A Machine Vision Technique for Grading of Harvested Mangoes Based on Maturity and Quality

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***Abstract*— In agricultural and food industry, the proper grading of fruits is very important to increase the profitability. In this paper, a scheme for automated grading of mango (Mangifera Indica L.) according to maturity level in terms of actual-days-to-rot and quality attributes, such as size, shape, and surface defect has been proposed. The proposed scheme works on intelligent machine vision-based techniques for grading of mangoes in four different categories, which are determined on the basis of market distance and market value. In this system, video image is captured by a charge couple device camera placed on the top of a conveyer belt carrying mangoes, thereafter several image processing techniques are applied to collect features, which are sensitive to the maturity and quality. For maturity prediction in terms of actual-days-to-rot, support vector regression has been employed and for the estimation of quality from the quality attributes, multiattribute decision making system has been adopted. Finally, fuzzy incremental learning algorithm has been used for grading based on maturity and quality. The performance accuracy achieved using this proposed system for grading of mango fruit is nearly 87%. Moreover, the repeatability of the proposed system is found to be 100%.**

***Index Terms*— Maturity, quality, video image, grading, SVR, MADM, fuzzyincremental learning.**

I. Introduction

MANGO is popular fruit, due to its flavor, taste, and nutrition value. Mangoes trees are cultivated in different favorable regions. During summer mangoes are harvested from gardens and then transported to various markets by distributors. According to distance and demand of market quality, the distributors demand batches of homogeneous quality and maturity, while the intrinsic of these agricultural products varies even for one particular variety originated from same garden at same time. The variations become much wider due to variation in variety, location and weather condition at the time of harvesting. The grading of mangoes is thus an essential step; however it is a tedious job and it is difficult for the graders to maintain constant vigilance. If this task could be performed automatically by machine vision, the result would be more objective; it would also save labor and enhance output.

In past, much research work has been carried for automated grading of fruits through analyzing aroma using electronic nose, in order to estimate the ripeness of fruit [1]. In another work, a spectroscopy based fiber-optic and micro-optic device is presented [2] for testing and monitoring of quality and safety of foods. In the work, a micro-optic sensor has been used to discriminate different ageing levels of olive oil. Recently peach maturity prediction [3] has been performed by estimating the fruit flesh firmness using multivariate retrieval techniques applied to the reflectance spectra acquired with the spectrometer. These works of fruit grading mainly involves maturity estimation, through non-vision based system, these methods also have limitation in grading of fruits in mass scale within limited time frame. In these methods, primarily many features have been extracted and thereafter principal-component-analysis (PCA) has been employed to deduce feature dimension significantly, and finally classifiers have been used for grading.

The application of machine vision in agriculture has increased considerably in recent years. There are many fields in which computer vision is involved, including terrestrial and aerial mapping of natural resources, crop monitoring [4], quality control in food and agriculture [5]–[7], automatic guidance, non-destructive inspection of product properties, safety and quality control, process automation, medical diagnostics, aerial surveillance. Recently, online vision based measurement systems have been developed in many applications requiring visual inspection [8]–[11].

Many machine vision systems have been proposed for agricultural grading applications. Among these a direct color mapping system [12] is proposed to evaluate the quality of tomatoes and dates. In this method they converted three-dimensional RGB color space of interest specific to a given application, to one dimensional using a second order polynomial function, so that maturity becomes simple grayscale 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.

Similar kind of machine vision systems have been currently developed for fruit grading applications such as apples quality estimator [13], strawberry grading based on maturity and quality [14], peach grading by comparing peach ground

Manuscript received April 27, 2016; revised June 2, 2016; accepted June 5, 2016. Date of publication June 13, 2016; date of current version July 18, 2016. The associate editor coordinating the review of this paper and approving it for publication was Dr. Shanhong Xia.

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Digital Object Identifier 10.1109/JSEN.2016.2580221

color to reference peach [15], sweet tamarind sorting [16], jatrophacurcas color grading using mean RGB color intensity to analyze the red, green and blue (RGB), for sampling purpose, they used 5 samples of each grade in training stage and 6 samples for the testing stage [17], date fruit grading system [18] using RGB images to classify into three categories and obtained 80% accuracy and classification of mango according to degree of browning in mango skin [19].

However, all these presented methods are developed to detect the maturity level and/or quality level for grading of the fruits. The limitations and condition evaluation of these proposed system is that, they considered very few number of features even not validated with the other varieties of that particular fruit. No such system still proposed for prediction of *actual-days-to-rot*, which is very essential during transportation from one place to another and it also helps to select the market distance and market demand for sending fresh fruits (before start rotten). In most of the work, practical purpose of grading and the automated system for the purpose have not been taken into account.

In the proposed work authors developed an automated machine vision based system for grading of harvested mangoes based on *actual-days-to-rot* and quality level. The work can be considered as advancement over previous work on mangoes [20] in two perspectives. First one is the development of suitable algorithms for prediction of *actual-days-to-rot,* instead of previously developed prediction of maturity level and algorithm for estimation of mango quality on the basis of shape, size, and surface defects. The second advancement is to combine algorithms, for making the proposed system more useful for the vendors to grade mangoes according to given inputs of market distance and desired quality of the mangoes as in demand by the market. The prediction of *actual-days-to-rot* is more important than the maturity level, in decision making on the account of transportation delay. On the other hand some markets ready to pay much higher price for better quality mangoes. Therefore, mangoes are to be classified judiciously, by sensing suitable selected parameters.

