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Fuzzy classification of pre-harvest tomatoes for ripeness estimation – An approach based on automatic rule learning using decision tree

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ABSTRACT

Tomato (*Solanum lycopersicum*) ripeness estimation is an important process that affects its quality evaluation and marketing. However, the slow speed, subjectivity, time consumption associated with manual assessment has been forcing the agriculture industry to apply automation through robots. The vision system of harvesting robot is responsible for two-tasks. The first task is the recognition of object (tomato) and second is the classification of recognized objects (tomatoes). In this paper, Fuzzy Rule-Based Classification approach (FRBCS) has been proposed to estimate the ripeness of tomatoes based on color. The two color depictions: red-green color difference and red-green color ratio are derived from extracted RGB color information. These are then compared as a criterion for classification. Fuzzy partitioning of the feature space into linguistic variables is done by means of a learning algorithm. A rule set is automatically generated from the derived feature set using Decision Trees. Mamdani fuzzy inference system is adopted for building the fuzzy rule based classification system that classifies the tomatoes into six maturity stages. Dataset used for experiments has been created using the real images that were collected from a farm. 70% of the total images were used for training and 30% images of the total were used for testing the dataset respectively. Training dataset is divided into six classes representing the six different stages of tomato ripeness. Experimental results showed the system achieved the ripeness classification accuracy of 94.29% using proposed FRBCS.

1. Introduction

India is an agriculture-based country. Agriculture plays a crucial role in the economy and is the prime source for country's national income. Fundamental factor responsible for consistent marketing of crops is its quality. For many crops, the main indicator of quality is its ripeness. The consumer (wholesaler or retailer) observes the quality of fresh fruits and vegetables from their visual or external appearance. The visual appearance of the crop is used to judge its ripeness, which is measured, by color, size, and shape. Out of these three factors, color is the most important factor. It has high influence on quality and consumers' preference. For many agricultural products, certain colors are preferred and demand higher selling prices. This is true for apples [1], broccoli [2], and cranberries [3]. Color is one of the most commonly used feature to evaluate maturity for various fruits, vegetables like tomatoes [4], watermelons [5], bananas [6], and dates [7]. Harvesting of fruits and vegetables at proper stage of maturity is of paramount significance for attaining desirable quality. The level of maturity helps in estimation of shelf life, selection of storage methods, and selection of processing operations for value addition. The maturity has been divided into two categories i.e. physiological maturity and horticultural maturity [8]. Horticultural (pre-harvest) maturity refers to the stage of development when a crop is ready for harvest. Physiological (post-harvest) maturity is the stage when a crop is capable of further development or ripening after it is harvested i.e. ready for eating or processing. Quality characteristics such as flavor, texture, and color are sustained when the fruit is harvested at an optimal stage of maturity. Therefore, ripeness monitoring and controlling has become a very important issue in crop industry.

Tomato is one of the most important food crops in India, which is marketed all over the country. It is a climacteric fruit i.e. it continues ripening even after it has been harvested. Quality of tomato is judged by its ripeness. Arbitrating the level of ripeness is feasible by analyzing the color of the tomato surface [9]. A classification chart by USDA (United States Department of Agriculture) discriminates six stages of ripening based on color namely green, breaker,

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Fig. 1. USDA six ripening stages.

turning, pink, light red, red [10]. Fig. 1 shows the different ripening stages of tomatoes. The harvesting time depends on the purpose and the distance over which they are to be transported. Tomato should be picked at mature green stage (turning stage) for long distance transport and at later stages of ripeness for short distance transport.

Until now, human graders usually estimate optimal harvest date and period of storage life visually with the help of classification chart and through practical experience. However, manual interpretation is subjective. It can also be affected due to tiredness. For the big farms and greenhouses, it is a time-consuming task. Hence, automation of ripeness assessment process is a big gain for agriculture industry. Automatic machine vision can eliminate the inconsistencies in ripeness estimation due to manual evaluation. Machine vision is known to be a useful tool for external feature measurements i.e. size, shape, color and defects.

Research on fruits and vegetable harvesting robots has been reported more than 20 years ago but none of them has been practically used so far [9,11–13]. The reason is that operational speed of robots is almost same or slower than the manual speed. Besides, the hardware requirement is too expensive. But with the advancement in data acquisition and storage techniques, the research on harvesting robots has again picked up the momentum and is an exciting research area among researchers [14–17]. Recent developments in agriculture industry have led to the demand for innovative methods that leave the crop intact and do not interfere in its natural growth [15].

This study has been conducted with a view to develop a machine vision system for the harvesting robot that performs the recognition of all the ripeness stages of tomatoes specially during turning stage. The proposed approach considers natural lighting conditions and does not interfere in the usual growth of tomatoes. This section further introduces the two tasks of the vision system of harvesting robot.

1.1. Recognition of tomatoes

The primary task of the vision system of harvesting robot is the recognition of tomatoes that is done by segmenting the tomatoes from the captured image. In this process, two major difficulties are faced by the harvesting robot. Firstly, it has to work under natural illumination condition and secondly, the background is complicated consisting of branches of leaves, plants and the tomatoes may be connected, overlapped, in bunch, or partially covered by branches and leaves. The segmentation process should be intelligent enough to separate the tomatoes from the complicated background. This process includes two parts. The first part deals in selection of color space to identify the required pixels i.e. pixels that are part of tomato and second considers clustering algorithms to cluster those identified pixels in an image.

1.1.1. Selection of color space and identifying required pixels

Color spaces commonly used by harvesting robots include RGB [18], HSI [19], L*a*b* and others. Statistical Hue feature of HSI color space is generally used but the disadvantage of variation in illumination is associated with this color space. Advantage of using RGB color space is that there is no need to do conversion operations since CCD (charged coupled device) signals are made of RGB components only. Whereas, L*a*b* color space makes more sense as it depicts the way, how humans visualize the color. Some approaches have been proposed that are based upon chromatic aberration of an image [20] which is the difference of red band and green band (RG difference) in RGB color space.

1.1.2. Clustering of required pixels

After the required pixels are identified, they are now clustered together. Common clustering algorithms include constant threshold segmentation, automatic threshold segmentation based on Otsu's threshold, K-means clustering and neural network.

Authors Yin et al. [21], proposed an automatic segmentation technique based on RG difference of an image for segmenting multi-tomatoes under complicated natural background. Authors Xiang et al. [20], examined and relatively evaluated three segmentation algorithms based on RG, normalized RG, and multi-band ratio. Authors Yin et al. [22] used L*a*b* color space and *k*-means clustering to segment the ripen tomato. Authors Wang et al. [23], compared two color spaces viz. hue average and RG difference and suggested that results were better for RG difference of image. Almost all these studies were done for recognition of ripe tomatoes. Since there are unripe tomatoes with ripe tomatoes on a plant, so it is necessary, that algorithm recognizes ripe tomatoes and unripe tomatoes both. Researchers Arefi and Motlagh did the classification of ripe tomato and unripe tomato using Artificial Neural Network (ANN) [24]. The background was removed using RG difference. The biggest disadvantage associated with RG difference method is that it is unable to segment green tomatoes from the background. Authors [25] proposed a segmentation technique that can segment ripe and unripe tomato from the complicated background under natural illumination. During background removal, the specular reflection highlights (white pixel) on the surface of the tomato, were also removed. Therefore, the algorithm interpolates the colored pixels in the neighborhood of the white pixel region to maintain the color integrity of the tomato. In our work, this technique has been used to segment the required objects (tomato) from the captured image.

1.2. Classification of recognized tomatoes

After the recognition of tomatoes, the next step is to classify them into different ripeness stages. Classification process is a comprised of two sub-processes: color feature representation and color categorization.

Color must be represented in such a way that it can be categorized. Color representation methods include color histograms, RGB, Hue Saturation Intensity (HSI), CIE Lab [26].

Color categorization is performed to classify the colors. Different methods include simple thresholding, color mapping [27], statistical analysis [23,28], fuzzy logic [29], neural networks [24].

