.53	84.26	80.78	82.69
CM_ Thermal	12	91.29	91.17	90.42	90.29
CCV_ Thermal	108	91.29	92.95	90.42	92.24
GLCM+CM_ Thermal	23	91.55	91.7	90.7	90.86
GLCM+CCV_ Thermal	119	91.88	92.62	91.07	91.88
GLCM+CM+CCV_ Thermal	131	92.45	93.4	91.69	92.74

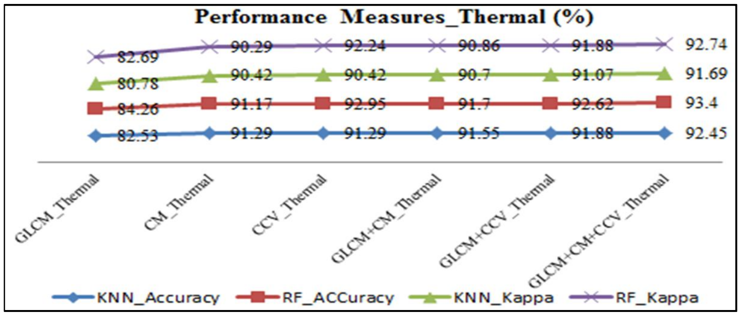

Figure 5. Performance measure of KNN and RF for all Thermal dataset

The accuracy of proposed work has been compared with previous work ([4], [11]) and ([3], [5]) for RGB and thermal dataset respectively. The comparison of the pre-sent work with the others for RGB and thermal dataset are figured out in Table III and Table IV with accuracy values are delineated in Fig. 6 and Fig. 7 respectively.

In [4], to classify eight varieties of fruits and in [11], to recognize diseases in fruits the color, texture and fusion of color-texture features have been extracted and classified with SVM with accuracy (32.29%, 69.79%, 83.33%) and (83.5%, 88.56%, 90.95%) respectively which is minimum compared to present work of RGB dataset classified with RF and KNN which is depicted in Fig 6.

TABLE III. COMPARISON OF PRESENT WORK WITH [4] AND [11] FOR RGB DATASET

Reference	Accuracy (%)			Classifier used
	Only Color	Only Texture	Fusion (Color+Texture)	
Proposed	100	97.72	100	RF, KNN
[4]	32.29	69.79	83.33	SVM
[11]	83.5	88.56	90.95	MSVM

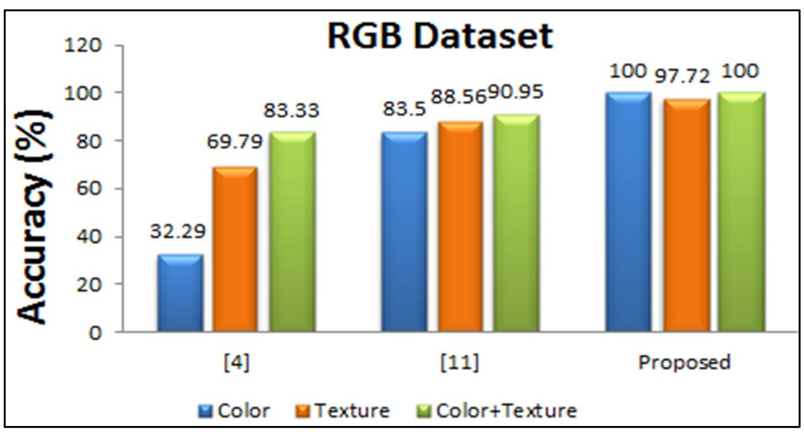

Figure 6. Comparison of present work with [4] and [11] for RGB dataset

For the thermal dataset, highest classification accuracy gained in the present work is 93.4% with RF classifier whereas the highest accuracy achieved by [3] and [5] are 83.5% and 89% respectively. The comparison is shown in Fig. 7.

TABLE IV. COMPARISON OF PRESENT WORK WITH [3] AND [5] FOR THERMAL DATASET

Ref	Accuracy (%)	Classifier used
Proposed	93.4	RF
[3]	83.5	RF
[5]	89	Fuzzy

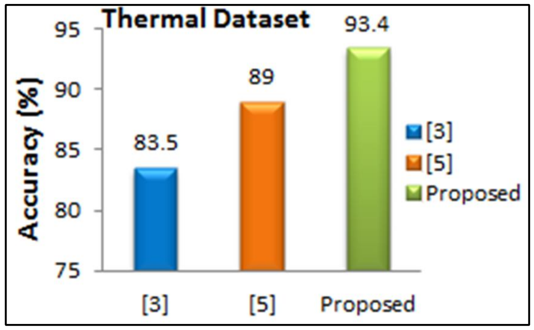

Figure 7. Comparison of present work with [3] and [5] for Thermal dataset

IV. Conclusions

The aim of this work is to boost the classification rate using color and texture based features for RGB and thermal image fruit dataset. The foremost objective of this work is to increase the value of infected fruit detection system. The present research work has been carried out to evaluate the performance based on texture and color features extracted from the RGB and thermal image data set prepared for fruits over the maximum classification accuracy results achievable from such a data sets. The Kappa and Accuracy measures were calculated for every dataset. The result shows that the fusion of several features gives increased classification accuracy than the usage of a single feature and that the combination of three features outruns the other feature fusions in terms of both accuracy and kappa value. Texture features are inferior as compared to other features. When compared to thermal images, RGB dataset gives good result with 100% accuracy. There is good scope in further improvement in the accuracy of classification for thermal image dataset. We will extend this work with the shape feature techniques.

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