The necessity, the key innovation of this proposed work and also the main concern of this paper is clearly summarized in the following:

- The proposed system not only predicts maturity level and quality level, but also predicts the *actual-days-to-rot* of mangoes. So the vendors can increase their profitability by reducing losses due to rotting of mangoes during transportation.
- The proposed system is so designed that it can automatically grades the entire lot of mangoes according to vendor specific inputs on quality and transportation delay.
- The proposed *real-time-system* has been rigorously validated on five different varieties of mangoes which are collected from different gardens and in different batches.

The main contribution of the present work is, development of a real time automated machine vision based system for grading of harvested mangoes according to maturity level in terms of *actual-days-to-rot* and the quality attributes like size, shape and surface defects. The prediction of *actual-days-to-rot* is more important than the maturity level, in decision making on the account of transportation delay. The proposed method is discussed in Section II. Theory of MADM and fuzzy algorithms is discussed in Section III and Section IV, respectively. The result and discussions is discussed in Section V. We summarize our work and conclude this paper in Section VI.

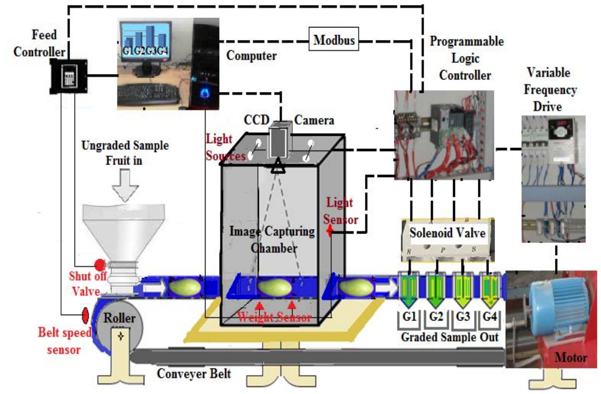

Fig. 1. Machine vision-based proposed system for real time mango fruit grading based on maturity level and quality.

II. Methods

Present section discusses about the methodology adopted in the proposed work for automated gradation of different varieties of harvested mangoes. The proposed real time machine vision based grading system considering maturity level and quality is shown in Fig. 1. A camera is placed on top of the artificially illuminated image capturing chamber (as shown in Fig. 1) for collecting images in video mode into computer. The camera in video mode was focused on conveyer belt through which the mangoes pass. The still frames were extracted from the video image at the frame rate of 30 fps (frames per second) with resolution of 640x480 in RGB mode. To minimize the motion blur shutter speed was controlled and fixed to the value of 1/200s. Still frame extraction rate i.e. fps and the shutter speed is automatically (using software) adjusted based on conveyor belt speed to get better still frame.

A belt speed sensor is used to monitor the conveyer belt speed and controlled accordingly. The conveyer belt contain specially marked (in four corners) plates and one mango in each plate is placed by the sample placer. Shut off valve is used to stop feeding of sample in the conveyor belt. This is controlled by the feed controller. Two weight sensors are attached at the bottom of the image capturing chamber to sense the weight of the mango when it is rolling over the sensors. The proposed algorithm was implemented in Lab VIEW ®Real Time Environment for automatic grading considering maturity level and quality. 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.

A. Material and Preprocessing

For the experimental works five different varieties of mangoes locally termed as “Kumrapali” (KU), “Amrapali” (AM), “Sori” (SO), “Langra” (LA) and “Himsagar” (HI) were collected from different places

TABLE I
STANDARD FOR GRADATION OF COMMERCIAL VARIETIES OF MANGOES

Grade	Attributes for gradation
G1 (Poor)	Premature or overmature mangoes having large skin and shape defects, with small size and weight are in this class. Generally such mangoes are not supplied to the consumer, but may be used for industrial processing.
G2 (Medium)	This class includes mangoes which are semimatureand satisfy the minimum quality requirements. The following defects, however, may be allowed, provided the mangoes retain their essential characteristics as regards the quality: defects in shape and skin. They have light weight and small size.
G3 (Good)	Mangoes in this class must be matured and good quality. They must be characteristic of the variety. They have medium size and weight, slight defects in shape and skin.
G4 (Very good)	Mangoes in this class must be matured, superior quality and must be characteristic of the variety. They must be big size, good shape and weight and free of defects, with the exception of very slight superficial defects.

of West Bengal, India. Total 200 numbers of each variety mangoes were collected in two phases, each phase 100 with an interval of 20 days. Each mango was used to pass through a conveyer belt and was presented to five independent experts who work in company for grading and packaging of the mango according to maturity level and quality. The experts predict the number of days left to get over matured and start rotten and the quality according to the convention of the company for recording of human experts score.

After capturing the image, different preprocessing issues, like still frame extraction, filtering, edge detection, background elimination, alignment of mango image are performed before extraction of features using different image processing method. Since the value of RGB is device dependent, so the camera was calibrated using method in [21], [22] to obtain the color calibration of camera for providing accurate and consistent color measurements.

B. Manual Grading Process

In general, mango grading is done by using the human experts. Human experts grade the mangoes using hands and eyes which cause lack of objectivity, efficiency and accuracy. Table I shows how the standard applies to commercial variety of mangoes to be supplied fresh to the consumers [23], for all classes, subjected to the special provisions for each class and the tolerances allowed. In relation to the evolution of the change of surface color, size, shape, weight may vary according to variety of mango. The appropriate degree of maturity corresponding to the varietal characteristics is also required to withstand transport and handling, and to arrive in satisfactory condition at the place of destination.

