A Machine Vision-Based Maturity Prediction System for Sorting of Harvested Mangoes

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***Abstract*— Seasonal fruits, like mango (Mangifera Indica L.), are harvested from gardens or farms in batches; the mangoes present in each batch are not uniformly matured, therefore, sorting of mangoes into different groups is necessary for transporting them into different locations. With this background, this paper proposes a machine vision-based system for classification of mangoes by predicting maturity level, and aimed to replace manual sorting system. The prediction of maturity level has been performed from the video signal collected by the Charge Coupled Device (CCD) camera placed on the top of the conveyer belt carrying mangoes. Extracted image frames from the video signal have been corrected and processed to extract various features, which were found to be more relevant for the prediction of maturity level. Recursive feature elimination technique in combination with support vector machine (SVM)-based classifier has been employed to identify the most relevant features among the initially chosen 27 features. Finally, the optimum set of reduced number of features have been obtained and used for classification of the mangoes into four different classes according to the maturity level. For classification, an ensemble of seven binary SVM classifiers has been combined in error correcting output code, and the minimum hamming distance-based rule has been applied in decision making phase. For the experimental study, the mangoes of five different varieties were collected from three different locations and in three different batches. The obtained experimental result found to provide an average classification accuracy up to 96%.**

***Index Terms*— Fruit sorting, image frame, machine vision, maturity identification, support vector machine (SVM).**

I. Introduction

SEASONAL fruits like mango are commercially produced in various farms, located in favorable geographical locations. During season, fruits are collected from trees in batches, and then sorted according to maturity level for transportation to different locations. Mangoes harvested from various trees in a lot are not uniformly matured, having maturity days left on an average 10–12 days, with a high standard deviation ±5 days; this also depends on the variety (species) of the mango. Thus, sorting according to the maturity level is necessary, as transportation times for different locations are different. In general, sorted most of the matured fruits must be sold to local markets and most of the prematured fruits can be shipped to customers over much greater distances.

At present, most farms use manual experts for sorting of the fruits, but as most of the fruits are seasonal, so getting sufficient number of manual experts during the period is difficult. On the other hand, manual sorting is time consuming, laborious, and suffers from the problem of inconsistency and inaccuracy in judgment by different human experts. Therefore, the scope of this paper is to develop a system, for sorting of mango into different groups, by predicting the number of days left before the mango gets over matured or rotten.

For maturity prediction, recently different authors have proposed different measurement techniques. Among these, Brezmes *et al.* [1] investigated the use of electronic nose, to access fruit maturity. They have used principal component analysis (PCA) for dimension reduction of the outputs of multiple sensors and finally fuzzy art map for classification, which resulted success rate of 96.4%. However, measurement time and after measurement refreshing time for the sensors was found to be 10 and 15 min, respectively, also involves complex sample handling process.

Larrain *et al.* [2] applied near-infrared spectroscopy for ripeness measurement of wine grapes, by analyzing the spectrum of the scattered light to obtain different parameters of ripeness in wine grapes, namely sugars (Brix), pH, and anthocyanin concentration. Finally, they have related these compositions with the ripeness, which were found to a nonlinear and also depends on the variety of the grapes.

Ben Saeed *et al.* [3] used optical sensor system comprising of four spectral bands, 570, 670, 750, and 870 nm for detection of maturity of oil palm fruits, using quadratic discriminant classifier they have obtained accuracy 85%.

On the other hand, machine vision-based inspection systems have been developed in recent years with the great progress of computer vision techniques. This application includes real time measurement of discrete surface defects of rail heads [4] using a line scan camera and frame grabber to capture rail gray scale images, which were normalized to identify the defects by comparing intensity levels using threshold technique. Similar comparison of intensity on gray scale image can also be observed recently in [5] to detect visual defects in liquid crystal display images using a local active contour model. The vision-based techniques [6] for lay length measurement of metallic wire ropes images converted to a gray scale and

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using Laplacian of Gaussian method to find the contour of the rope to estimate the lay length.

A vision-based inspection system using structure light has been proposed [7], where the weld dimensions directly measured using the coordinate of the pixels. Automated inspection systems are applied to metrological characterization of rubber profile [8] and to inspect the brake shoe of rolling stock [9] based on the measurements of the distance between the fitted curves rather than the number of pixel in the image. They mainly focus on the edge detection and dimension measurement from complex environment.