Authors Choi et al. [9], developed a tomato maturity index (TMI) based on hue value to indicate the degree of maturity. Tomatoes were picked at different maturity stages and images were taken under an experimental setup. RGB values obtained were converted to HSI color vales. A tomato maturity index (TMI) was developed to estimate the degree of maturity within each stage and to provide a continuous index over all maturity stages. The TMI was derived from the aggregated percent surface area below certain hue angles. Algorithm was tested on 120 tomatoes that were classified into six different stages. Classification results agreed with human grading in 77.5% of the tested results. Most of the misclassification occurred between green and breakers stages, between turning and pink, and between light red and red stages.

Takahashi et al. [30] proposed a robot system that used an easy operation human interface accompanied with a personal computer display to pick a tomato automatically. The hand of the proposed robot system was composed of scissor and CCD camera that can be actuated in the three orthogonal directions. RGB values of the images were analyzed and the relation between red-blue (R-B) and red-green (R-G) component was formulated as $B \leq 0.8972R$ and $G \leq 0.8972R$ respectively. If tomato satisfies these conditions, then it was judged as of red color, and was automatically picked by the robot system.

Also, Gezima et al. [28] judged the tomato maturity level using statistical technique and did the comparative study between L*a*b* and RGB color space. Tomatoes were classified into five different maturity stages: 10–20% of full maturity, 30–40% of full maturity, 50–60% of full maturity, 70–80% of full maturity, and full maturity. Unripe stage of tomatoes was not considered during classification. Images were taken under artificial background using an experimental setup containing CCD camera, high-frequency switching setup, monitor, PC, tomato and black carpet. Initially, background was removed and converted to white pixel using $R < 2$ in RGB or $b^* < -3$ in L*a*b* color spaces. Correlation was obtained between histogram of each color system and maturity. In the study, highest value were showed at G(36) and R(35) in RGB color space and at L(50) in L*a*b* color space. The experiments also revealed that with increase of maturity the level of a* increases and b* remains unchanged. 70% accuracy was achieved using RGB color space and 96% by utilizing a* mean.

Zhang et al. [17] sorted the tomatoes into defective and healthy sample based on shape, maturity (color), size, surface defects. Color analysis was done based on the average values of red, green, and blue components. Overall accuracy of the system was 90.61%.

Syahrir et al. [4] estimated the shelf life of tomato by judging their maturity. Images of tomato were taken from top using PC camera under artificial background. Before extracting a* values, images were enhanced in spatial domain using image filtering and thresholding techniques. Using the a* values the expiry date of tomato was predicted [28]. 50 samples were used in testing and classified as rotten or not rotten. Successful rate of 90% was achieved in estimating the tomato maturity.

Yin et al. [31] assertively discussed tomato maturity under natural conditions. Difference between area percentage of red and yellow-green component was used to represent the color feature. Neural network was established to decide the maturity and its accuracy was 95.26%. Lee et al. [27] used third order polynomial to map three-dimensional RGB values to one-dimensional value for quality evaluation of tomato and dates. System achieved 95% accuracy in case of tomato maturity detection.

Wang et al. [23], compared and analyzed RGB and HSI color models as a criterion for maturity judgment of tomato. Tomato image samples were taken under natural illumination in the greenhouse using a CCD camera. Samples collected were divided into 5 different stages: breaker, turning, pink, light red, and red. In the preprocessing stage, the RGB image was converted to gray image using red-green color difference after which the Otsu's method was implemented for segmentation and extraction of tomato fruit region. It was shown that hue component was more appropriate than saturation and intensity for judging the maturity stage of tomato. In addition, the hue average tends to decrease progressively with change of maturity. In HSI model, the average accuracy rate achieved was 93%. Whereas in RGB color model, red-green color difference mean seems more assuring than average R, G, B values for judging the maturity. In addition, the red-green color difference value tends to increase with increase in maturity. The average accuracy rate achieved for this model was 96%. However, for both the models the error was reported mainly at the pink stage of maturity.

The work discussed above mainly used statistical analysis. However, as compared to statistical classifiers artificial neural networks (ANNs) are considered more flexible in modeling a problem more accurately and are relatively much easier. They have the advantage of changing inputs and outputs, interpolation and exploration, fault tolerance and noise immunity [32]. The work done by authors [33] compared Bayesian learning & NN classifiers for grading carrots showing that the NN approach performed better than Bayesian learning. But if the features are normally distributed, statistical learning can perform equally well or better as ANNs does [34]. The biggest disadvantage of ANN model is that it lacks a profound theoretical basis for its designing. For a given problem, it is difficult to choose the best topological structure i.e. the number of hidden layers, nodes in each hidden layer, and types of transfer function in neurons of different hidden layers. One needs to try different settings for the problem to give the best result.

Authors Elhariri et al. [35], investigated the multiclass support vector machine (SVM) approach and random forest (RF) for the estimation of tomato and bell pepper ripeness. A dataset of total 250 images for tomato and 175 images of bell-pepper has been collected from farm. This proposed approach consists of three phases; namely pre-processing, feature extraction, and classification phases. In preprocessing phase, image was resized and background was removed. Next, feature vector was formed as a combination of 1D 16X4X4 HSV histogram and nine color moments for each channel of HSV using a technique namely principal component analysis (PCA). One-against-One multi-class support vector machine (SVM) and random forest (RF) using 10-fold cross validation were compared for ripeness stage classification. Experimental results showed that SVM achieved higher accuracy than RF. System [35] achieved the accuracy of about 92.72% and 93.89% for tomato and bell-pepper respectively.

In contrast with the traditional learning techniques, the human experience of generating multidimensional decisions using imprecise and ambiguous information is better simulated by fuzzy logic. Based on membership functions, knowledge base can be built in the way that is more practical. Many practical classification problems have been found to be suitable in fuzzy logic for food equality evaluation, grading of fruits such as apples, mango etc. with computer vision. A fuzzy classifier was developed for sorting apples based on watercore severity using solidity feature [36]. Another interesting application of fuzzy logic was used for grading of mozafati dates using fuzzy inference system (FIS) [37]. In a research paper [38], fuzzy rule based classification approach was used to judge the ripeness stage of mango.

Fuzzy logic is also explored for estimating the various ripening stages of tomatoes. Authors [39], proposed the tomato quality rating method based on fuzzy model. Visual attributes like size, color, shape, defects, and abnormalities were obtained using image processing. A fuzzy method was proposed by mapping various fuzzy consumer aspects to overall quality classes. Iraji et al. [29], compared two methods, Fuzzy Mamdani Inference and Adaptive Fuzzy Neural Network (ANFIS) for classification of tomatoes. Images of tomatoes in RGB color space were taken on black background. Seven factors based upon shape, size and texture were taken to classify the tomatoes into nine classes. In their proposed system, ANFIS reported less error and more accuracy.

Concisely, learning techniques such as artificial neural network (ANN), statistical learning, fuzzy logic, decision trees, SVM have been applied progressively for crop quality evaluation using computer vision (CV) in recent years. However, ANN and statistical learning remains the prime methods [32]. ANN has limitation on generalization of the results that can over-fit the data. SVM has high classification accuracy for crisp data. In the problem that is studied, the nature of level of ripeness stages is itself fuzzy in nature.

Fuzzy logic is capable of dealing with vague, ambiguous and incomplete information. It models the problem in the way, as humans perceive it. Moreover, fuzzy classifier takes less time as compared to ANN and SVM.

Nature of agriculture systems creates the need for modeling systems that are robust, interpretable, noise tolerant, takes less time, and are extensible. Fuzzy logic has these characteristics and is being examined for use in control and modeling in many agriculture systems. Fuzzy rule based classification system (FRBCS) is a useful tool based on fuzzy logic to deal with classification problems [40]. These systems are used for good performance. They have capability to build interpretable model that uses common linguistic terms for use in problem domain. FRBCS allows the mingling of information from different sources i.e. expert knowledge, mathematical models or empirical measures. The rules are close to nature of human thinking process. Disadvantage associated with fuzzy logic is that its performance is based upon how well it was tuned and is difficult to model in case of n-dimensional problem. It is difficult to determine the membership function (MF) because the same can be defined in different ways by different people [41]. Therefore, for classification we have proposed fuzzy rule based classification system (FRBCS), which proves to be more promising than other learning algorithms. The proposed fuzzy classification system automatically detects the pre-harvest ripeness of tomato without interfering in its growth under natural conditions.

