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Research Article

Banana Maturity Classification Using Hybrid Features On Various Classifiers

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ABSTRACT

Fruits are grown based on the climatic conditions and its requirement. Ripening is an important phase in horticulture and a fruit is categorized as either climacteric or non-climacteric. Climacteric fruit ripens even after harvesting whereas non-climacteric does not ripen off the tree. Therefore at a particular unripe stage all the fruits are harvested. This paper describes the banana ripening process and explains how image processing is utilized for banana ripeness classification using Histogram of Oriented Gradients (HOG), zernike and resnet features.To bring an automated ripeness recognition system in image processing Naïve Bayes (NB), K-Nearest Neighbor (KNN), Decision Tree and Random Forest (RF) classifiers are analyzed. Experimental results prove that the proposed hybrid features using RF classifier gives most accurate results.

Keywords: Ripening, Resnet, Histogrom Oriented Gradients, Zernike moments

1. INTRODUCTION

In the present market, both the fruit and vegetable industry is subject to selection. Ripening is the method by which fruits achieve their desirable flavor, quality, color and other characteristics of texture. Checking and grading maturity is a well-known method in all sectors. Here banana fruit is considered to find the matured and unmatured state. Matured stage is the ripened banana and unmatured stage is the unripened banana. Some of the matured bananas might be very soft and it will be difficult for the traders to carry those matured bananas.

There are many techniques in image processing for classifying the maturity of all types of fruits. Here banana is considered to classify its maturity level as matured or unmatured. Normal camera is used as the sensor for capturing the banana images. If the banana becomes very softer means then it is difficult for trading. In order to increase the profit of trading banana it is harvested at an earlier stage by using artificial methods. There are certain limitations while manually identifying whether banana is matured or not. Sometimes it may be rotten. So it’s a difficult as well as time consuming process. It requires man power to check each stage of ripening.

Mainly the visual appearance of banana fruit plays a major role in the feature extraction and in classification stage. The color and textural features are important to identify the maturation phase. A hybrid feature extraction technique that incorporates zernike moments and resnet features has been used in the proposed method to enhance the efficiency of the classification phase. The proposed method will identify the fruits ripeness using four classification technique namely the naïve bayes classifier, decision tree, random forest and KNN classifier.

Some of the techniques used for detecting the maturity levels of banana are very fast, fair, safe and of low cost to implement. Tapre and Jain[1]considered to utilize the image processing technique with a caustic feature extraction method. They concluded that there is an increase in pulp for peeling the banana, increase in total sugar level, very low intensity level of green colour and decreased firmness in the matured bananas. Gomes et al. [2] have suggested a Ripening Colour Index (RCI) model for classifying the ripening level of bananas using the Lab colour space. The evaluation in the brown color of the banana peel is dome through RGB and Lab colour values is illustrated in [3]. This technique does not illustrate about the banana ripening level and suggests that it requires a detailed study for identifying the effect of brightness based on colour values. Star fruit maturity classification technique was developed in [4]. It depends on the fruit peel hue values. These techniques are prone to error because of the presence of difference in marginal colour between the successive levels of fruit ripeness, as they focuses on finding accurate threshold values or range of values.

Segun E Adebayo et.al [5] introduced that the backscattering details with reference readings use wavelength laser diodes for estimating the quality and bananas are differentiated based on the maturation phase of banana. Support Vector Machine(SVM) classifier is used to determine the quality of the banana and also classify the ripening stage of banana. They concluded that wavelengths values yield coherent results with all the assessed models. Udomsak Paeanpairoj et al. [6] introduced a classification technique which has been applied on durian ripening fruit through diffusion gas analysis. They analyzed various algorithms like DT, KNN, NB, Neural Network and SVM. Various experiments were conducted and it proved that SVM is more accurate compared to other algorithm.