In recent years, machine vision and image processing techniques have been found increasingly useful in the process automation includes textile industry [10], where the PCA for dimension reduction and finally fuzzy c-means was used to classify the texture features into two classes. Vision-based inspection systems also used in the calibration process of satin glass with various gray and color tonality finishes [11].

The above methods are the example of vision-based measurement techniques for the machine products and or manufacturing applications, whereas this paper applies machine vision technique in natural product, where much higher subject variability is common. In this paper, color images have been considered in comparison with gray scale images.

Vision-based surface measurement also successfully applied in segmenting and measuring image features, such as the nucleus as well as the micronucleus [12] and 3-D coordinate measurement of cross cutting feature points on the surface of a large-scale workpiece [13].

In most of the fruits, the surface color changes with maturity, therefore, many machine vision-based techniques have been proposed for ripeness measurement using surface color of agricultural products [14]–[17], and so on. This technique has attracted many commercial houses due to exponential reduction of computational and camera cost.

Many machine vision systems have been proposed for agricultural grading applications. These applications include direct color mapping system to evaluate the quality of tomatoes and dates [18], apples [19], and palm oil fresh fruit bunches [20]. Among these, recently, Lee *et al.* [18] proposed a method to convert 3-D RGB color space of interest specific to a given application, to 1-D using a second-order polynomial function, so that maturity becomes simple gray scale function in the transformed domain. They obtained the coefficients of the polynomial using least squared error method of suitable selected 13 test samples of tomato, 95% accuracy was obtained when tested on 18 samples to classify in six different categories.

Recently, Zheng and Lu [21] applied least square support vector machine (LS-SVM), to classify the mango according to the degree of browning in the skin of the mango. For classification, they have converted the RGB image into CIELab image, from there they have extracted several features through fractal analysis, which was finally presented to the LS-SVM for classification and obtained the correct classification rates of 85%–88%.

Since, the different maturity level of mangoes may have the same average surface colors, there are also possibilities of variation of skin color of the same maturity level mangoes originated from different trees or garden and even from the same garden, but in different batch [22]. These variations throw challenges to the direct mathematical hypothesis drawn by relating skin color with the maturity level [18]. In addition, changes of skin color during ripening process of different varieties of the mango are different, makes the maturity prediction system calibrated for one variety system, not usable for other variety. Therefore, there is a need of some systems, which can easily learn from the examples present in a generalized manner.

This paper aimed at development of low-cost automated system for sorting of harvested mangoes into four groups, according to the days left, before it gets over matured or rotten, with the help of image collected from the conveyer belt containing nontouching mangoes. An ensemble of binary support vector machine (SVM) classification model has been used for sorting of the mango into four different categories. To meet the real time response as required for sorting of mangoes while passing through conveyer belt, an optimum set of features have been selected with the help of SVM-recursive feature elimination (SVM-RFE), which limits the number of computations in comparison with the PCA-based dimensional reduction techniques [1], [10], [15]. In addition, an easily achievable classifier training and feature selection procedure is presented to avoid sophisticated calibration as required in most of the techniques [1], [2], [18].

For classification, the proposed system extracts various features from the RGB image (provided by the camera) of the mango itself, rather than converting the RGB color space into some different color space [6], [21], which requires additional calculation. Since the SVM-based classification model is being employed, which can map the feature space into some higher dimension hyperspace with the help of kernel function, for making the classification easier. In addition, it is not necessary that the machine should also visualize the images as per human perception of color. From [22], it was revealed that skin color of a particular variety of the mangoes not only dependent with the maturity level but also found to be vary with the geographical location of the garden as well as weather during the time (indicated as gardenwise and batchwise variations). In spite of the variations of skin color over different batches and gardens, the maturity levelwise variation was found to be more prominent, which makes the classification into four categories possible with the help of multiple features. This paper can be considered as extended version of [22], with an objective to improve the performance and reduction of computation to meet real time target, along with validation by testing in different training data set.

The organization of this paper is as follows. The materials and methods are discussed in Sections II and III, respectively. The obtained results are presented in Section IV. The discussion and conclusion are presented in Sections V and VI, respectively.