The research of tomato maturity evaluation is generally conducted using an artificial background that interferes with the natural growth of the fruit. This may result in harvesting of under-grown or over-grown fruits. The issues relating to tomato identification under natural and complicated background have not been put forward earlier. Moreover, generally three levels of maturity (under-ripe, ripe, and overripe) have been selected by the existing literatures. However, there is need to classify them into six different stages especially the turning stage which is the deciding factor for harvesting, under natural conditions and background without interfering with their natural growth.

The paper is organized as follows. Section 2 explains the concepts of FRBCS, decision trees, fuzzy inference system (FIS). Section 3 presents the methodology adopted for the proposed system in detail. Section 4 discusses the experimental results. Section 5 presents the conclusion and the future research directions.

2. Theory

This section gives the brief overview of the concepts of fuzzy rule based classification systems (FRBCS), decision trees, and fuzzy inference system.

2.1. Fuzzy rule based classification system (FRBCS)

It is one of the most prevalent approaches used in pattern classification problems due to its advantage of interpretability. FRBCS have been recently applied in classification problems for medical applications, geographical systems etc. Fuzzy logic helps in quickly transforming the expert knowledge into the computer program in form of simple if-then-rules. Moreover, expert knowledge reduces the search space when optimizing the system. The process of designing a fuzzy rule based classification system involves the following steps:

- Step 1: define the input and output attributes.
- Step 2: feature space fuzzy partitioning or construct membership functions (MFs).
- Step 3: generate fuzzy rule base for the system.
- Step 4: feed the MFs and rule base to fuzzy inference system (FIS).
- Step 5: defuzzify the output.

2.2. Decision trees

A decision tree (DT) is a tree-based exemplification of knowledge used to represent the classification rules [42]. Internal nodes of tree represents test on an attribute, each branch represents outcome of test and leaf node represents class label. Traversing the branch from root to leaf node decodes the information enclosed in the form of if-then statements and each branch leads to the single rule [43]. Therefore, DT can be exploited to automatically generate the rules without the need of a human expert. Advantages of using DT are that first, it does not require data normalization and blank values to be removed. Second, it is able to handle both numerical and categorical data. Third, the description for the condition is easily explained by Boolean logic, which is desirable. Fourth, it performs well with large datasets and analyzes those using standard computing resources in reasonable time. Moreover, the rules are automatically modified based on the experimental dataset provided to the decision trees.

2.3. Fuzzy inference system

A fuzzy inference system (FIS) is a system that uses fuzzy set theory to map inputs (features) to outputs (classes). Two types of FIS are Mamdani and Sugeno. Mamdani's fuzzy inference method [44] is the most commonly seen fuzzy methodology proposed in 1975 by Ebrahim Mamdani. It is based on Lotfi Zadeh's work on fuzzy algorithms for complex systems and decision processes. *Mamdani-type inference*, expects the output membership functions to be fuzzy sets. Advantage of Mamdani system is that it has widespread acceptance and is well suited to human input. Whereas, Sugeno-type systems are similar to Mamdani-type systems except that the output membership functions are either linear or constant. Further, Mamdani FIS is briefly discussed further as it has been used in the proposed system. FIS uses a collection of fuzzy membership functions and rules for reasoning data. The most commonly used membership functions are: triangular, trapezoidal, bell curves, Gaussian, and sigmoidal. Of these, the simplest is the triangular membership function, and it has the function name *trimf*. It is a collection of three points forming a triangle. The rules are of the form:

if p then q, where p and q are fuzzy statements

The set of rules in a FIS is known as knowledge base. The functional operations in FIS proceed as follows: fuzzification of the input, fuzzy inference (apply implication method), aggregation of all outputs, and defuzzification. MATLAB fuzzy logic toolbox provides facility for the development of fuzzy-logic systems using both the graphical user interface (GUI) tools and command line functionality. The FIS GUI tool can be started in MATLAB using the command *fuzzy*. The FIS Editor GUI tool allows editing the features of the fuzzy inference system, such as the number of input and output variables, the defuzzification method used. It consists of five primary tools:-

- Fuzzy Inference System (FIS) Editor

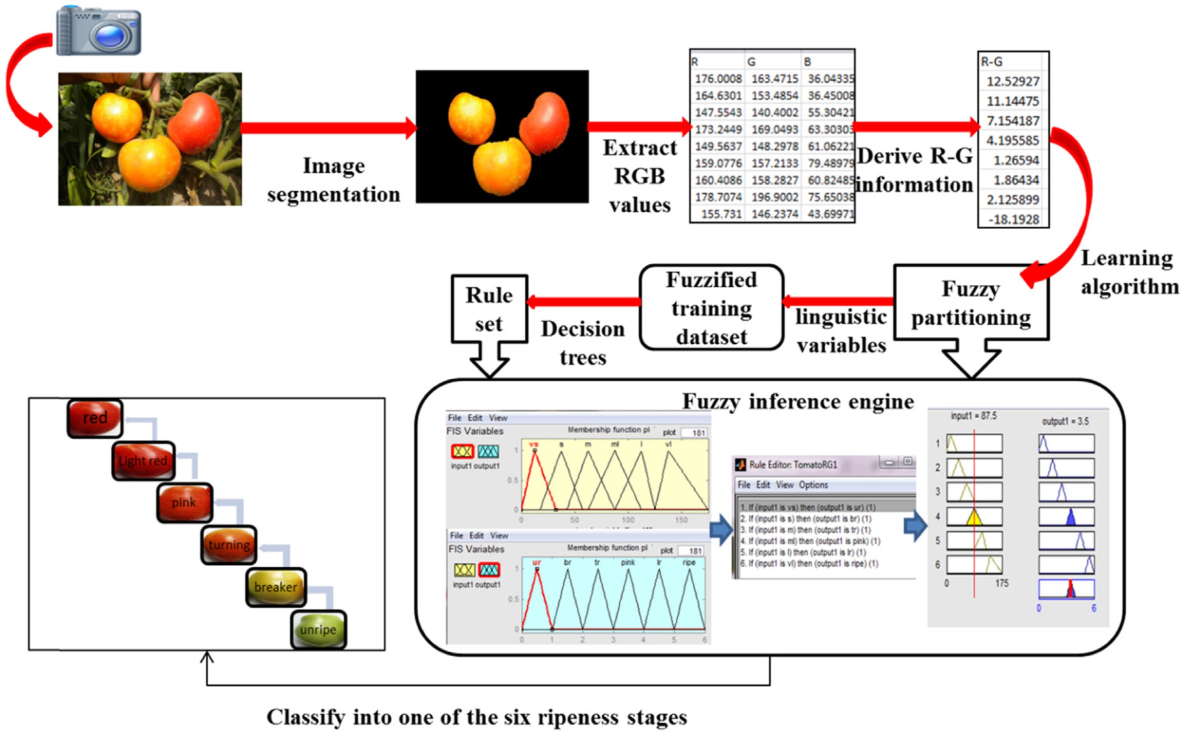

Fig. 2. Workflow of the proposed system.

- Membership Function Editor
- Rule Editor
- Rule Viewer
- Surface Viewer

3. Methodology

3.1. Overview of the proposed system

In the work presented, the images of tomato are taken from an open farm. These images are based on six different maturity stages. Tomatoes are segmented from the captured images under natural complicated background. Specular highlights due to natural illumination are removed, while at the same time the color integrity of the tomato image is also maintained. Red-green color difference is used as the input feature vector. Fuzzy rule based classification system is used to classify the tomatoes into six maturity stages. Membership functions are built using learning algorithm and rules are constructed automatically using decision trees. The work presented provides the self-sufficient decision-making means for the harvesting robot without the need of any human expert. Fig. 2 displays the workflow of the proposed system.