SVM has been extensively used in [7], for discriminating the six stages of a Tomato using the histograms of hue, saturation and value along with colour moments as feature vector. They had concluded that the SVM outperforms than LDA technique. Sanaeifaret al.[8] have segmented the banana fingers by thresholding channel. The RGB, Lab and HSV colour spaces mean values are extracted as the feature vectors and classification is done by Support Vector Regression. The benefit of using these techniques to classify the fruits makes feature learning easier. But the limitation is that they need large number of training samples, wide-ranging memory and selection of kernel function parameters.

A colour recognition algorithm was introduced in [9] to identify the ripening and unripening phase of banana. They use three bin histogram technique and R, G and B component of banana image as features fed as input to the Artificial Neural Network (ANN) with error propagation. ANN has input layer, hidden layer and output neurons layer as 9, 45 and 1 respectively. The maximum number of epochs is 400. But the disadvantage is in choosing colour threshold values and providing outcomes with a smaller banana images database. In order to recognize the ripening stage of bananas categories namely unripened stage, ripenened stage and over ripenend stage[10]. ANN is used with seven hidden node layers. It is trained and tested with 60 samples only. Seven hidden layers are used to provide a good topology as the accuracy level depends on it. But it consumes more time. Mendoza et al. gives the applications where the banana ripening classification helps [11].

The remaining of the chapter is organized as follows: Section 2 describes the detail implementation of proposed work. Section 3 demonstrates the experimental results and analysis followed by conclusion in Section 4.

2. PROPOSED METHODOLOGY

The architectural design of the proposed method for identifying the maturity of the banana fruit is shown in Figure 1. The input source image is taken from database. Data augmentation processing is done on the database in order to increase the number of inputs with the available input images. Input images with higher resolution gives more accurate values. Here preprocessing is done where it will help to focus only on the banana fruit very clearly. The proposed system will provide better results if the image background is of very of light color preferably white. Then canny edge detection is done. Once these processes are completed, next step is feature extraction. It includes HOG, zernike feature extraction and Resnet feature extraction. These extracted values are used as input to classifier.

The proposed method analyzes four classifiers namely NB, DT, RF and KNN. The Classifiers are trained with the feature vector values to classify ripeness stage of banana. Once the system is trained the proposed method can be checked for accuracy by giving testing samples as input. Among these four classifiers RF classifier provides better results. The algorithm of maturity classification of banana is shown in Algorithm 1.