II. Materials

For this paper, the mangoes of five different varieties locally termed as Kumrapali (KU), Amrapali (AM), Sori (SO), Langra (LA), and Himsagar (HI) were collected from three different gardens, located at West Bengal, India. Totally, 1350 mangoes were collected in three batches with an interval of one week in between batches. In each batch for each of the variety, 90 number of mangoes were collected, with the average of 30 mangoes from each garden. Steps were taken to ensure randomness in the mango collection process from the gardens in each batch. For comparison purpose, three independent human experts work in the relevant field were selected for manual identification of maturity. Each mango (number tagged) was used to pass through a conveyer belt every day until it rotten and was presented to the experts for recording of human expert predicted expiry date. The day of getting over matured (identified by softness) or rotten ($>5\%$ black/brown spot), were recorded as expiry day for each of the mango. With availability of the expiry days, all the images were grouped into four different categories, M1, M2, M3, and M4, according to some fluidal cutoff days left before expiry. The M1 group consists of images taken before 12 days of expiry, M2 in between 9 and 12 days, M3 in between 5 and 8 days, and M4 in between 1 and 4 days. After collecting the images, these were stored in a manner as used during transportation. In this process, totally 16 400 number of images were collected, with on an average 3280 number of images for each of the variety and 820 for each of the group or class. Among the average of 3280 images, for each of the variety, four different training and testing data sets were created, which are as follows.

1) *Random*: using randomly selected two-third of the images over all the three gardens and batches in training data set, and remaining one third in testing data set.
2) *Batchwise*: contains images of randomly selected two batches over all the three gardens in training data set and remaining one batch in testing data set.
3) *Gardenwise*: contains images of randomly selected two gardens over all the three batches in training data set and remaining one garden in testing data set.
4) *Day 1*: using randomly selected two third of the first day images (day of harvesting) over all the three gardens and batches in training data set, and remaining one third in testing data set.

A Charge Coupled Device (CCD) camera placed on the artificially illuminated image collection chamber, as shown in Fig. 1, was used for collecting images into computer through USB 2.0 port. The camera was focused on conveyer belt through which the mangoes pass, the frame rate of the camera was 30 frames/s with resolution of 640×480 in the RGB mode. To minimize the motion blur, shutter speed was controlled and fixed to the value of 1/1200 s. The conveyer belt contains plates with special markings in the four corners. One mango in each plate is placed by the sample placer.

The proposed algorithm was implemented in Lab VIEW Real Time Environment for automatic sorting. The light intensity inside the image capturing chamber is measured with the help of lux meter (Instek-GLS-301) and consequently controlled by light intensity controller to the desired value of 120 Lux. Since the value of the RGB is device dependent, so

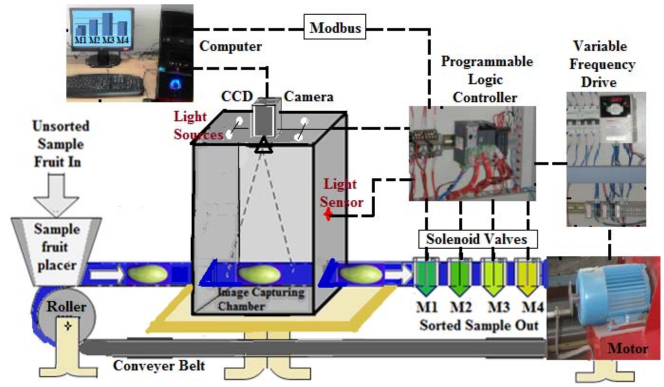

Fig. 1. Proposed machine vision-based automated fruit sorting system.

the camera was calibrated using the method in [24] to obtain both intrinsic and extrinsic camera parameters for providing accurate and consistent color measurements.

III. Methods

In the proposed method, the suitable frames containing full image of each plate as identified by the four special markings on the plates are considered for preprocessing in order to remove motion blur and noises. After preprocessing and normalization, the proposed algorithm extracts the suitable set of optimum features to form the feature vector, which then presented to the already trained ensemble classification model for classifying into any of the mentioned category, i.e., M1, M2, M3, and M4. To find the optimum set of features as required to improve performance and to reduce computation SVM-RFE-based technique was employed on the initially selected 27 features, which showed some sort of correlation with respect to maturity as revealed in [22]. Various training and testing procedure have been adopted to judge the proposed system performances in different way, so that the training procedure can be simplified to make the system acceptable for the vendors. The following sections describe each step in details.

A. Preprocessing of Image

Frames collected from video signal were found to be contaminated with motion blur artifact and noises. For elimination of motion blur, deblurring wiener filter as detailed in [25] has been used followed by denoising using pseudomedian filter [26], as it is computationally simpler and possesses many of the properties of the median filter. Then, the images were converted to binary image and consequently the boundary were traced using graph contour tracking method based on popular chain code [27]. After tracing of the boundary, the image of the mango was aligned in vertical position by finding the maximum axial length, as shown in Fig. 2. This alignment is required as the mango can be at any position within a plate. The details of these steps can be found in [22].