3.2. Image acquisition

Various kind of tomato images were captured in the field under natural lighting conditions. A charged coupled device (CCD) camera (Nikon Coolpix S220V1.0, resolution 3648 × 2736 pixels) has been used for capturing the images of tomato. Around 90 images were taken as samples from the open field without any artificial lighting system. Each image contains minimum one tomato and maximum of five tomatoes. Images were taken during daytime. Pictures include overlapped, connected, and partially covered by branches and leaves, immature, mature, and partially mature tomatoes.

3.3. Preprocessing of data

Since the images captured were of very large size (3648 × 2736 pixels), they are first scaled to 1/8th of their size to speed up the calculations.

3.4. Image segmentation

Segmentation method [25] used in this paper comprises of three main steps. First, the specular reflection or glare due to natural lighting conditions is removed and interpolated with the neighboring colored pixels. Second, the background and foreground image are separated using *k*-means clustering in L*a*b* color space. The aim is to get the colored image of the foreground that contains the tomatoes. The image is then converted from colored to binary image using the adaptive Otsu's method that yields good segmentation results than the conventional one. For separating the overlapped and touching tomatoes, watershed segmentation is applied on the single channel of the image. The channel is chosen dynamically based upon the maximum threshold value, which changes the three-dimensional concern into one-dimensional concern. Finally, intersection is done on the two images obtained from adaptive Otsu's threshold and watershed segmentation to get the final binary-segmented image. The colored segmented image is reconstructed using multiply operation between the binary image and the original image. Fig. 3 displays the flowchart of image segmentation process.

3.5. Color feature representation

Color is most widely used feature in image retrieval and classification problems. For estimating the tomato ripeness, color is the most important factor. Many color feature depiction for tomato images such as L*a*b*, HSV, RGB, HSI exit in literature as discussed in Section 1. In its initial stages of ripening, tomato consists of high content of green color and very low red content, as it ripens the

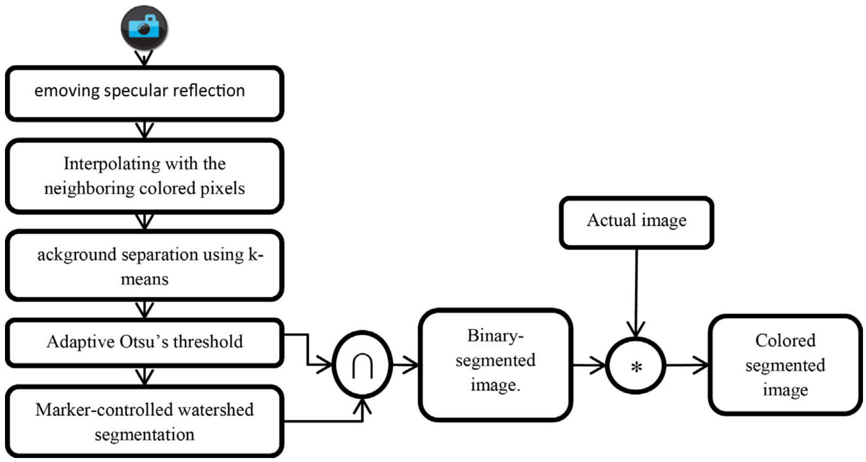

Fig. 3. Flowchart for Image segmentation process.

content of green color decreases and red color increases. Therefore, in our work, RGB color is extracted and two color feature depictions viz. red-green difference (R-G), and red-green ratio (R/G) are derived from it. Advantages are two fold, since RGB color space is used so there is no need to do conversion operations because CCD signals are made of RGB components only. Second, both the color feature depictions R-G and R/G behave linearly with the variation of ripeness stages. This helps in better perception among different stages (refer Fig. 11 in Section 4).

Red (R), green (G) and blue (B) values are extracted for the segmented image I obtained from previous step (Section 3.4). After extracting the R, G, B values, average value of red and green components is calculated. Red-green difference and red-green ratio is obtained using Eqs. (1) and (2) respectively.

$$\text{R-G} = mean\,(I\,(:, :, 1)) - mean\,(I\,(:, :, 2)) \tag{1}$$

$$\text{R-G} = mean\,(I\,(:, :, 1))\,/mean\,(I\,(:, :, 2)) \tag{2}$$

Where, $I(:,:,1)$ is the red component of the image I
$I(:,:,2)$ is the green component of the image I

3.6. Classification using fuzzy rule based decision system

The ripeness of tomato is fundamentally fuzzy in nature. The color changes from green to tannish yellowish-green to pink to the tones of red gradually. This means, there is no threshold value (crisp value) based on which decision on the ripeness of tomato can be taken. Hence, this problem can be exhibited precisely using fuzzy. Fig. 4 displays the flowchart for the classification using fuzzy rule based decision system. Detailed discussion of the steps involved is given as follows.

3.6.1. Step1. Define the input and output attributes

The input is the training dataset feature vector and their corresponding classes. The output is one of the six ripeness stages for each tomato image in the testing dataset. Input feature vector is the red-green difference (R-G) produced in previous step (Section 3.5). The output attribute i.e. class attribute has six classes. Class C_1 represents the green/unripe stage (ur), C_2 is the breaker stage (br), C_3 is the turning stage (tr), C_4 is the pink stage (pink), C_5 is the light red stage (lr) and C_6 is the ripe or red stage (red).

3.6.2. Step2. Feature space fuzzy partitioning (membership functions (MFs)) using learning algorithm

Fuzzy partitions or MFs are constructed for the input attribute using a learning algorithm [45] to generate a set of fuzzy rules (FRs) suitable for the classification system. The algorithm proposed by the researchers [45] uses triangular membership function, which is considered to be simplest among all the membership function types. The same has been used in the proposed FRBCS. Fuzzy regions for the input attribute 'A' are created by mining the proper interval values, boundaries of each region in the axis of A. Initial intervals for the fuzzy regions or MFs in the universe of discourse $X = [X_{\min}, X_{\max}]$ are given by Eqs. (3) and (4).

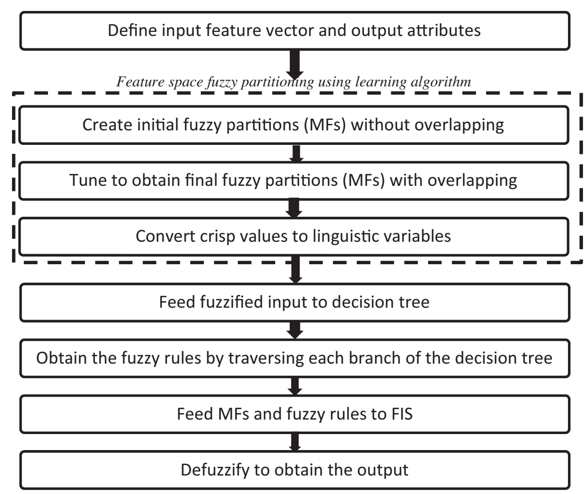

Fig. 4. Flowchart for the classification using fuzzy rule based decision system.

$$\text{Interval}\,(A) = \{u_1, u_2, u_3, \ldots, u_{\max}\} \tag{3}$$

Where, $u_1 = X_{\min}$, $u_2 = Incr(A)$, ..., and $u_{\max} = Incr(A) * k$ and $u_{\max-1} < A^{\max} \leq u_{\max}$ $X_{\min}$ = minimum value of X, $X_{\max}$ = maximum value of X

$$\text{Incr}\,(A) = \left\lfloor \frac{A^{\min} + A^{\max}}{|A|} \times w \right\rfloor \tag{4}$$

$A^{\min}$ = minimum value of A.$A^{\max}$ = maximum value of A.$|A|$ = number of distinct values of Aw = is the positive integer user-defined weight.k = is the positive integer (1, 2, 3..., n)

In the proposed system, 'A' represents the feature vector R-G, which is the input attribute in the training dataset. $X = [0..., 255]$ is the universe of discourse of attribute A since the color value of image varies from 0 to 255. As per the values obtained for input attribute A, $A^{\min} = -18$, $A^{\max} = 165$, $|A| = 116$. 'w' is used to control the number of regions that needs to be created.