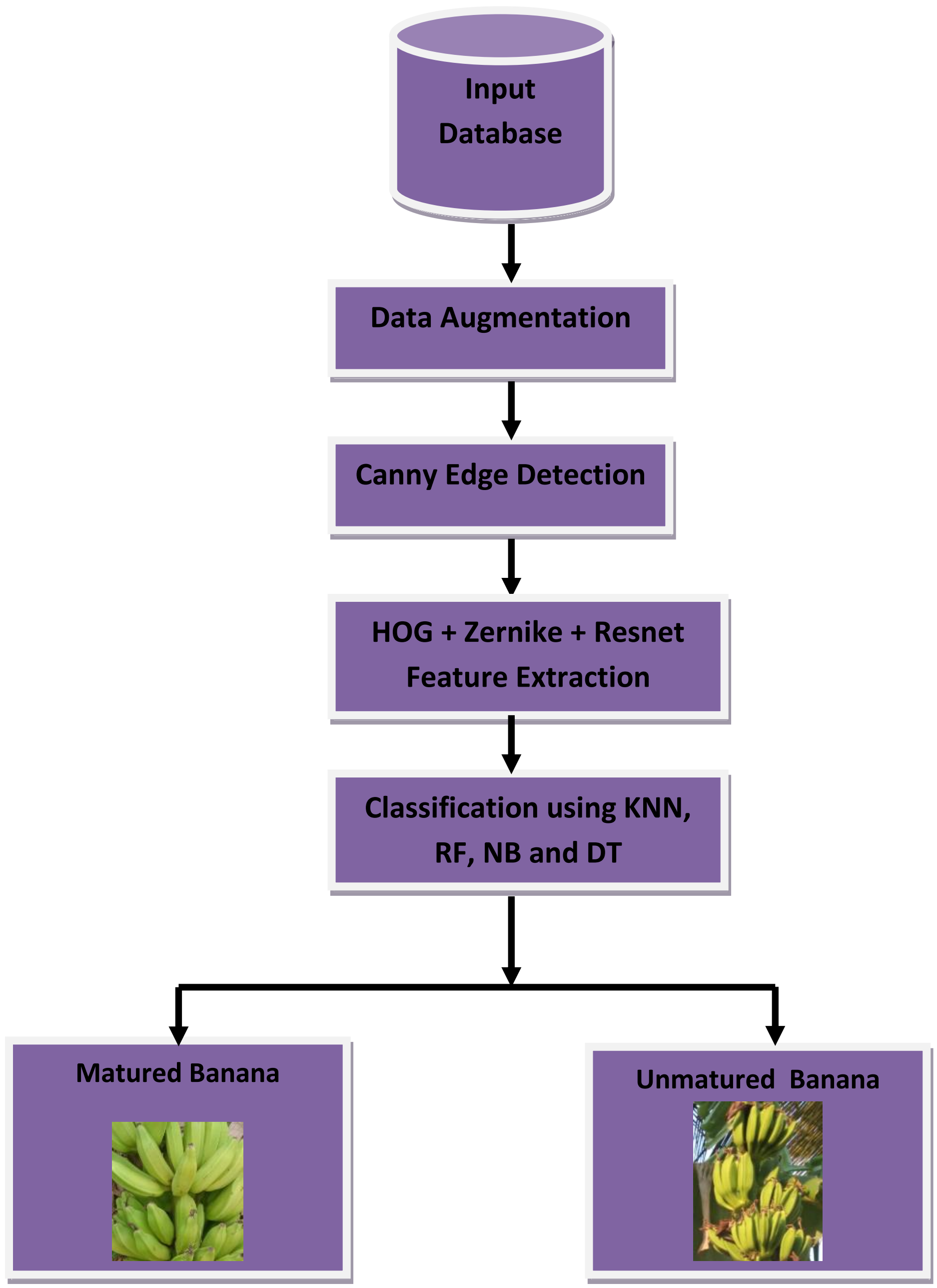

Fig. 1 System Architecture of the Proposed System

Algorithm1: Matured Banana and Unmatured Banana Classification System

Input: Fruit image

Output: Classified maturity of banana fruit (Matured Banana and Unmatured Banana)

Steps:

Step 1 : Read the input image from database
Step 2: Apply preprocessing to improve image quality
Step 3: Apply data augmentation to increase the size of database.
Step 4: Find the edges of banana using canny edge detection method.
Step 5: Extract HOG features, Zernike moment features and Resnet features.
Step 6: Concatenate the three features mentioned in step 5.
Step7: Store the extracted features in knowledge base along with its labels as matured and unmatured banana.
Step 8: Apply the classifiers like Random forest, Naïve bayes, Decision tree and KNN.
Step 9: Display the classified fruit as matured banana or unmatured banana

2.1 DATA AUGMENTATION

Data augmentation technique is used to expand the size of a training dataset artificially by producing some changes as the modified versions of images in the dataset. To train the deep learning neural network using large number of data result better models are created. The data augmentation technique creates variations in the banana images that are used for improving the capability of the models to generalize into a new model. Image shifts, Image flips, Image rotation, Image brightness and image zoom are the different transforms used in data augmentation process to create a new dataset. In this work, image rotation and image brightness are used.

2.2 CANNY EDGE DETECTION

The Canny edge detector is used to detect the edges of banana fruit. It is a multi-stage edge detector. It uses a filter based on the derivative of a Gaussian in order To compute the gradient intensities canny filter based on the Gaussian derivative is used. The Gaussian is used to reduce the noise present in the banana image.