B. Extraction of Features

During ripening process of mango, the change in the skin color are more predominant in the apex region (as marked in

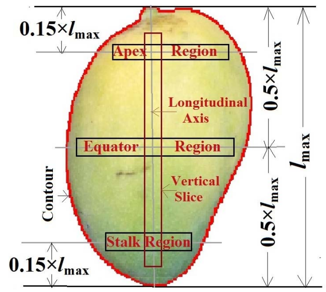

Fig. 2. Preprocessed, boundary traced, and aligned image of mango, with marking of different regions from which color-based different features have been extracted.

TABLE I
LIST OF EXTRACTED FEATURES

Label	Description
fv_1, fv_2, and fv_3	Average R, G and B value of the entire mango
fv_4, fv_5, and fv_6	Gradient of R, G and B value along the longitudinal axis
fv_7, fv_8, and fv_9	Average R, G and B value of the Apex region
fv_{10}, fv_{11}, and fv_{12}	Average R, G and B value of the Equator region
fv_{13}, fv_{14}, and fv_{15}	Average R, G and B value of the Stalk region
fv_{16}, fv_{17}, and fv_{18}	Differences of average R, G and B value of the entire mango
fv_{19}, fv_{20}, and fv_{21}	Differences of average R value for the apex, equator and stalk region
fv_{22}, fv_{23}, and fv_{24}	Differences of average G value for the apex, equator and stalk region
fv_{25}, fv_{26}, and fv_{27}	Differences of average B value for the apex, equator and stalk region

the Fig. 2) when compared any other region like equator and stalk. Specifically, the R and G value of the color image found to be decreasing from the apex region to stalk region. The slope was also found to be a function of maturity. Therefore, a number of features were initially chosen on the basis of following observations for investigation. Among these, 27 features were selected; these features have shown some sort of correlation with respect to maturity. For all the five varieties of the mango, the list of these features are listed in Table I, the details of the calculation procedures can be found in [22]. All the features were normalized as zero mean and unit standard deviation.

C. Feature Selection and Classification

The generalization performance of a classifier depends primarily on the selection of good features, i.e., the features that represent maximal separation between the classes [28]. On the other hand, reducing the number of features will reduce the computation required, which is the main interest for this kind of real time application.

In this case, the multivariate method of feature selection by backward elimination is applied [29]. Backward selection is often found to be suitable to find the optimal set of features, rather than the best feature as in the case of the forward selection method [29]. In addition, the multivariate method considers the predictive power of features jointly, rather than independently. Hence, it can identify those features that are individually irrelevant, but may become relevant in the context of others and can eliminate redundant features that might be individually relevant.

In this paper, the recursive feature elimination (RFE) technique was combined with the SVM-based classifiers for the selection of features, and the same SVM model was used for classification.

1) Theory of SVM and SVM-RFE Technique: A brief theory of the SVM and SVM-RFE, taken from [29], is presented here for ready reference. The basic idea of the SVM is to map data into a high-dimensional space and find an optimum separating hyper-plane (OSH) with the maximal margin. Given training vectors $x_k \in R^n$, $k = 1, \ldots, m$ in two classes, and a vector of labels $y \in R^m$ such that $y_k \in \{1, -1\}$, the SVM solves a quadratic optimization problem

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{k=1}^{m} \xi_k$$

subject to $y_k \left(w^T \Theta(x_k) + b\right) \geq 1 - \xi_k$ and $\xi_k \geq 0$ for $k = 1, 2, ..m$, where training data are mapped to a higher dimensional space by the function Θ, C is a penalty parameter on the training error, w is a weight vector, b is bias, and ξ_k is called a slack variable.

To overcome the problem of bias of the OSH, when imbalanced training data are presented, cost-based learning strategies are implemented. The total misclassification cost, $C \sum_{k=1}^{m} \xi_k$ is replaced with two terms, one for each class $C \sum_{k=1}^{m} \xi_k \rightarrow C_+ \sum_{k \epsilon y_+} \xi_k + C_- \sum_{k \epsilon y_-} \xi_k$, where C_+ and C_- are the soft-margin constants for the two classes $y_+ \equiv (y_k = +1)\, y_- \equiv (y_k = -1)$. For any testing instance x, the decision function (predictor) is, $f(x) = \mathrm{sgn}\left(\sum_{k=1}^{m} \alpha_k y_k k(x, x_k) + b\right)$, where sgn[.] is the sign function, α_k are Lagrange multipliers, and $\alpha_k \geq 0 \forall k$, $\sum_{k=1}^{m} \alpha_k y_k = 0$.