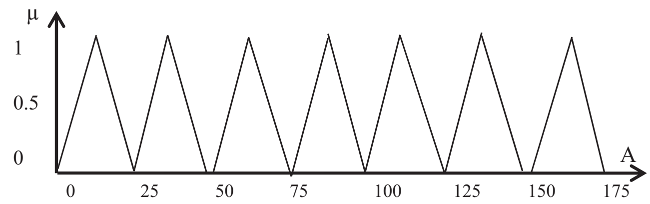

Fig. 5. Intial intervals for the attribute A.

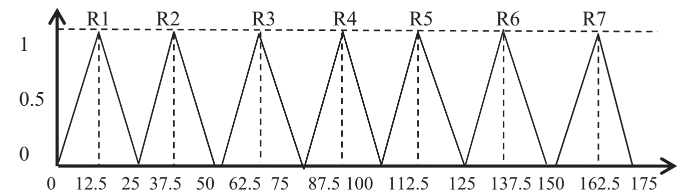

Fig. 6. Initial MFs without overlapping.

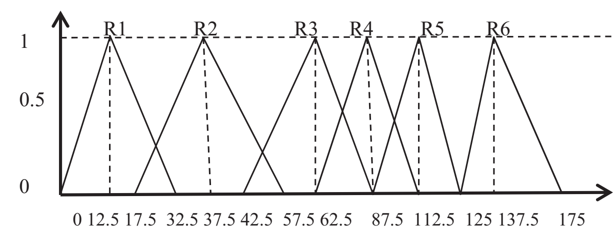

Fig. 7. Final MFs with overlapping.

Using Eq. (4), for $w = 20$, Incr(A) = 25 and for $w = 40$, Incr(A) = 50, i.e. choice $w = 20$ is the optimum choice as it will create reasonable number of fuzzy regions. Now according to Eq. (3), $u_1 = 0$, $u_2 = 25 \times 1$, $u_3 = 25 \times 2$, $u_4 = 25 \times 3$, $u_5 = 25 \times 4$, $u_6 = 25 \times 5$, $u_7 = 25 \times 6$, $u_8 = 25 \times 7$. The last unit will be $u_8 = 25 \times 7$, since it satisfies the condition: $150 < A^{\max} = 165 \leq 175$ as given in Eq. (3). But for $k = 8$ the condition is not satisfied because $175 \nless A^{\max} = 165 \leq 200$

Using Eqs. (3) and (4), we get the initial intervals for the input attribute 'A', i.e. Interval(A) = {0, 25, 50, 75, 100, 125, 150, 175}. Fig. 5 shows the graph for the Interval(A). These are the initial fuzzy partitions for the input attribute A that will be tuned to get the final fuzzy partitions as discussed further.

The distinct values of input attribute A are now represented by the set of fuzzy regions $\{R_1, R_2 \ldots R_k\}$. Any kth region R_k is defined as the set of three parameters as $R_k = \left\{R_k^l, M_k, R_k^u\right\}$, where, R_k^l is the lower limit value, M_k is the modal value, and R_k^u is the upper limit value. The modal value M_k for any region $R_k(R_k^l, R_k^u)$ is computed using Eq. (5).

$$M_k = \frac{R_k^l + R_k^u}{2} \tag{5}$$

The initial lower parameter, R_k^l and upper parameter, R_{k+1}^u obtained for the adjacent fuzzy regions R_k and R_{k+1} respectively are now tuned based on the overlap degree between them to using Eqs. (6) and (7). The modal value remains same in all the cases.

$$\left(R_{k_{new}}^u, R_{k+1_{new}}^l\right) = \begin{cases} R_{k_{new}}^u, R_{k+1_{new}}^l = \textit{inital values}, & \textit{overlap}\,(R_k, R_{k+1}) = 0 \\ \textit{merge}(R_k, R_{k+1})\,\textit{and} \begin{cases} R_{k_{new}}^l = R_k^l \\ R_{k+1_{new}}^u = R_{k+1}^u \end{cases}, & \textit{overlap}\,(R_k, R_{k+1}) = 1 \\ \begin{cases} R_{k_{new}}^u = \left(R_{k+1}^u - R_{k+1}^l\right) * \alpha + R_{k+1}^l \\ R_{k+1_{new}}^l = R_k^u - \left(R_k^u - R_k^l\right) * \alpha \end{cases}, & \textit{overlap}\,(R_k, R_{k+1}) = \alpha \end{cases} \tag{6}$$

$$\textit{Overlap}\,(R_k, R_{k+1}) = \frac{c_{com}^i(R_k, R_{k+1})}{c_{all}^i(R_k, R_{k+1})} \tag{7}$$

Overlap (R_k, R_{k+1}) is the measure which gives the degree of overlap between the adjacent fuzzy regions R_k and R_{k+1}. $C_{all}^i\,(R_k, R_{k+1})$ denotes the set of common classes of regions R_k and R_{k+1}, $C_{com}^i\,(R_k, R_{k+1})$ denotes the set of all classes of regions R_k and R_{k+1}. The overlap degree for the input attribute R-G between the adjacent regions is given in Table 1. In this table, column "Region" shows the initial regions for the input attribute R-G, column "Classes" shows the set of classes covered by the respective regions.

After tuning the interval values using the learning algorithm, the regions R_6 and R_7 are merged into one region and finally six regions are obtained. The membership degree 'μ' of an input value, say x, is decided by a MF defined on the range of numeric values of the input attribute. Triangular MF is employed for computing the degree of value 'x' that belongs to region R_k, given by Eq. (8).

$$\mu\left(x, R_k^l, M_k, R_k^u\right) = \max\left(0, \min\left(\frac{x - R_k^l}{M_k - R_k^l}, \frac{R_k^u - x}{R_k^u - M_k}\right)\right) \tag{8}$$

Fig. 6 shows the fuzzy partitions (initial MFs) obtained for the R-G attribute without overlapping and Fig. 7 shows the fuzzy partitions (final MFs) obtained with overlapping between the regions respectively.

Degree of membership of each value in the training dataset is obtained using Eq. (8) and the fuzzy regions obtained are shown in Fig. 7. Table 2 below shows some of the fuzzified values from the training dataset. Based on their degree of membership, the crisp values are converted to linguistic variables. Region names very small (vs) corresponds to region R1, small (s) to R2, medium (m) to R3, medium large (ml) to R4, large (l) to R5, very large (vl) to R6. Column "R-G" shows the crisp values of red-green color difference from the training dataset and Column "Region" shows the

Table 1
Overlap degree between the adjacent regions.

A	Region R_k	Classes	Overlap (R_k, R_{k+1})	R_k^u	R_{k+1}^l	M_k	Merge (R_k, R_{k+1})
	R_1	{C1, C2}	$(R_1, R_2) = 0.3$	$R_1^u = 32.5$		$M_1 = 12.5$	
	R_2	{C2, C3}	$(R_2, R_3) = 0.3$	$R_2^u = 57.5$	$R_2^l = 17.5$	$M_2 = 37.5$	
	R_3	{C3, C4}	$(R_3, R_4) = 0.5$	$R_3^u = 87.5$	$R_3^l = 42.5$	$M_3 = 62.5$	
R-G	R_4	{C4}	$(R_4, R_5) = 0.5$	$R_4^u = 125$	$R_4^l = 62.5$	$M_4 = 87.5$	
	R_5	{C4, C5}	$(R_5, R_6) = 0$		$R_5^l = 87.5$	$M_5 = 112.5$	
	R_6	{C6}	$(R_6, R_7) = 1$			$M_6 = 137.5$	Merge (R_6, R_7)
	R_7	{C6}				$M_7 = 162.5$	

Table 2
Crisp values changes to fuzzy values (linguistic variables).