C. Automated Grading Process

The automated mango fruit grading process in this proposed work is divided into two groups, one is maturity estimation in terms of *actual-days-to-rot* and second one is determination of quality. In the proposed work two layer classification (i.e. first layer is SVR and MADM and the second layer fuzzy incremental learning) technique is used. In the first layer prediction of maturity level in terms of *actual-days-to-rot* using SVR and evaluation of quality using MADM is done separately, as the vendors can enter these two inputs in the proposed system, based on the market distance and market value. In the second stage fuzzy incremental learning algorithm has been applied to classify the mango into four different grades, also the vendors can choose any combination of grade from the combinations listed in Table VI.

In our previous work [20], the maturity of these mango varieties, have been successfully estimated with the help of optimum set of features obtained using of Support Vector Machine (SVM) based Recursive Feature Elimination (RFE) technique. For classification of the mangoes into four different classes (M1-premature, M2-semimature, M3-mature, M4-overmature) according to maturity level, an ensemble of 7 binary SVM classifiers has been combined in Error Correcting Output Code (ECOC), and the minimum hamming distance based rule has been applied in decision making phase.

In the proposed system images are captured using 10MP camera. It is quite obvious, higher resolution camera can provide better performance at the cost of computation. The resolution of extracted still frame (at the rate of 30fps) was 640X480. Since resolution 640X480 is common standards and cameras with this resolution are cheaper therefore in present system, it has been considered.

For this, Support Vector Regression (SVR) is used to determine the number of actual days that the harvested mangoes can be sent and MADM system has been employed for estimation of mango quality from the quality attributes like shape, size and surface defects. Finally fuzzy incremental learning algorithm has been applied to combine the decisions of SVR and MADM on maturity and quality respectively, for final gradation of mangoes into the four different categories. The different steps of complete grading process are shown in Fig. 2 and the sample images of the four different grades of mango is shown in Fig. 3.

The following section presents the details of prediction of *actual-days-to-rot* and feature extraction processes for estimation of quality, followed by brief theory of MADM and fuzzy.

1) Maturity Prediction in Terms of Actual-Days-to-Rot: Before experimental works, each mango was presented to five independent experts for recording expert's opinion. The average nearest integer of the five expert's opinion was considered as expert predicted *days-to-rot*. Only those mangoes were collected which having *days-to-rot* in the range of 5 to 14 days, and for each case (i.e. *days-to-rot)* total 10 number of mangoes were collected, having accumulated total of 100. The same procedure was followed to collect another 100 number of mangoes in 2^{nd} phase. After collection, mangoes were tagged by some serial number and images of the mangoes were collected by a CCD camera starting from day-0. Then the mangoes were placed in the package in the same manner as used for the transport of the mangoes to different cities. On the next day each mango was taken out from the package

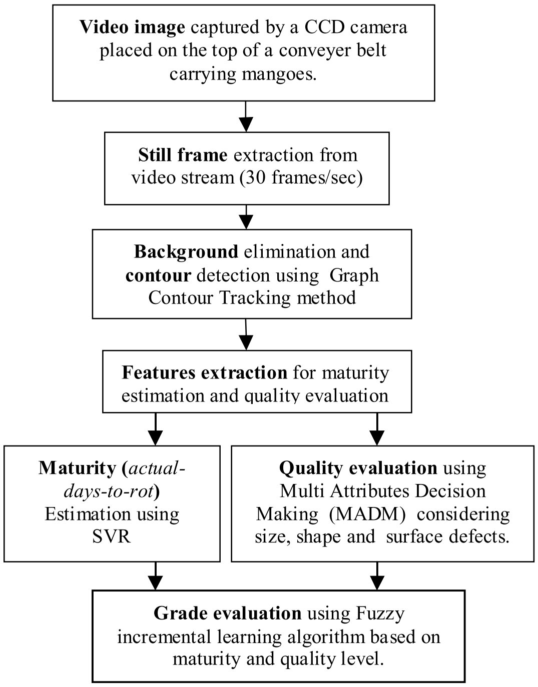

Fig. 2. Flowdiagram of proposed machine vision-based mango grading process.

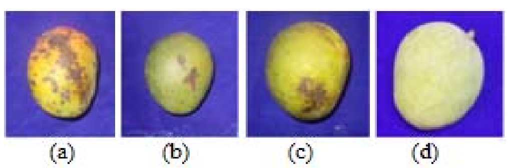

Fig. 3. Sample images of different grades of mango: (a) G1-poor, (b) G2-medium, (c) G3-good, and (d) G4-very good.

carefully for taking image for the day-1 and also presented to the five experts and their predicted *days-to-rot* were recorded, the same process was followed for all the days.

The mangoes which started rotten after some days were removed from the package and no further processing was done of these mangoes. In this manner total 2184 number of images of mango were collected. One interesting observation was that the expert predicted days were not also correct, some mango start rotten before the *days-to-rot* and some after. In the work a mango was considered rotten if 2% of the skin surface gets dark color (as per the convention of the company). The corresponding days were considered as *actual-days-to-rot*. Images of different maturity level for same mango of five different varieties are shown in Fig. 4.

For the training and testing of the SVR model, all the 27 features extracted, details discussed in previous study [24] from the images of mango were arranged in a matrix column wise called feature matrix, where each row represent a feature vector and having dimension $d=27$ i.e. the total number of features extracted from a particular image of a mango. Total number of rows is 2184, i.e. the size of the total number of images. The feature vectors in the feature matrix were arranged according to the increasing order of *actual-days-to-rot*.