The RFE technique [29] is based on the value of the margin on a different set of features. The feature selection is performed through a sequential backward elimination procedure followed by the margin maximization principle [29]. In this paper, with a particular feature q, i.e., to be removed from the feature subspace $S(q \in S)$ during certain iteration, the ranking score r_q is calculated using $r_q = \left|W^2(\alpha, \alpha^*) - W^2_{-q}(\alpha, \alpha^*)\right|$, where W^2_{-q} denotes the predictivity ability of the SVM [29] after removal of qth feature from the feature vector. Then, the feature q with the smallest ranking score is eliminated from feature subspace S, and a rank is assigned on the basis of iteration number to the eliminated feature.

2) SVM-Based Classification: In present approach, to classify the maturity levels into four different classes, total $2^{4-1} - 1 = 7$ numbers of binary SVMs were combined by the minimum Hamming distance rule in such a way that each of them aimed at separating a different combination of classes. The code word used for the four different classes are listed in Table II, and were formulated according to popular exhaustive coding technique [30], this coding consist of all

TABLE II
EXHAUSTIVE CODING FOR THE FOUR-CLASS PROBLEM

Class	Classifiers						
	C^1	C^2	C^3	C^4	C^5	C^6	C^7
M1	1	1	1	1	1	1	1
M2	0	0	0	0	1	1	1
M3	0	0	1	1	0	0	1
M4	0	1	0	1	0	1	0

possible nontrivial and nonrepeating codes. In this formulation, the individual classifiers are trained on several meta two-class problems, where individual metaclasses include some combination of the original classes. For example, classifier C^3 recognizes two metaclasses, original classes M1 and M3 constitute one class and the M2 and M4 constitute the second class. During testing, each classifier outputs a -1 or 1 (-1 considered as 0) creating a seven long output code vector. This vector is compared with each code word in the code matrix, and the class whose code word has the shortest Hamming distance to the output vector is chosen as the ensemble decision.

3) Training, Testing, and SVM Parameters Optimization: Initially, the classification model was trained and consequently tested using k-fold ($k = 6$) cross-validation (cv) technique [31], in this scheme, the whole training data set ($\approx$3280 images) is divided into six subsets with five subsets used to train and construct the SVM decision surface, the remaining subset used for testing. This was repeated for other subsets so that all subsets are used, after the repetitive cycle of training and testing process, the classification performance of the individual run was averaged and presented by means of four measures, i.e., sensitivity (SE), Specificity (SP), predictivity (PR), and accuracy (AC), calculated using

$$sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$specificity = \frac{TN}{TN + FP} \tag{2}$$

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

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{4}$$

These cv tests are mainly for optimization of the SVM classifiers parameters like C and kernel function. The classification performance with different kernel functions, such as linear, polynomial (upto second order), and RBF kernels of the form $k(x,x^{/}) = \exp\left(-\gamma\, ||x-x^{/}||^2\right)$, were investigated, for selection of proper C value, and the kernel parameter like γ, these parameters were varied iteratively through grid search process and each iteration k-fold cv test was performed to obtain average classification performance.

4) Feature Selection: After finalizing the SVM model, the feature selection process with the SVM-RFE was computed. Altogether 27 features were applied to the model. In each iteration of RFE (say ith), the value of ranking score r_q of the remaining $(27 - i)$ features were obtained and then the feature with the lowest r_q value was removed, and a rank $R = 27 - i$ was assigned to that removed feature. The next cycle starts with the $\{27 - (i + 1)\}$ number of features, and continues to remove the next least important feature of rank $R = 27 - (i + 1)$. This process was continued until there is only one feature remaining. Finally, at the end of the process, margin-based overall ranking of all the features were obtained according to their importance on classification.

After finding the ranks of the features, the classifiers model was again cross validated to find the optimum subset of feature, in this process, first the top ranked feature alone in the feature vector is used for training and testing, and average classification performance was obtained. In the next cycle, same process is repeated for top two ranked features in the feature vector, this cyclic process was repeated for 27 cycles, so that by rankwise inclusion of one feature at a time leads at obtaining classification performance for the entire feature subsets.