R-G	Region	R-G	Region	R-G	Region	R-G	Region
2.13	vs	34.50	s	70.73	m	118.18	l
−18.19	vs	33.06	s	75.88	ml	123.47	l
9.49	vs	25.44	s	91.29	ml	162.20	vl
9.18	vs	28.26	s	85.19	ml	146.68	vl
−14.36	vs	66.15	m	89.83	ml	150.09	vl
6.63	vs	52.56	m	100.86	l	152.96	vl
26.65	s	70.32	m	104.98	l	144.94	vl

linguistic variables to which they are mapped according to their degree of membership.

3.6.3. Step3. Generate rule base for the system using Decision Trees

A rule base is formed from the extracted features and is given as an input to a fuzzy classification system. The rule base is obtained mostly by perception and expert's domain knowledge. In our work, we present the use of decision tree (DT) to generate the rules automatically from the feature set. This eliminates the need of human expert for generating the rules. Widely adopted J48 (a WEKA implementation of C4.5 algorithm) [46] is used for constructing decision tree. Input to the algorithm is the set of extracted features and their corresponding class labels. The output is the decision tree, having root node, which represents the top node of the tree, leaf node represents the class labels, other nodes represent the attribute feature, and branches represent each possible value of the feature node from which they originate. The training dataset obtained in step 2 containing the fuzzy linguistics values and the conforming output class, is given as an input to the J48 algorithm. Fig. 8 shows the DT obtained. Six rules obtained are listed below.

Rules obtained by traversing each branch of the tree shown in Fig. 8 are:

Rule 1. If rg = vs then Class is ur
Rule 2. If rg = s then Class is br
Rule 3. If rg = m then Class is tr
Rule 4. If rg = ml then Class is ml
Rule 5. If rg = l then Class is lr
Rule 6. If rg = vl then Class is ripe

3.6.4. Step 4. Fuzzy inference process

After defining membership function and generating the "if-then" rules, the next step is to build the fuzzy inference engine. In fuzzy inference process, data is collected from the environment and is used to derive decision through rules and MFs. In this paper, Mamdani Fuzzy Inference System (MFIS) is used to evaluate and classify the tomatoes into six categories. Developed membership functions for the input space in step 2 and rules learned in step 3 are fed into the fuzzy inference engine. To develop membership function of output category, the range of input variable R-G is determined for each of the six classes of tomato ripeness. The output of each rule is combined through the aggregation operator that is set to *max* and the resulting fuzzy set is defuzzified to produce the output of the system. The implication factor determines the process of shaping the fuzzy set in the output MFs based on the results of the input MFs. The implication factor is set to *min* and the OR and AND operators are set to *max* and *min*, respectively. The defuzzification phase is performed using the COG (Center of Gravity) method. The output of the system is the ripeness class of the tomato. Overview of the proposed fuzzy rule based classification system is shown in Fig. 9.

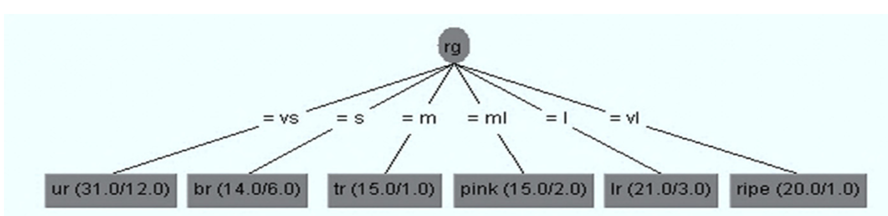

Fig. 8. Decision tree obtained using J48 algorithm.

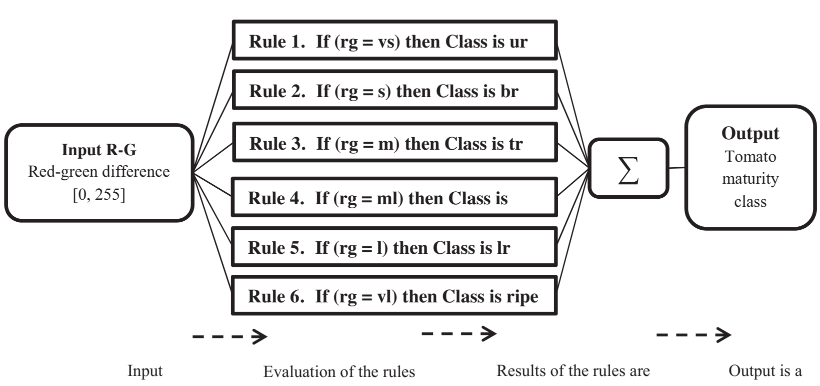

Fig. 9. Structure of the proposed FRBCS.

4. Results and discussions

Images are collected from the open farm and MATLAB R2009b is used to implement the algorithm as discussed in Section 3 under image acquisition.

In this section, three different color feature representation avgRGB, R-G, R/G are analyzed. Analysis is done for all the images of tomato in the database. Based on their behavior, as discussed further, two color representations R-G and R/G are chosen for the experiments. Both the color representations are compared based on their classification accuracy, kappa statistics and RMSE for four different learning algorithms namely NaiveBayes, SVM, Multilayer Perceptron (MLP), RandomTree. It has been observed during experiments that R-G performs better than R/G, so R-G is chosen as the color representation feature for the proposed system. The implementation of fuzzy inference system using MATLAB is also shown in this section. The proposed system is analyzed based on classification accuracy, kappa statistics and Root Mean Squared Error (RMSE). Detailed accuracy for each of the six classes of the tomato ripeness is also discussed for the proposed system. The proposed system is compared with the state-of-art learning algorithms based on classification accuracy, true positive (TP) rate, false positive (FP) rate and F-measure, kappa statistics and RMSE. The details of the entire analysis are discussed in the rest of the section.

4.1. Analysis of different color feature representations in RGB color model

The averages of each color component for all the tomato sample images in RGB color model were measured for the analysis. Fig. 10 shows the changing trend of averages of Red (avgR), Green (avgG), and Blue (avgB) color components at different maturity stages. With increase of tomato maturity, the average of red tends to increase while average of green tends to decrease. However, average of blue shows the non-linear behavior. At pink and light red stage, the value of red does not show significant change. However, the value of green shows a significant fall. Henceforth, the average of red is alone not sufficient for discriminating between different maturity stages. Fig. 11 shows the changing trend of Red-Green

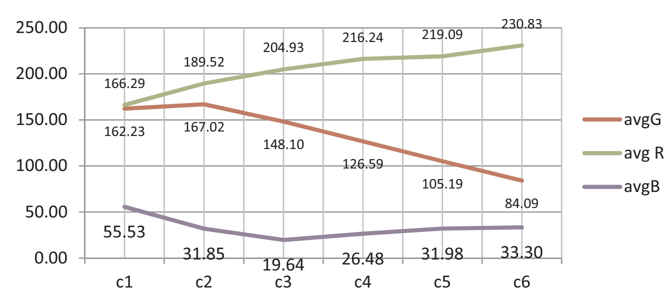

Fig. 10. line graph showing the behavior of average R, G and B component values of the tomato images for each of the six classes.

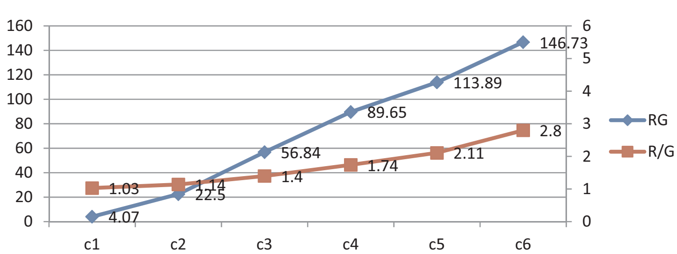

Fig. 11. Line graph showing the behavior of average R-G, R/G values of the tomato images for each of the six classes.

Table 3
Average R, G and B component values of the tomato images for each of the six classes.

Classes	avgR	avgG	avgB
c1	166.29	162.23	55.53
c2	189.52	167.02	31.85
c3	204.93	148.10	19.64
c4	216.24	126.59	26.48
c5	219.09	105.19	31.98
c6	230.83	84.09	33.30

Table 4
Red-green difference, Red-green ratio values of the tomato images for each of the six classes.