The general criteria for canny edge detection include:

1. Detection of banana edges with a minimum error rate, which means that the edge detection of banana should accurately catch as many edges as possible.
2. The banana edge point detected from the prewitt operator should accurately localize on the center of the banana edge.
3. A given banana edge in the image should be marked once, and noise present in the image should not create any false banana edges.

2.3 FEATURE EXTRACTION

Feature extraction method plays important role in classification process. Here features are extracted using HOG, Zernike moments and ResNet neural network approach. The process of these feature extraction techniques is explained. The classification accuracy mainly depends upon the optimality of feature extraction.

2.3.1 HOG FEATURE EXTRACTION

HOG feature extraction is one of the local shape feature extraction technique. The local shape of the banana peel is due to the increase in the maturity level of banana. The HOG descriptor extracts the local shape information. It is extracted by calculating the local edge directions and the intensity gradients on a dense grid. To extract the HOG features, the ROI must be equally divided into image cells. The adjacent cells are formed to an image block. The pixel gradients are calculated by means of Prewitt operator. Thus histogram was generated for each block .Further it was normalized by the L1-normalization.

2.3.2 ZERNIKE MOMENT FEATURE EXTRACTION

Zernike moments feature extraction extracts the shape descriptors of the banana image and these Zernike moment features are rotation invariant because of its Orthogonality property. But there is a high complexity while computing the Zernike moments. The proposed work is aimed at evaluation of Zernike moments for various patterns of banana images. Zernike Moments are the statistical measure of pixel distribution and it allows capturing global shapes information of banana fruit. They capture both the global and the geometric information of the banana fruit. It explores more information on the entire image rather than providing single boundary point information and the global properties from boundary-based representations are also found. The general form of Zernike moment of order n with m repetition over the complete banana image is as follows:

$$m_{pq} = \sum_{j} \sum_{y} x^{p} y^{\otimes} f(x,y) \qquad (1)$$

Where N is the size of the banana image and f(x,y) is the gray levels of individual image pixels. m_{pq} is the discrete banana image moment.

2.3.3 RESNET FEATURE EXTRACTION

The proposed method uses 194 layers. The residual unit present in a ResNetis comprised of a block with three convolutional layers. ResFeatures are the outcome of these residual units. The entire shape of the banana image contained within the region of interest is extracted as the Resnet features. ResFeaturesare viewed as the outcome of a deep filter bank. This ResFeature vector output is of the form w×h×d. Here w and h represent width and height of the resultant feature vector and d represents number of convolutional layer channels. ResFeatures are comprised of 2-D arrays with d dimensions.

Residual networks consist of residual units. It is expressed as:

$$\begin{aligned} y_i &= h(x_i) + F(x_i, w_i) \\ x_{i+1} &= f(y_i) \end{aligned} \qquad (2)$$

where F represents the residual function, f represents the ReLU function, w_i represents the weight matrix and x_i, is the i-th layer input and y_i is i^{th}layer output. The identity mapping value h is represented by

$$h(x_i) = x_i \qquad (3)$$

The residual function F is defined in as:

$$F(x_i, w_i) = w_i \cdot \sigma\left(B(w_i') \cdot \sigma\big(B(x_i)\big)\right) \qquad (4)$$

2.4 CLASSIFICATION

Classification is the way toward gathering of information depending on the comparative attributes. The attributes extracted using Resnet, Zernike moment and HOG descriptor are fed as input to the random forest, Naïve bayes, Decision Tree and KNN classifiers. These classifiers discriminate the maturity level of banana from the input data. They divide the input images in to two classes. One class containing matured banana images and the other one has un-matured banana images. The process of these classification techniques is explained. Also relative examination is done to decide the accuracy of these classifiers.