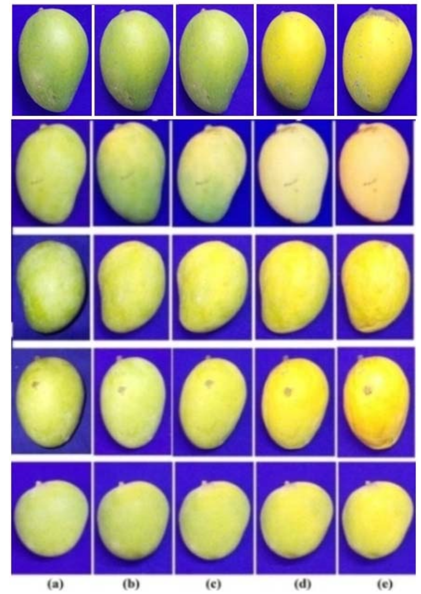

Fig. 4. Images of five varieties of mango having different maturity level. first row: "AM", second row: "KU", third row "SO" and fourth row "LA" and fifth row "HI", taken with an interval of two days. Images shown in: (a) pre-matured; (b) semi-matured (c)-(d); matured; and (e) is called the over-matured and rotten one.

That is initial rows constitute the feature vectors of those mangoes, which had only one days left to get over matured. Similarly next set of rows for those mangoes having 2 days left, and it was up to 16 days, though collected mangoes was up to 14 days as predicted by experts, but actually some mangoes sustained up to 16 days. Then *actual-days-to-rot* was considered as a target value for each of the feature vector. This process helped to increase the data set size, for training and testing.

Then from this feature matrix training and testing data set was created, by drawing 50% of the feature vectors for training and remaining 50% for testing the performance of the SVR model. The drawing process for training data set was random from each class, where a class contains all the feature vectors of those mango images having same number of days left for *actual-days-to-rot*. Half of the feature vectors were kept for training and remaining half for testing. This process was followed for all the classes.

After forming the training and testing data set next task was to form the SVR model. There are three parameters for controlling the regression model, the loss function, the kernel and additional capacity control $\hat{C}$. In the present work these parameters were obtained experimentally, by training the SVR model with training data set and evaluating the performance of SVR model with the help of testing data set.

Initial experiments were performed for selection of kernel function. The performance of the SVR was evaluated with different types of kernel function like linear, polynomial and Gaussian-RBF. Among this the Gaussian-RBF of form $\mathcal{K}(\vec{\chi}_k, \chi) = exp\left(-\gamma \, \|\vec{\chi}_k - \chi\|^{\mathbf{2}}\right)$, produced best performance.

Another set of experiments were done on proper adjustment of $\hat{C}$ value, loss function (ε) and γ for Gaussian–RBF.

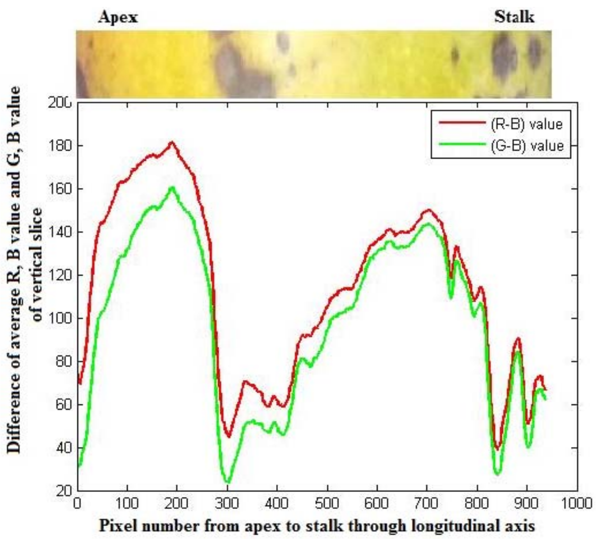

Fig. 5. Variation of difference of average R and B value and average G and B value along vertical slice from apex to stalk of "AM" variety mango.

In this case $\varepsilon\,\hat{C}$, and γ were varied iteratively in the range between 1000 to 1, 0.01 to 0.1 and 0.0001 to 10, respectively, and average classification accuracy was monitored on each iteration, which suggests $\hat{C}$ should be between 300 to 330, ε in between 0.03 to 0.05 and γ in between 0.22 to 0.31 to get maximum performance.

2) Feature Extraction for Quality Attributes:

a) Size calculation: The size of mango is an important quality attribute for grading, the bigger size is considered of better quality. The size is estimated by calculating the length of maximum major axis (longitudinal axis)and maximum minor axis (transverse axis), of the mango image. To compute these lengths first mango image is rotated in such a way that the apex will be at the top then the image is binaries to separate the fruit image from its background as shown in Fig. 6(a). The maximum major axis (L_{max}) is detected in the vertical direction and maximum minor axis (W_{max}) is detected in the horizontal direction as shown in Fig. 6(b). Then the total number of the pixels (Np) on these two axis is found. The actual lengths are measured by vernire scale and the rate between the pixel and the actual length is called A, and is calculated by:

$$A = \frac{\text{the pixels}}{\text{actual length}}\ (\text{pixel/mm})$$

Through a lot of trials and calculations, for 10MP camera keeping distance from camera to the object is 20cm, the value of A is gotten 14.1 (pixels/mm). The length of this two axis is calculated by the following equation.

$$(L_{max} + W_{max}) = Np/A = Np/14.1$$

b) Determination of surface defects: Surface defects is the another quality attribute used by the farmer or customer. Experimentally it is seen that the blue value is very high in defect pixels compare to healthy pixels. The difference of average R, B (i.e. R-B) value and G, B (i.e. G-B) value of vertical slice through the longitudinal axis from apex to stalk is shown in Fig. 5. The vertical slice from apex to stalk of "AM" variety is shown at the top of the graph. It is clearly noticed from the graph that the average R-B value and G-B value of the vertical slice, both are very less (less than 80) for defect pixels and very high (80 to near about190) in healthy pixels. So using simple thresholding method the defect pixels is identified. Experimentally it is also noticed that this threshold value is different for different varieties of mango. Then the number of defect pixels are calculated where from the percentage of defect area is determined.