D. Development of Hardware Model

The proposed algorithm was realized by the Lab VIEW, programming language in personal computer with the help of various library files form image processing toolbox. The algorithm takes video image coming from the camera and thereafter extracts and processes the frames to assign the passing mango into particular class, which then communicate with the programmable logic controller (PLC) through modbus ports, the PLC then trigger the respective solenoid valve so that the mango goes to assigned bin. The PLC also used to control the conveyer belt speed by controlling the speed of three-phase induction motor through variable frequency drive (shown in Fig. 1). The maximum conveyer belt speed was 2 m/s, and the gap between two mangoes as placed the sample placer was $\sim$25 cm. Therefore, minimum time delay between two consecutive mango passes through image capturing chamber is 125 ms. A GUI was created, through which user can train the system by feeding the daywise images of some mango with some tag number and the day of expiry for the respective tag number.

IV. RESULTS AND ANALYSIS

This section summarizes the obtained results at various stages of work starting from optimization of the SVM model parameters.

A. Feature Selection

During the selection of the optimal set of features by the SVM-RFE, it was observed that the features that were eliminated in the successive iteration of backward elimination were sensitive to the variety of the mango, as well as to the model parameters. The variation of classification accuracy with respect to rankwise (as obtained using the SVM-RFE) by cumulatively including one feature at a time is shown in Fig. 3, for three different mango varieties. From the figure, it can be observed that classification accuracy curves get saturated after inclusion of a certain number of features, which provides the

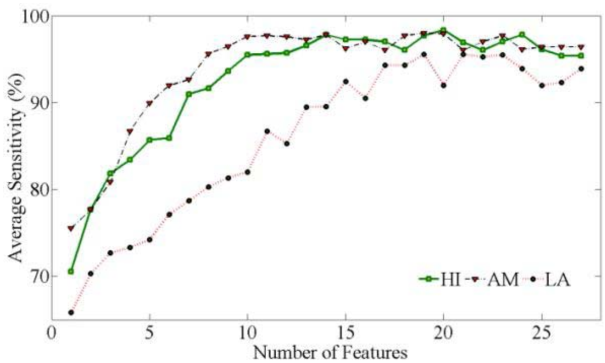

Fig. 3. Number of feature retained in the feature vector versus classification accuracy for the three varieties of mangoes, i.e., HI, AM, and LA.

TABLE III

FEATURE RANKING AND OPTIMUM FEATURE SUBSET

Variety	Optimum set of features (rank wise)
KU	$f_7, f_{21}, f_1, f_8, f_4, f_{19}, f_{16}, f_5, f_{24}, f_{14}, f_2, f_{23}, f_{10}, f_{13}, f_{27}$,
AM	$f_4, f_{21}, f_{23}, f_5, f_1, f_{10}, f_7, f_{27}, f_{18}, f_2$
SO	$f_7, f_8, f_4, f_{16}, f_{21}, f_1, f_{24}, f_2, f_5, f_{19}, f_{27}, f_{13}, f_{10}$
LA	$f_1, f_8, f_{15}, f_{19}, f_2, f_{18}, f_{11}, f_{10}, f_{23}, f_7, f_{26}, f_{16}, f_3, f_{17}, f_6, f_{21}, f_4, f_{27}, f_{13}$
HI	$f_{23}, f_7, f_{21}, f_4, f_{13}, f_5, f_1, f_{16}, f_{22}, f_{19}, f_{20}, f_8, f_2, f_{11}$

opportunity to reduce the number of features. It can also be observed that after inclusion of 10 features for the AM variety, the classification accuracy does not improve substantially, thus for the AM, these top 10 features can be used as the optimum feature set. Similarly, the number of features in the optimum set for the KU, SO, LA, and HI were found to be 15, 13, 19, and 14, respectively. The optimum set of features selected for the individual varieties of mangoes are listed in Table III.

Among the selected features in the respective optimum sets of different varieties, it can be observed that mainly the features originated from R value dominate on the other hand color of the apex region and its difference from stalk are the most common. The features of the KU and SO are almost common, but there are slight alterations in the feature ranking. In these two cases, the different features originated from R color space dominate. In the case of the AM, difference-based features originated from R and G color spaces are predominant. In the LA features, originated from all the R, G, and B values and over the entire regions, i.e., apex equator and stalk region can be observed in the optimum set. In the HI, R and G-related features originated from apex, equator and stalk regions are playing major role.