Classes	R-G	R/G
c1	4.07	1.03
c2	22.50	1.14
c3	56.84	1.40
c4	89.65	1.74
c5	113.89	2.11
c6	146.73	2.80

difference and Red-Green ratio. The variations of red-green difference and red-green ratio are close to linearity. When growing from pink to light-red stage, both red-green difference and red-green ratio shows a significant change. Therefore, both the color depictions are suitable for judging the tomato maturity.

Table 3 shows the average red, green and blue values of all the tomato images for each of the six classes of tomato ripeness. Table 4 shows the values of red-green difference and red-green ratio of all the tomato images for each of the six classes. Column "Classes" lists different maturity stages where class c1 represents the green stage, c2 represents the breaker stage, c3 represents the turning stage, c4 represents the pink stage, c5 represents the light-red stage, and c6 represents the red stage.

Since both R-G and R/G shows the linear behavior with the increase in tomato maturity. Both the color depictions are compared for different classification algorithms to investigate which of the two color representations should be used to get better classification results of tomato maturity. Four learning algorithms namely NaiveBayes, SVM, Multilayer Perceptron (MLP), RandomTree were used to compare the two color depictions R-G and R/G. 70% of the dataset is used for training and 30% of the dataset is used for testing. Fifteen runs were performed for each of the algorithm for both the color depictions. For every run, the test and train data was randomized keeping the same percentage split.

Classification accuracy, kappa statistics and RMSE is recorded for both R-G and R/G for all the four algorithms. Classification accuracy is the percentage of correctly classified images out of total number of testing images taken. Kappa Statistic [47] is a measure of the agreement between the predicted and the true class. Value of 1.0 signifies complete agreement. For this reason, a higher value was expected for a classifier that has more coinciding predicted and actual values.

Root Mean Squared Error (RMSE) [47] shows the error in the predicted class and actual class to which the instance in a dataset belongs. RMSE should have lower values for more accurate classification results.

WEKA [48] was used to obtain the classification results of these algorithms. Average of the classification values obtained for fifteen runs was calculated and plotted. Fig. 12 shows the classification accuracy for tomato ripeness obtained by applying four learning algorithms. Fig. 13 shows the kappa statistics and Root Mean Square Error (RMSE) of R-G and R/G for all the four learning algorithms.

It can be observed from Fig. 13 that kappa coefficient for R-G is higher than that for R/G for all the learning algorithms indicating the higher agreement between the predicted and true class of

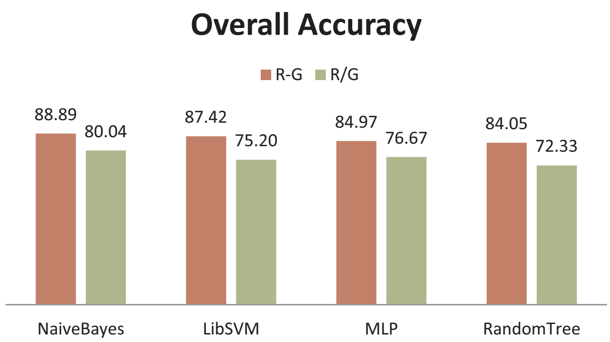

Fig. 12. Classification accuracy of R-G and R/G for different learning algorithms.

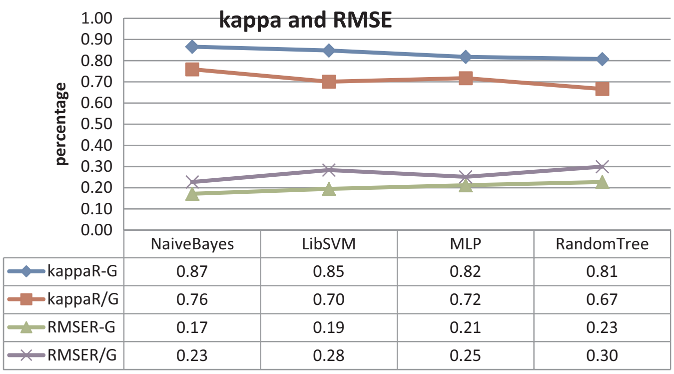

Fig. 13. kappa statistics and RMSE of R-G and R/G for different learning algorithms.

the tomato image. In addition, lower values of RMSE for R-G are obtained showing the classification results are better for R-G color depiction than that for R/G. The important outcome is that R-G is capable of classifying tomato images better than that R/G for any learning algorithm. Henceforth, R-G has been chosen as the color depiction feature for our proposed fuzzy rule based classification system.

4.2. Fuzzy rule based classification system

MATLAB 7.0 is used to implement the proposed fuzzy classification system. Figs. 14 and 15 show the membership functions for the input and output variables. Input variable is R-G having six regions namely – vs (very small), s (small), m (medium), ml (medium large), l (large) and vl (very large). Output variable has six classes that signify the maturity stage of the tomato image. Output has six classes namely ur (unripe), br (breaker), tr (turning), pink, lr (light red) and ripe. Rules are obtained using decision trees as discussed in Section 3.

For evaluating the proposed FRBCS, the sample dataset of tomato images is randomly split into two partitions viz. 70% of the dataset is used for training and 30% of the dataset is used for testing.

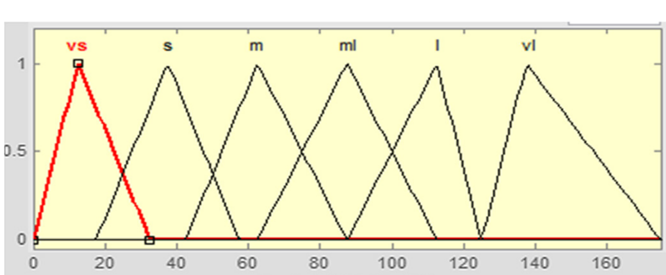

Fig. 14. Membership function for the input variable "R-G".

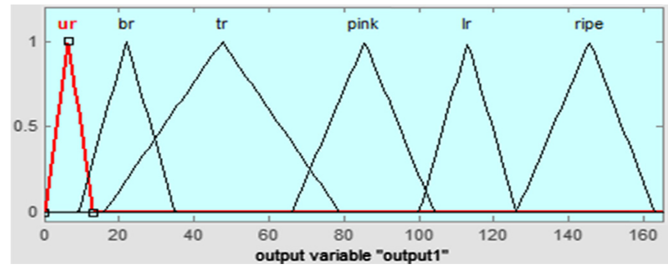

Fig. 15. Membership function for the output class. Classification results using proposed FRBCS for tomato ripeness.

Table 5
Evaluation metrics for the proposed FRBCS.

Total number of testing instances	36
Correctly classified instances	33 (94.29%)
Incorrectly classified instances	2 (5.71%)
Kappa statistics	0.95

Table 6
Confusion matrix.

a	b	c	d	e	f	
4	0	0	0	0	0	a = ur
0	5	0	0	0	0	b = br
0	0	6	0	0	0	c = tr
0	0	0	5	0	0	d = pink
0	0	0	2	8	0	e = lr
0	0	0	0	0	6	f = ripe

Table 7
Detailed accuracy by class.