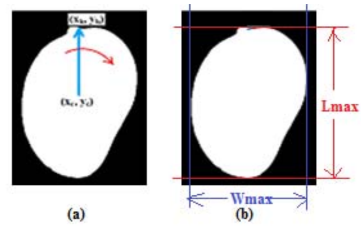

Fig. 6. Binary image of the AM variety mango (a) extraction of contour and centroid (b) calculation of L_{max} and W_{max}.

c) Shape measurement: In the proposed system mangoes are considered adequately by two-dimensional perspectives and the shape of mangoes are retrieved using Fourier Descriptors [25]. Presently, there are many methods available for analyzing shape of an object, ranging from a simple multiple point features method to a complicated geometric features approach. Authors [26], [27] provide detailed mathematical explanation of Fourier Descriptors (FD) for object recognition, matching and registration. Authors [28] investigated the use of Fourier descriptors in distinguishing star fruits using computer vision. One unique feature of this method is that it uses global image descriptors instead of the local ones, making it more applicable to real-world images. Before this method could be implemented, several image pre-processing steps were performed on the mango image.

The image is firstly binarised and secondly, processed via a sequence of morphological image processing. Finally, the object centroid is extracted using first-order geometric moments and derived using Green's theorem as shown in Fig. 6(a). Mathematically, the two-dimensional centroid (x_c, y_c) is calculated as follows:

$$\mathrm{x_c} = \frac{\sum_{k=0}^{N} y_k\left(x_k^2 - x_{k-1}^2\right) - x_k^2(y_k - y_{k-1})}{2\sum_{k=0}^{N} y_k\left(x_k - x_{k-1}\right) - x_k(y_k - y_{k-1})} \tag{1}$$

and

$$y_c = \frac{\sum_{k=0}^{N} y_k^2\left(x_k - x_{k-1}\right) - x_k\left(y_k^2 - y_{k-1}^2\right)}{2\sum_{k=0}^{N} y_k\left(x_k - x_{k-1}\right) - x_k(y_k - y_{k-1})} \tag{2}$$

where, N is the total number of boundary pixel defined in a clockwise direction from anystarting point; (x_k, y_k) is the coordinate of the boundary pixel, k. The distance of each boundary point to the centroid is calculated as follows:

$$R\left(k\right) = \sqrt{(x_k - x_c)^2 + (y_k - y_c)^2} \tag{3}$$

The $R(k)$ is then subjected to Discrete Fourier Transform (DFT), yielding a one dimensional feature vector of the mango image. In Fourier space, such transformation is mathematically implemented as follows:

$$| F(m) | = \frac{1}{N} \times \sqrt{\left[\sum_{k=0}^{N} R(k) Cos\left(\frac{2\pi mk}{N}\right)\right]^2 + \left[\sum_{k=0}^{N} R(k) Sin\left(\frac{2\pi mk}{N}\right)\right]^2} \quad (4)$$

Since the descriptors are influenced by the shape of the contour and by the initial point of the contour, therefore, calculating and examining each harmonic component in $F(m)$ provide an indication of the shape of mango. For a given shape, the plot of Fourier descriptors produces a pattern or fingerprint which uniquely describe this shape. Theoretically, the order of Fourier descriptors ranges from zero to infinity. However, one favorable property common to Fourier descriptors is that the high-quality boundary shape representation can be obtained using only a few lower-order coefficients. Therefore, only the first few components of $F(m)$ are distinct and generally required to distinguish the difference between mango shapes. In this work a shape training set and shape test set is created for each variety of each cultivar to discriminate good mango shape from misshapen ones. But in practical applications it is variety dependent because shape of mango has natural and acceptable variability from one variety to another.

III. Theory of Multi Attribute Decision Making (MADM)

A Multi Attribute Decision Making (MADM) method specified how attribute information is to be process in order to arrive at a choice. It can assign different weight to different attributes of the object according to different standards to achieve the simplification of the multi-attribute problems. The i^{th}alternatives score can be determined with the magnitude of the index P_i ($i = 1, 2, \ldots, m$):

$$P_i = \sum_{j=1}^{n} w_j (m_{ij})_{normal} \quad (5)$$

where, w_j is the weight of the attribution j, $(m_{ij})_{normal}$ represents the normalized value of m_{ij} of the attribution j of alternatives i, n is the number of indices. Considering the sum of all weights equals to 1 i.e. $w_1 + w_2 + w_3 = 1$. And P_i is the overall or composite score of the alternative A_i.

Normally, the index (size, shape and surface defects) conflicts with one another during multi indices grading. For example, some mangoes have large sizes but their surface is defective so as to have an influence when they are placed together. To solve these problems, Multi Attribute Decision Making (MADM) is adopted in this system. It can assign different weights to different attributes of the object according to different standards to achieve the simplification of the multi-attribute problems.