2.4.1 KNN Classifier

KNN is one of the case-based learning methods that utilizes all the training data for classification. In recognizing the maturity of banana, non-parametric method the k-Nearest Neighbors classifier is used for classification. The output of k-Nearest Neighbors classifier is a class membership (matured banana or un-matured banana). The maturity of banana fruit is classified using the voting concept. Voting is done by neighbors. The majority vote of the neighbors is assigned to the corresponding class. For example , If k = 1, then the object is assigned to the class of that single nearest neighbor .K nearest neighbors stores all available classes and classifies the new class based on the similarity measure. In the proposed system KNN classifier is also used to classify the banana fruit. For KNN classifier large amount of memory is needed for processing the data. It is essential to change the value of K each and every time and it seems to be complex sometimes. For each and every training sample, the data point distance is calculated

2.4.2 RANDOM FOREST CLASSIFIER

The RF is one of the ensemble learning approaches that uses binary decision trees. The random forest was tree was built with binary decision trees. As the number of binary decision trees increases the accuracy of classification also increases. But this will lead to more calculation.

The features extracted using Resnet neural network and Zernike moments are fed as input to the RF classifier. The annotated 2 labels for classification are: 1 – matured banana, 2 –un-matured banana. It provides best classification results in predicting the maturity of banana. The algorithmic procedure for Random Forest classifier is discussed below. Initially "K" features are selected randomly from total "m" features where k << m. Then the node "d" is calculated using the best split point using the "K" features. Next the nodes are splitted into daughter nodes using the best split technique. Then forest is created. Finally this process is process is performed "n" number times to create "n" number of trees.

In the next phase, with the created random forest, prediction has to be done. The random forest prediction has the following steps. The test features are taken and the rules of each randomly created decision tree are used to predict the outcome and predicted outcomes are stored. Next each predicted target votes are calculated. Then consider the highly voted predicted target as the final prediction using this RF algorithm. Here the target is matured banana and non-matured banana classification.

2.4.3 NAIVE BAYES CLASSIFIER

Naïve Bayes classifier algorithm is based on the maximum likelihood called the Bayes Theorem. The naive assumes of class conditional independence to reduce the computational cost. It assumes that in a given class the effect of an attribute value is independent of the values of the other attributes which is known as class conditional independence. The NB Algorithm is a probabilistic algorithm that is sequential in nature, following steps of execution, classification, estimation, and prediction. For finding relations between the diseases, symptoms, and medications, there is various data mining existing solution, but these algorithms have their own limitations; numerous iterations, binning of the continuous arguments, high computational time, etc. NB overcomes various limitations including the omission of complex iterative estimations of the parameter and can be applied on a large dataset in real time.

2.4.4 DECISION TREE

Decision trees are powerful and popular tools for classification and prediction. It represents rules, which can be understood by humans and used in knowledge system such as database. It requires no domain knowledge or parameter setting and can handle high dimensional data. Hence it is more appropriate for exploratory knowledge discovery. This work uses C5.0 decision tree for classification with a representation using nodes and internodes. The root and internal nodes are the test cases that are used to separate the instances with different features. Internal nodes themselves are the result of attribute test cases. Leaf nodes denote the class variable. Each node for the decision tree is found by calculating the highest information gain for all attributes and if a specific attribute gives an unambiguous end product (explicit classification of class attribute), the branch of this attribute is terminated and then target value is assigned to it.

3. EXPERIMENTAL RESULTS

The main aim of this work is to identify the maturity level of the banana fruits. The deep features are extracted using the proposed Resnet approach and the shape features are extracted using the HOG descriptor and Zernike moments. Then classification is done using RF, NB, DT and KNN classifier. This section starts with the explanation of dataset which is followed by the performance metrics. The experimental results of the proposed method are analyzed. Finally, the comparison of proposed method is analyzed.

3.1 DATASET USED

Experiments are conducted in a database consisting of 310 fruit images captured directly from a farm. The captured images are pre-processed for research. The images taken from camera and the pre-processed images are shown in Fig. 2 and 3 respectively. The bananas of various categories like chakka, nadu, pachai and others are captured. The dataset images are divided into 70 train images and 240 test images.

Fig. 2 Images Captured from Camera

Fig. 3 Pre-processed Images of Fig. 2

3.2 PERFORMANCE METRICS

The performance of the proposed method is compared with the existing methods. To analyze the performance of the classifiers, many performance evaluation metrics are available. Among them Precision Rate, Recall Rate, F-Measure and accuracy are used as a performance metric for this work.