B. Selection of SVM Model Parameters

After selection of optimum set of features, for the individual varieties, cv tests were conducted for selection of proper kernel function. In this paper, the Gaussian RBF kernel has shown to perform similar to or better than polynomial and linear kernels. The optimum values of the SVM parameters like C and γ for the classification models, were chosen through grid search. The optimum values of C and γ for all the varieties of mangoes are listed in Table IV.

TABLE IV

OPTIMUM PARAMETERS VALUES FOR RESPECTIVE SVM MODELS

SVM Parameters	Mango Varieties				
	KU	AM	SO	LA	HI
C	57	62	69	32	47
γ	0.19	0.14	0.25	0.36	0.22

TABLE V

CONFUSION MATRIX ON TRAINING DATA SET

		True Class			
	Class	M1	M2	M3	M4
Predicted Class	M1	546	15	5	0
	M2	12	544	9	0
	M3	1	13	535	11
	M4	0	7	20	530

TABLE VI

VARIOUS PARAMETERS FOR CLASSIFIER PERFORMANCE EVALUATION ON TRAINING DATA SET

	FN	FP	TP	TN	SE	SP	PR	AC
M1	20	13	546	1669	96.5	99.2	97.7	98.5
M2	21	35	544	1648	96.3	97.9	94.0	97.5
M3	25	34	535	1654	95.5	98.0	94.0	97.4
M4	27	11	530	1680	95.2	99.3	98.0	98.3

TABLE VII

CONFUSION MATRIX ON TESTING DATA SET

		True Class			
	Class	M1	M2	M3	M4
Predicted Class	M1	272	10	2	0
	M2	8	267	7	0
	M3	0	10	262	8
	M4	0	7	12	259

TABLE VIII

VARIOUS PARAMETERS FOR CLASSIFIER PERFORMANCE EVALUATION ON TESTING DATA SET

	FN	FP	TP	TN	SE	SP	PR	AC
M1	12	8	272	832	95.8	99.0	97.1	98.2
M2	15	27	267	815	94.7	96.8	90.8	96.3
M3	18	21	262	823	93.6	97.5	92.6	96.5
M4	19	8	259	838	93.2	99.1	97.0	97.6

C. Testing of Classification Performance

After optimizing the respective SVM classification models for each of the mango varieties, the individual classification models were trained and tested with the four different data sets as mentioned in Section II. In each case, the classifiers were trained with the images present in the training data set and then tested with the images present in the separately kept testing data set, for normalizing the features obtained from the testing data set images, the same scale factors were used as obtained from the respective training data set.

TABLE IX
CLASSIFICATION ACCURACY (%) WITH DIFFERENT TESTING DATA SETS FOR ALL THE VARIETIES OF MANGO

CLASS	RANDOM					BATCH WISE					GARDEN WISE					DAY-1				
	KU	AM	SO	LA	HI	KU	AM	SO	LA	HI	KU	AM	SO	LA	HI	KU	AM	SO	LA	HI
M1	97.2	98.8	97.6	95.3	98.2	94.8	97.1	95.1	92.4	96.7	94.6	96.8	94.9	91.7	96.4	93.9	96.5	94.5	90.8	95.7
M2	96.8	97.6	97.1	94.6	96.3	93.6	96.5	94.5	91.6	94.6	93.2	95.4	93.9	91.1	93.9	93.2	95.1	93.2	89.6	94.2
M3	96.4	97.4	96.6	94.7	96.5	93.2	96.3	94.1	91.2	94.4	92.5	94.8	93.5	90.8	93.7	91.9	94.4	93.0	89.1	95.7
M4	96.5	98.4	96.8	95.1	97.6	94.3	96.8	94.7	91.9	96.6	93.9	95.8	94.7	91.3	96.3	92.8	95.5	93.8	90.4	96.4

TABLE X
AVERAGE CLASSIFICATION ACCURACY (%) BY THE THREE HUMAN EXPERTS FOR HI VARIETY OVER ALL THE TESTING DATA SET OF MANGOES

CLASS	DATASET			
	Random	Batch Wise	Garden Wise	Day 1
M1	90.2	91.7	92.2	90.3
M2	92.3	92.2	94.1	91.6
M3	93.6	94.1	93.3	94.7
M4	95.8	95.4	96.8	96.1

The performance of the classification model for the HI variety on training data set is listed in Tables V and VI. Table V lists the confusion matrix obtained from the six-fold cv test with total 2248 images present in the training data set.