IV. Theory of Fuzzy Algorithm

Fuzzy Inference System (FIS) based on Takagi-Sugeno model [29] shown in Fig. 7, where the antecedents are fuzzy and the consequent is crisp. The two inputs of FIS, maturity and quality level are first fuzyfied into a fuzzy set. The fuzzy model proposed [30], [31] is widely used for generating rules using input-output data [32]. A practical application of kernel-based fuzzy discriminant analysis [33] and feature extraction using fuzzy maxi-mum margin criterion [34] is discussed. We have two data points that corresponds to normalized value of maturity level and quality level. The set of input-output data pairs is given as follows:

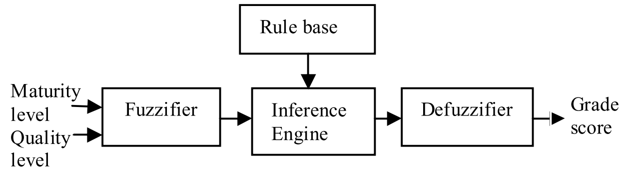

Fig. 7. Fuzzy inference system (FIS).

$$(x_1^{(i)}, x_2^{(i)}; g^{(i)}).$$

Here $x_1^{(i)}$ and $x_2^{(i)}$ are the normalized values of inputs, and $g^{(i)}$ is the output of i^{th} mango sample. Here we generated a set of fuzzy rules using different steps [35] from the above data and used these fuzzy rules to determine mapping $f : (x_1, x_2) \to g$.

Rules obtained from each pair of input-output data as:

$$R_i = IF x_1^{(i)}\ is\ r_a\left(\mu_{r_a}^{(i)}\right)\ and\ x_2^{(i)}\ is\ r_b\left(\mu_{r_b}^{(i)}\right)$$
$$THEN\ g^{(i)}\ is\ r_c\left(\mu_{r_c}^{(i)}\right) \quad (6)$$

Where R_i is the i^{th} rule, r_a and r_b are the fuzzy sets representing different regions of the input space, r_c is the fuzzy set representing the region in the output space, and $\mu^{(i)'}$s are the corresponding membership values. In each rule, there are two atomic clauses in the antecedent part. Centroid defuzzification method is used to determine the output grade g for given input x_1 and x_2. The fuzzy training and testing algorithm used for mango grading is shown in Table VII and Table VIII respectively.

V. Result And Discussions

The obtained results are grouped into two subsections, first section presented the obtained results for prediction of maturity in terms of *actual-days-to-rot* and second section obtained the results for estimation of quality using MADM, with the help of the four attributes. The last section presents the final results on grading of mangoes with the help of fuzzy incremental learning algorithm.

A. Maturity Estimation in Terms of Actual-Days-to-Rot

After finalization of the SVR model, it was tested for the evaluation of the performance. In this case first the optimized SVR model was trained with the training data set (half of the total data set) and then tested with another half, and consequently performance was calculated. Then the same process was repeated with the earlier testing dataset used for training and earlier training data set used in testing. Error was

TABLE II
PERFORMANCE ANALYSIS FOR AM VARIETY

Actual-days-to-rot	Performance in %	
	Manual	SVR
1	100	100
2	100	98.8
3	99.1	97.2
4	97.6	96.1
5	96.7	94.4
6	95.8	93.8
7	94.5	92.3
8	91.7	89.8
9	89.6	87.6
10	86.3	84.3
11	83.6	79.5
12	79.7	76.7
13	71.6	70.3
14	64.2	66.2
15	58.5	61.3
16	48.7	54.1
Average	84.8	83.9

TABLE III
RESULTS OF SOME MANGO SIZES

Variety **(Local Name)**	Actual Length		Detecting Pixels		Calculating Length	
	L_{max} (mm)	W_{max} (mm)	L_{max} (mm)	W_{max} (mm)	L_{max} (mm)	W_{max} (mm)
KU	106.3	66.2	1515	942	107.4	66.8
AM	104.2	69.0	1482	978	105.1	69.4
SO	76.1	521	1082	740	76.7	52.5
LA	61.0	45.2	868	644	61.6	45.7
HI	69.2	57.3	982	812	69.7	57.6

calculated by calculating the deviation in between *predicted-days-to-rot* and *actual-days-to-rot,* and then the typical performance becomes *100-%Error,* which represents the agreement in % for the prediction. The average performances were calculated and presented in Table II, class wise i.e. with the *actual-days-to-rot*.

From the Table II, it can be observed that the average performance for the proposed vision based automatic technique as good as the manual expert based technique, which are 83.9% and 84.8% respectively. It can be also observed that the manual technique is more accurate for those cases when the *actual-days-to-rot* less than 14 days. On the other hand the proposed technique shown better performance when the *actual-days-to-rot* more than 14 days.

B. Quality Evaluation

The quality evaluation depends on the proper estimation of the three attributes i.e. size, shape, and surface defects. The experimental result, of these attributes are discussed here.

1) Size Gradation Test: The mango size gradation is implemented by a threshold which is set according to the length of mango major axis and minor axis considering the different varieties of mango. The error between the actual length and the measured length is within 3% as shown in Table III.

2) Surface Defect Gradation Test: For experimental work, mangoes of five different varieties were used as the sample to analyze the amount of surface defected. The number of defective pixels are calculated and distinguished to validate the gradation effect of the experts and the result is shown in Table IV.