Precision, also called as the positive predictive value is the fraction of retrieved action instances that are relevant. Precision is calculated by means of Eq. (5)

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Where TP = True Positive (matured banana that are identified as matured banana)
FP = False Positive (unmatured banana that are identified as matured banana)

Recall, also known as sensitivity is the fraction of relevant instances that are retrieved. Recall is calculated by means of Eq.(6)

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

Where TP = True Positive (matured banana that are identified as matured banana)
FN = False Negative (matured banana that are identified as unmatured banana)

F-measure, combines precision and recall called as the harmonic mean of precision and recall. The balanced F-score is calculated by means of Eq.(7)

$$F_m = 2\,\frac{Precision*Recall}{(Precision+Recall)} \quad (7)$$

The proportion of accurately anticipated perception to the all-out perceptions is *accuracy* which is the most instinctive presentation measure. The Accuracy is calculated by means of Eq.(8)

$$Accuracy = \frac{TP+TN}{TP+Tn+FN+FP} \quad (8)$$

Some sample images of matured and un-matured bananas from the dataset is shown in Fig. 4. The output of canny edge detection for images in Fig. 4 is shown in Fig. 5.

(a)

(b)

Fig. 4. Sample Input Images (a) Matured Bananas (b) Unmatured Bananas

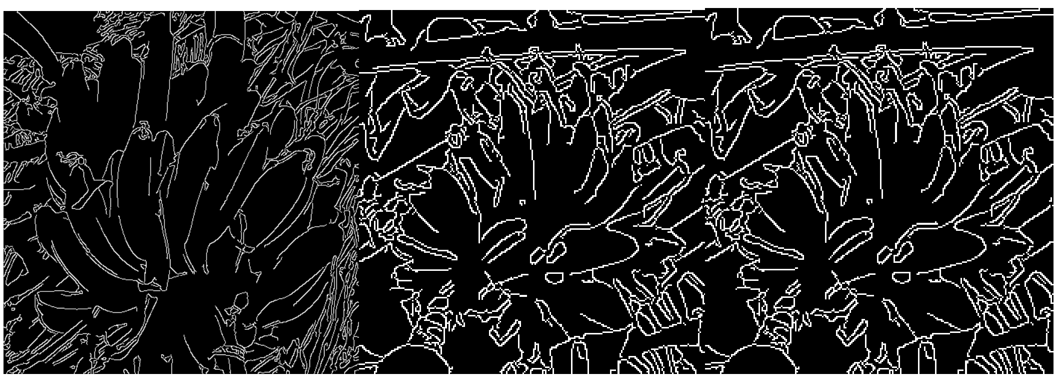

Fig. 5. Images after applying Canny Edge Detection

The results obtained by the proposed method are shown in Table 1. In Table 1, accuracy, precision, recall and F- measure for various classifiers of individual and hybrid features are shown.

Table. 1 PERFORMANCE ANALYSIS OF THE PROPOSED METHOD

Features	Classifier	Accuracy	Precision	Recall	F Measure
Zernike	KNN	0.8364	0.8098	0.7556	0.7753
	RF	0.8848	0.9164	0.7958	0.8329
	NB	0.7152	0.6365	0.6306	0.6332
	DT	0.7879	0.7329	0.7361	0.7345
Resnet_prop	KNN	0.8485	0.815	0.7917	0.8019
	RF	0.8727	0.8949	0.7806	0.8153
	NB	0.7091	0.6366	0.6403	0.6383
	DT	0.7758	0.7163	0.7069	0.7112
Resnet_prop, Zernike	KNN	0.8788	0.8503	0.8403	0.845
	RF	0.9552	0.9627	0.9034	0.9199
	NB	0.8061	0.7577	0.7833	0.7678
	DT	0.8485	0.8072	0.8194	0.8128