Table VI lists the performance parameters derived from the confusion matrix of Table V. Similarly, Table VIII lists the performance parameters derived from the confusion matrix of Table VII obtained for the testing data set, which contains remaining 1124 number of images for random data set of the HI variety. In the similar fashion, all the classification models for the five varieties of mangoes were trained and tested with all the four data set. Table IX lists the obtained accuracy for all the varieties over the four data sets. The average classification accuracy obtained with the same four testing data sets for all varieties of mangoes by three human experts in the case of the HI variety is listed in Table X.

V. DISCUSSION

The features extracted from the RGB color space found to be reasonable, and computationally light in comparison with the transforming the whole image in other color space and then extraction of features. The feature selection through the SVM-RFE found to reduce number of features without much compromising performance, reduction of number of features reduce the computation, which is very significant in real processes, the time taken by the computer (Intel i5, 2.4 GHz with 2-GB RAM) found to be ~50 ms. In comparison with the other techniques [1], [10], [15], [20], where the PCA has been used for dimensionality reduction, required to calculate all the by features followed conversion. The ensemble classification models developed with the binary SVM classifiers found to have good generalization ability, as evident form the small differences in performance measures with training (seen) and testing (unseen) data set. The classification performance also found to be reasonable same over all the classes, in comparison with the human experts performance, where it can be observed that (Table X) the average accuracy drops significantly for predicting M1 and M2 classes, which contain the raw mangoes. The performance of human experts for identifying the M4 class is reasonable good and sometime better that the machine, which might be because human experts also check the firmness for prediction. On the other hand, human experts' prediction performance does not vary significantly with the different testing data set, in comparison with the machine-based performance. This might be because the experts are having past experience and they are able to provide more generalized solution.

In classification performances of different classification models, as listed in Table IX, shows that the LA variety are least recognisable, and AM having the highest performance, which is in line with the fact that the changes in skin color for LA with maturity is not so significant, in comparison with the AM and HI variety where the apex region takes reddish shade during ripening process.

The classification performances found to be vary with different data set as listed in Table IX. The performance is the highest in the case of random data set, which is quite obvious as it contains the images from different gardens and batches and the classification model is able to learn the variations. The performance drops in all other data sets, the performances with batchwise data set are slightly better than gardenwise, more interestingly, this is true for all the variety and all the classes. This might be pointing out that the batchwise variation of skin color is less than gardenwise, which is at different geographical location and may be due to different constituents of soils. The classification performance is the lowest in case of day-1 data set, which is because there were less number of images present in the data set, therefore, the classifiers are not able to learn the features space properly, however, this performance is better than the human experts. On the other hand, when all the day-1 images were presented to the classification model trained with random data set found to provide similar performance as presented in the case of random test data set.

In comparison with the performance presented [4], which resulted the maximum recall of 80.41% and 93.10% for two types of defect and in case of performance of the inspection system [7], the false positive rate is 3.2% and false negative rate is 5.6%, whereas in this paper, 1.4% and 4.1% (average over all four classes) on training data set, 1.9% and 5.6% on testing data set, respectively.

VI. Conclusion

This paper proposes a machine vision-based system, suitable for grouping for mango according to the expiry day available after harvesting. The average performance of the proposed machine vision-based system found to be better than the human experts. The application lies with the fact that it can be used with conveyer belt for faster sorting of the mango. The main applicability of the proposed technique is that vendors can easily select the groups, i.e., M1, M2, M3, and M4 according to their choice of days, on the basis of transportation delays and accordingly they can train the classification model by only feeding the images of the mangoes and respective expiry date. This is in sharp contrast with the other proposed techniques that are aimed to measure exact maturity, which may not necessary for this application. This method also bypass the calibration requirement of sensor output with respect to maturity, this is quite important from application point of view that vendor can locally tune their system according to their variety and the time of harvesting.

The results presented in this paper contain detail analysis with the randomly selected samples from different regions and in different times. The performance also found to be reasonable good in comparison with human experts and other work [21]. The proposed technique can also be extended with other varieties of the mango and also for other fruits.

The main drawback of the proposed technique is long training time and misclassification occur due to scratches or black spot (occur often by skin damage) on the skin. However, the classification system trained in previous year so by the other vendor can be readily used, and the image collection for further training can be performed in parallel.

The future scope of work is to realize the algorithm within some embedded or FPGA-based devices. It also includes extending the system for grading according to quality and maturity.

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