TABLE IV
RESULT OF SURFACE DEFECTS ANALYSIS

Variety **(Local Name)**	Total Pixels	Defective Pixels	% of Surface Area Defected	
			System	Expert
KU	1007340	21150	2.1	2
AM	1008171	32212	3.2	3
SO	600516	5618	2.6	3
LA	419248	17185	4.1	4
HI	598036	11369	1.9	2

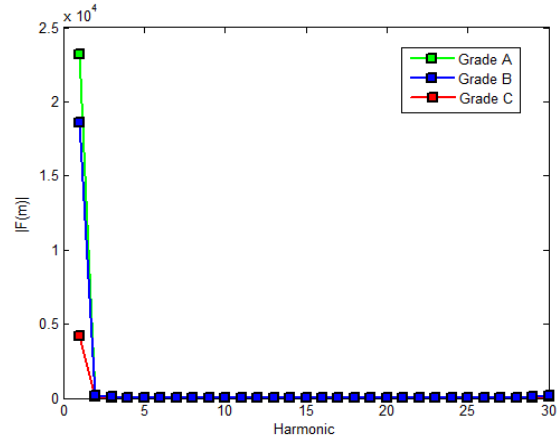

Fig. 8. Shape analysis based on Fourier Descriptor for AM variety.

3) Shape Gradation Test: Shape analysis based on Fourier Descriptor for each shape category of AM variety is shown in Fig. 8. Clearly from Fig. 8 the grades A, B and C (i.e. good, medium and poor) can be characterized by $|F(3)|$. The method based on direct thresholding cannot be used because of the difficulty in establishing a single and effective shape threshold. A different approach is needed to solve this type of pattern recognition problem. Statistical approaches are generally characterized by having an explicit underlying probability model, which provides the probability of being in each class rather than a simple classification [36]. Support Vector Machine based statistical approach is used to recognize the pattern to determine the shape of the mango.

4) Quality Evaluation: The automated mango grading system is designed to evaluate quality by three indices simultaneously using. Multi Attribute Decision Making (MADM). In this quality evaluation system, $j = 1, 2, 3$ expresses the size, shape and surface defects considering the sum of all weights equals to 1 i.e. $w_1 + w_2 + w_3 = 1$. P_i is the overall or composite score of the alternative A_i. The alternative with the highest value of P_i, shown in Table V indicates the best quality. As all the attributes are consider in normalized domain, it can be applicable for all variety. Final selection of w_1, w_2 *and* w_3 are by the knowledge of experts and vendors. Vendor can also change these weights manually considering market demand and mango varieties. The analysis for the four different quality levels of mango are shown in Fig. 9.

TABLE V
DECISION TABLE IN MADM METHODS

Alternatives (A_i)	Size (w_1=0.35)	Shape (w_2=0.15)	Surface Quality (w_3=0.5)	Composite Score (P_i)
Alt 1	0.9	0.9	0.9	0.9
Alt 2	0.5	0.7	0.8	0.68
Alt 3	0.7	0.65	0.8	0.74
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Alt N	0.85	0.8	0.7	0.77

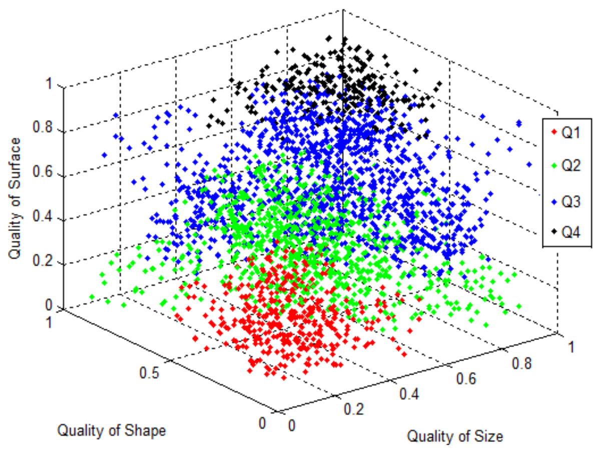

Fig. 9. Quality analysis using quality attributes of size, shape and surface quality of AM variety.

TABLE VI
LIST OF COMBINATION OF DIFFERENT GRADES FOR AM VARIETY

Grades	Description
M1Q1	Poor quality can be transported 9 to 12 days
M1Q2	Medium quality can be transported 9 to 12 days
M1Q3	Good quality can be transported 9 to 12 days
M1Q4	Very good quality can be transported 9 to 12 days
M2Q1	Poor quality can be transported 5 to 8 days
M2Q2	Medium quality can be transported 5 to 8 days
M2Q3	Good quality can be transported 5 to 8 days
M2Q4	Very good quality can be transported 5 to 8 days
M3Q1	Poor quality can be transported 1 to 4 days
M3Q2	Medium quality can be transported 1 to 4 days
M3Q3	Good quality can be transported 1 to 4 days
M3Q4	Very good quality can be transported 1 to 4 days
M4Q1	Poor quality should be sent local market or industry
M4Q2	Medium quality should be sent local market or industry
M4Q3	Good quality should be sent local market or industry
M4Q4	Very good quality should be sent local market or industry

C. Grading of Mangoes

The whole automated mango grading system was conducted for the five different varieties of mango and the performance accuracy of the proposed system is obtained and shown in Table X. Though actual gradation here is four (G1-poor, G2-medium, G3-good, and G4-very good), the vendor may want any gradation among the listed sixteen numbers of combination in Table VI. The analysis of these total 16 different combinations considering four different maturity level and four different quality level of "AM" variety is shown in Fig. 10. The final four different grades are analyzed using fuzzy incremental learning algorithm and shown in Fig. 11. The confusion table of the experimental result of proposed system of AM variety is shown in Tables IX. The performance accuracy for all the five different varieties are listed in Table X, showed that all the varieties are fitted together well and enable to achieve the mango gradation action.