Class	TP rate	FP rate	Precision	Recall	*F*-measure
Unripe (ur)	1.000	0.000	1.000	1.000	1.000
Breaker (br)	1.000	0.000	1.000	1.000	1.000
Turning (tr)	1.000	0.000	1.000	1.000	1.000
Pink	1.000	0.064	0.710	1.000	0.830
Light red (lr)	0.800	0.000	1.000	0.800	0.889
Ripe	1.000	0.000	1.000	1.000	1.000

Total of 116 tomato images were obtained after the segmentation procedure. Out of total 116 images, 80 images were used for training the proposed FRBCS and 36 images were used for testing the system. Results obtained are listed in Tables 5–7. Table 5 shows the classification accuracy, kappa statistics and RMSE of the system. Table 7 displays the detailed accuracy for each of the six classes. For every class, True Positive rate (TP), False Positive Rate (FP), Precision, Recall and F-measure is calculated using the confusion matrix shown in Table 6. The True Positive (TP) rate is the proportion of images which were classified as class x, among all images which truly have class x. It is equivalent to Recall. The False Positive (FP) rate is the proportion of images which were classified as class x, but they belong to a different class, among all images which are not of class x. The Precision is the proportion of the images which truly have class *x* among all those which were classified as class x. The F-Measure is simply a combined measure for precision and recall. True positive rate, false positive rate, precision, recall, F-measure are calculated using Eqs. (9)–(12).

$$Tp\ rate = \frac{TP}{TP + FN} \tag{9}$$

$$FP\ rate = \frac{FP}{FP + TN} \tag{10}$$

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

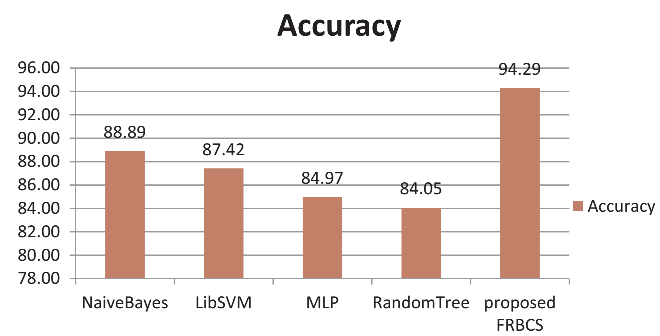

Fig. 16. Accuracy comparison of the proposed system with state-of-art learning algorithms.

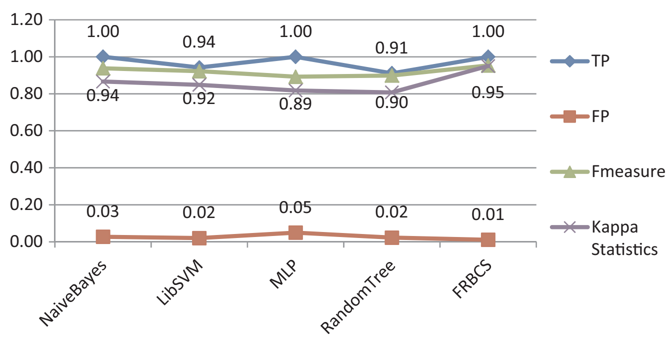

Fig. 17. Comparing TP rate, FP rate, F-measure of the proposed system with state-of-art learning algorithms.

$$Fmeasure = \frac{2 \times Precsion \times Recall}{Precsion + Recall} \quad (12)$$

Where, TP = true positives, TN = true negatives, FP = false negatives, FN = false negativesFrom Table 7, we can observe that tomato images are correctly classified with the true positive rate of 1.0 for the all the classes except light red stage. However, false positive rate of 0.064 can be observed in the pink class i.e. some images are incorrectly predicted as pink class. The reason for this is that, tomato images whose true class is light red are incorrectly classified into pink stage. The same can be seen in confusion matrix (Table 6). This error results in dropout in precision for the pink class and in F-measure for both the pink and light red class.The proposed FRBCS is compared with other state-of-art learning algorithms such as NaiveBayes, SVM, MLP and RandomTree. Although, SVM and MLP are preferred for multiple inputs multiple output systems (MIMO)/multiple inputs single output systems (MISO) systems and high number of input dimensions, but comparative assessment has been done as these are the state-of-art learning algorithms. Fig. 16 shows the comparison graph for the overall accuracy of the proposed system and other learning algorithms. Highest classification accuracy of 94.29% is achieved by the proposed fuzzy rule based classification system. Fig. 17 displays the comparison of TP rate, FP rate and F-measure of the proposed system with other learning algorithms. True positive rate of 1.0 is achieved by NaiveBayes, MLP and proposed FRBCS but the kappa statistics is higher for proposed FRBCS than NaiveBayes and MLP. This shows that the agreement between the predicted and actual class is much better in case of proposed FRBCS. Also, FRBCS has highest F-measure value of 0.95 and lowest FP rate of 0.01 amongst all the learning algorithms. These values indicate the good classification capability of the proposed FRBCS.

5. Conclusion

Machine vision using soft computing techniques has a large number of industrial applications. Soft computing includes a set of techniques that aim to exploit tolerance for imprecision, uncertain or partial truth to achieve traceability, robustness and low cost solution. Machine vision is considered to be useful tool for external feature measurements. Due to these properties, machine vision along with soft computing has been used in agriculture industry also. Automation of ripeness assessment process is a big gain for the industry and it abolishes the inconsistencies due to manual evaluation.

There are various soft computing techniques such as statistical learning, artificial neural network and fuzzy logic. Amongst these, fuzzy logic is the one that models the problem in a manner that is very similar to human thinking process. As discussed in Section 1, fuzzy logic has not been explored much for tomato ripeness classification. The problem being studied in this paper is estimation of tomato ripeness which itself is fuzzy in nature and cannot be represented in terms of crisp values. For the same reason, fuzzy logic is applied in the proposed work.

Moreover, the works related to tomato recognition as discussed in literature has been carried out under artificial background. These techniques cannot be utilized for estimating the ripeness of tomato before harvesting. Some researchers proposed the algorithm for tomato recognition that has been done under natural background also but it did not take into the account the expected highlights on the tomato surface due to natural illumination conditions [20,21]. The white pixels of specular highlights on the tomato surface gets removed during segmentation process which results in loss of color information. However, color is the most important factor to judge the ripeness of tomato and has high influence on quality and consumer's preference.

Henceforth, the proposed approach focuses on three research motivations. First, to develop a fuzzy rule-based classification system that can detect all the six ripeness stages of the tomatoes. Second, the system should be able to detect the ripeness of tomato without interfering in its growth under natural conditions. Third, while segmenting the tomato from the background, the color integrity should be maintained so as to have minimum loss of information.

In the proposed system, color images of the tomatoes were taken from the open farm without interfering with their natural growth under natural conditions. Red-green color difference has been used as the feature space as it tends to increase progressively with the increase in ripeness of tomato. A detailed analysis of different color feature representations (averages of R, G and B, R-G and R/G) has been done. It is shown that red-green color difference has the good classification capability than from individual components R, G, B or red-green ratio in RGB color space. In the work presented, decision trees are expended for automatic rule learning that repudiates the need of a human expert. This system is capable of segmenting even unripe tomato images, whose color (i.e. green) is same as that of the background (containing leaves and branches) with a good effect. This makes the classification of unripe tomatoes also possible. Automatic fuzzy partitioning of the feature space into linguistic terms has been done using a learning algorithm. However, the number of initial fuzzy partitions depends on a user-defined variable, which is the biggest disadvantage associated with the systems based on fuzzy logic. But the learning algorithm deployed [45], automatically tuned the initial fuzzy partitions created into the reasonable number of final fuzzy partitions. High true positive rate and lower false positive rate for the proposed fuzzy rule base classification proves that the algorithm is more effective than any other learning algorithm. Additionally, the effectiveness of the system has been demonstrated by the high classification accuracy of 94.29% achieved by the system over other learning algorithms.

The main limitation confronted in the research is the dataset size that is needed to be larger to have more training images per class, which can improve the performance of the system. Another limitation is that the accuracy rate of segmentation has to be improved to improve the overall accuracy of the classification.

Various research directions and challenges could be considered for future research. The proposed approach can be applied to other classification fields other than ripeness classification. For exporting of the crops, it can be used for choosing the optimal ripeness stage. For long distance transportation, the climacteric fruits can be picked at early stage of ripeness while for short distance they can be picked up at later stages of ripeness. The proposed approach can also be applied to automate the estimation of ripeness process for other climacteric crops such as mango and bell pepper.

From the viewpoint of utilized approach in the proposed system, some more future research directions can be considered. Color models other than RGB such as HSI, L*a*b* can be considered for feature extraction and representation. External features other than color such as shape, size, and texture can be involved for classification of tomato. This will help in better quality evaluation.

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