As observed from Table 1, the precision, recall, F-measure, accuracy of the KNN classification method using Zernike features ranges from75-83%, then by using Resnet feature it ranges from 79-84% and when both the Resnet and Zernike features are combined as hybrid features then it ranges from 84-87%. Similarly for Random forest classification method using Zernike features ranges from79-91%, then by using Resnet feature it ranges from 79-89% and when both the Resnet and Zernike features are combined as hybrid features then it ranges from 90-95%.Similarly for Naïve bayes classification method using Zernike features ranges from63-71%, then by using Resnet feature it ranges from 63-70% and when both the Resnet and Zernike features are combined as hybrid features then it ranges from 75-80%. Finally for Decision tree using Zernike features ranges from73-78%, then by using Resnet feature it ranges from 70-77% and when both the resnet and Zernike features are combined as hybrid features then it ranges from 80-84%.

So it is concluded from Table 1 when the resnet and Zernike features are combined to produce a hybrid feature then the random forest classifier provides an accuracy of 95.52%which is better than all the other three classifiers. Figures 5 and 6 show the comparison of the accuracy and F-measure with all the four classifiers. The testing is performed on 70% of total banana image set with to improve the performance indices.

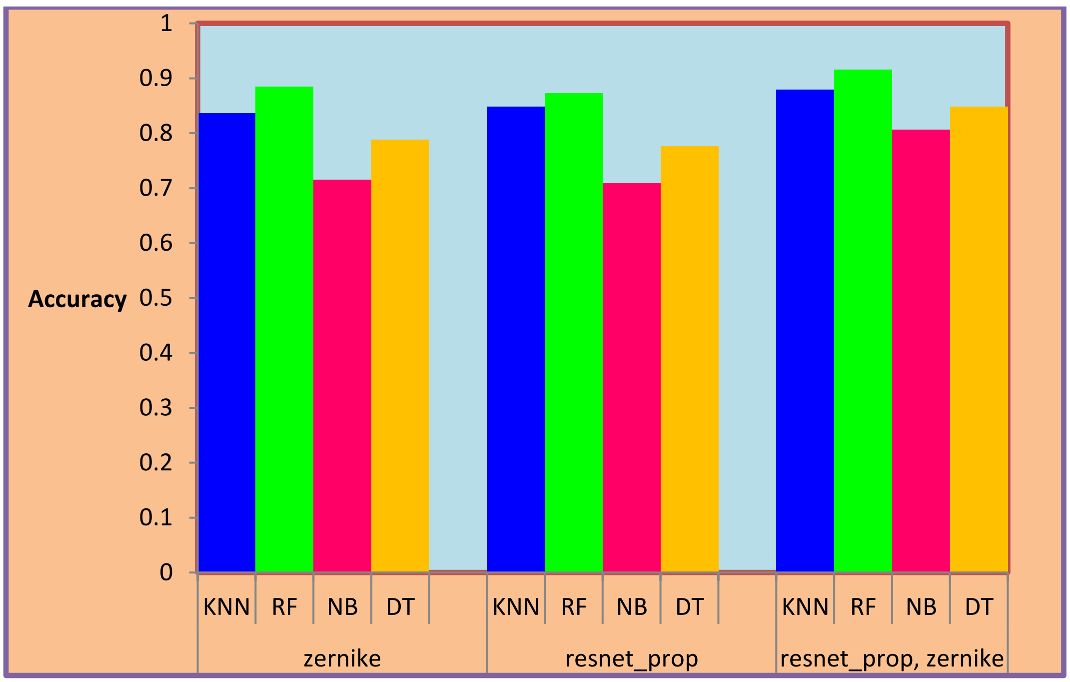

Fig.6 Comparison of Accuracy with four classifiers

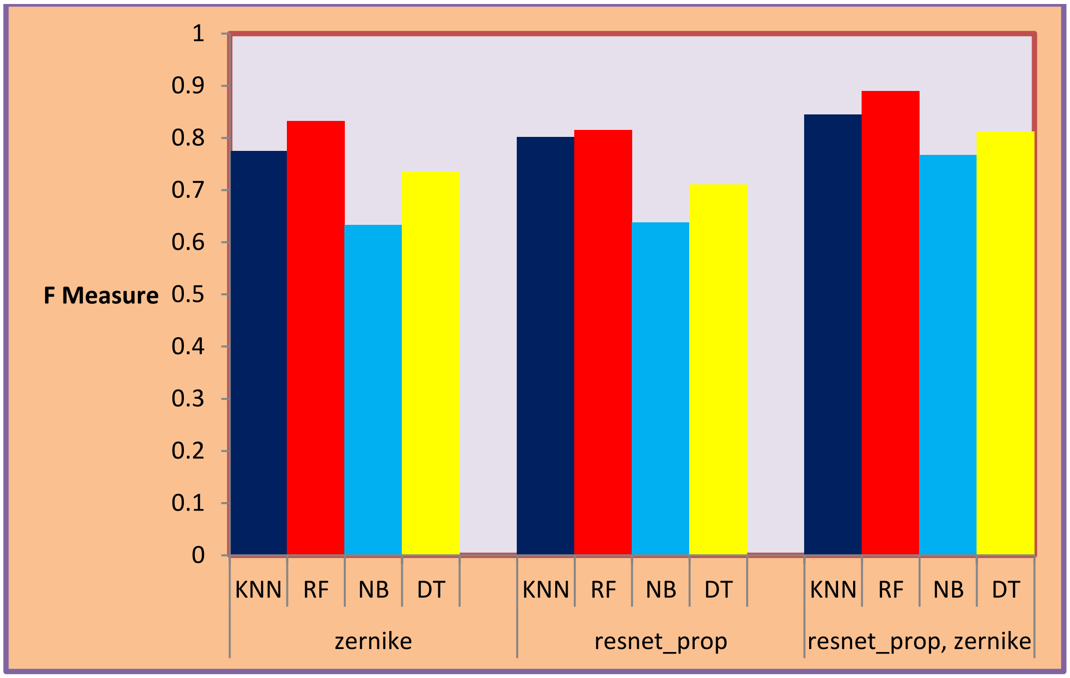

Fig. 7 Comparison of F measure with four classifiers