However, it should be noted that the experts gradation is also subject to error, so that 100% agreement cannot be expected. The present study, thus, confirms that the proposed system

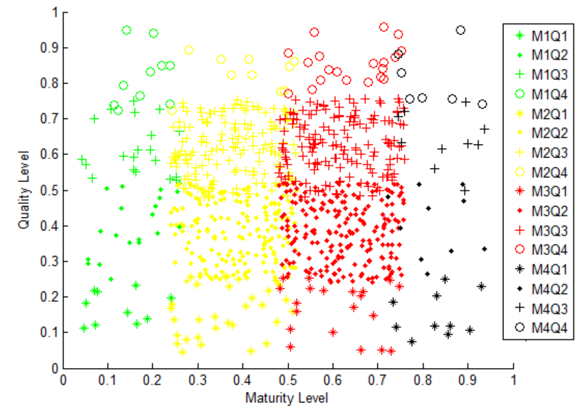

Fig. 10. Grading analysis of different maturity level and quality level of AM variety.

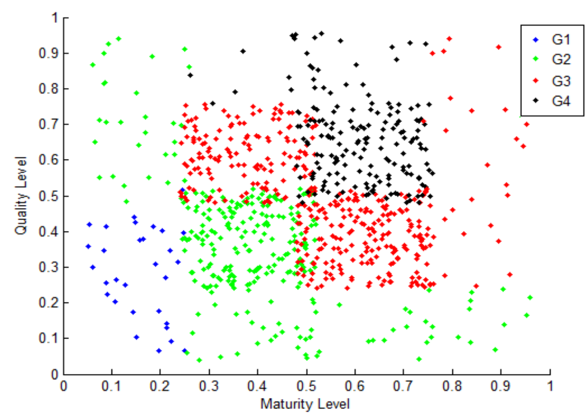

Fig. 11. Analysis of four different grades of AM variety.

TABLE VII
FUZZY TRAINING ALGORITHM

Step 1: Maturity level, quality level and corresponding average expert's score of a mango sample are given as input.
Step 2: ***if*** the two inputs are in existing class, then
if all the atomic clause of the antecedent and the consequent is matched with an existing rule *// rule is already in the rule base*
Go** to **Step 1
Step3: A new rule is generated with the antecedent and the consequent as the grade declared by the human expert's.
The rule along with the membership grade of each atomic clause of the antecedent are added in the rule base.
Go** to **Step 1

TABLE VIII
FUZZY TESTING ALGORITHM

Step 1: Maturity and quality for an unknown mango sample are given as input.
Step 2: Calculate the membership grade (μ_i) and fuzzy region (r_i) of the two inputs.
Step3: Search for matching rules from the rule base.
***for** j = 1: number of rules*
m_j *= product of the membership grade of each atomic clause in the antecedent.*
g_j *= centre value of output region.*
end for
Step 4: Centroid defuzzification formula is used to calculate the grade of unknown mango sample.
Calculated grade$=\frac{\sum_{j=1}^{k} m_j * g_j}{\sum_{j=1}^{k} m_j}$
where, k is the number of fuzzy rules in the rule base.

TABLE IX
CONFUSION TABLE OF PROPOSED SYSTEM FOR AM VARIETY

	Recognized Grade				
	Grade	G1	G2	G3	G4
Input Grade	G1	48	5	1	0
	G2	7	207	16	0
	G3	0	11	222	14
	G4	0	2	11	107

TABLE X
PERFORMANCE ANALYSIS OF PROPOSED SYSTEM

Variety (Local Name)	**Performance Accuracy G1**	**G2**	**G3**	**G4**
KU	88.1	88.4	87.4	87.3
AM	88.8	89.2	90.2	87.8
SO	85.6	86.0	86.2	86.4
LA	84.2	85.5	85.8	85.8
HI	85.2	87.6	86.6	87.0

predicts the *actual-days-to-rot* and estimates mango quality with considerable accuracy using machine vision exhibiting at the same time an effective human visual perception. In fact, the results of this study are quite promising and precise. Out of 10% mango wrongly graded by the system are also graded wrongly to the level of nearly 8% by the human experts thus confirming subject perception of human vision. However, when the same samples are validated by executing the proposed system, the repeatability is found to be again 100%.

VI. CONCLUSIONS AND FUTURE WORK

In this research we built a proposed model of a mango fruit grading system including both: the hardware and the software. The hardware includes the conveyer belt speed control mechanism, feed control, camera control, light intensity control and switching control. The software system analyzes the still frame extraction, preprocessing of image, features extraction and finally gradation. Proposed grading system grades the mango into four grades (though actual gradation can be extended up to sixteen) based on experts perception. Results show that the mango grading algorithm is designed viable and accurate. Mango size error is less than 3%, the *actual-days-to-rot* prediction accuracy is 84%, accuracy for measurement of shape is 91% and the accuracy for measurement of surface defect is over 90%. The average time to grade one mango is approximately 0.4 second.

We observed problems in detecting the firmness from this vision based measurement. An impact sensor may be used for firmness detection. The limitation of this proposed system is that the motion of the mangoes within the conveyer belt interferes with accurate assessment of shape, although motion has little effect on determining the size. In the proposed method the suitable frames containing full image of mangoes, which are identified by the four special markings on the plates in the conveyer belt are considered for pre-processing to reduce the effect of motion of mangoes within the conveyer belt and the noises due to vibration. Though in case of mango grading by the proposed system we have considered one side of mango image, a mechanical set up may be introduced to rotate the mango within the conveyor belt to get the image of the other side.

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