The Proposed method with hybrid features and RF classifier is compared with Gomes et al.[2], Sanaeifer et al.[8],Saad et al. [12], Mendoza et al. [11] and Senthilarasi et al. [13].Table 2 compares the proposed method with other methods in terms of all performance metrics.

Table 2 Comparison of Proposed Method with other methods

Ripening Level	**Accuracy**	**Precision**	**Recall**	**F-Score**
Gomes et al., 2013 [2]	43	0.44	0.28	0.34
Sanaeiferet al., 2016 [8]	53.30	0.48	0.34	0.40
Saad et al, 2009 [12]	49.11	0.43	0.3	0.35
Mendoza et al., 2004 [11]	74.07	0.76	0.59	0.67
Senthilarasi et al., 2020 [13]	94.85	0.95	0.89	0.92
Proposed Method	95.52	0.96	0.90	0.92

From Table 2, it is observed that the proposed method with RF classifier and hybrid features achieves higher accuracy, precision, recall and F-score than all other methods.

4. CONCLUSION

The proposed system efficiently detects the maturity of banana. The proposed system is developed with the combination of two features namely Zernike and the resnet features. These features make the algorithm more robust against all type of issues during banana maturity detection. A decision on the banana maturity is made using four classifiers namely KNN, Naïve bayes, Decision tree and Random Forest classifier. It is found that random forest classification outperforms than the other three classifiers. The proposed system is evaluated on the images of collected dataset specifically developed for identifying the maturity of the banana as matured banana or unmatured banana. An analysis is made on the proposed system with the existing systems. It is found that the proposed method using Random forest classifier based on the Zernike and resnet features provides better results than the existing methods. The proposed system has a much better accuracy of 91%.

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