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# Fruit maturity estimation based on Fuzzy Classification

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***Abstract*—In this paper an efficient approach of fruit maturity classification based on apparent color of the specimen is implemented by the aid of fuzzy inference system (FIS). Heuristically acquired hue and its corresponding saturation and lightness are the attributes of choice, which are utilized to classify the sample into three classes; Raw, Ripe, and Overripe. The membership functions and fuzzy rules required by the Mamdani FIS are estimated by the approach of classification tree. The experimentation is performed upon 200 guava samples. The fuzzy system is trained upon 60% of the dataset, yielding 93.4% classification accuracy.**

***Keywords*— classification tree; fruit sorting; fuzzy classification; fuzzy inference system;**

## I. Introduction

Automatic fruit grading and sorting is quite popular in the field of orchard management and is implemented all over the world, concerning wide range of fruits and different classification techniques. The aim of fruit sorting is to package congruent fruits in terms of size, shape, color, and maturity level. Sorting by a human based upon these specifications is quite a tiresome task. A human worker repetitively grading numerous specimen of fruit will suffer from fatigue and boredom. Human nature is prone to such emotions due to monotony in routine. A simple task of picking, analyzing and sorting could easily be performed by a machine vision system. Replacing a human worker by a machine is feasible and economical, saving employee workforce with improved performance at a much faster speed [1].

Automated way of imitating the human sense of grading is quite complex. Various aspects of every fruit can play essential role in discrimination of factors affecting human decision, which leads to unique mathematically represented traits they could possess. Most common of all is the color developed during maturity transition. Various fruits are different in appearance; therefore, a specific logic of maturity perception is not valid for every fruit. Certain fruits develop different fragrances or color transition indicating maturity stages, other change texture and develop symptoms of maturity through discolorations and deteriorations. Hence it is rational to develop specimen-explicit approach to formulate feature space, ensuring a viable classification.

In the research proposed in [2] experimentation is performed through supervised classification methods that are SVM, linear and logistic regression, and decision trees upon a dataset of bruised apples. Feature detection was performed by hyperspectral cameras. Above 90% accuracy was reported. In [3], an approach for nectarine classification is proposed by analyzing skin feature histogram. 100% accuracy rate was reported by the use of histogram vectors computed in Rg (Red and grey) or YR(luminance and normalized Red) color layers. A date sorting and quality grading system is proposed in [4]. External date features are extracted by RGB image and is further classified into 1,2 and 3 class respectively. 80% accuracy has been reported by implementing back propagation algorithm. The research proposed in [5] objectifies the approach to acquire ripeness scales during the phenolic maturity of olives and grape seeds. The snapshots of grape seeds and olives are acquired along their maturity, in order to acquire any texture changes and color transition indicating maturity of the specimen. The classification is performed by Support Vector Regression(SVR). A fig grading system is proposed in [6]. The proposed algorithm determines color intensity and diameter of each fig in order to determine the color and size. Split area of the developed rip within the fig was also calculated. An estimation of 95.2 % accuracy was reported.

Fuzzy Inference Systems have grown quite popular regarding regression and classification. Being robust in nature as compared to adaptivity of neural networks, they can prove to be quite capable for highly inseparable problems by operating in a logical manner. In [7], an experimentation for classification of tomatoes is performed based on fuzzy rule based classification. The experimentation is performed on 70% of dataset yielding a reported accuracy of 94.29% on the remaining 30% test set. Input color retrieval is done by Red-Green color difference and color ratio and fuzzy membership functions and rules are acquired by a decision tree algorithm.

In this paper, fuzzy classification of guavas is implemented, targeting three maturity stages Raw, Ripe and Overripe. The experimentation is performed upon 200 guava samples. The classification is performed based on apparent color, so as to mimic a human perception for grading a guava in terms of ripeness.

## II. Proposed Method

The objective is to identify the post-harvest maturity of the fruit. We have established the concept of target class as rough maturity estimations such as Raw, Ripe and Overripe, that are

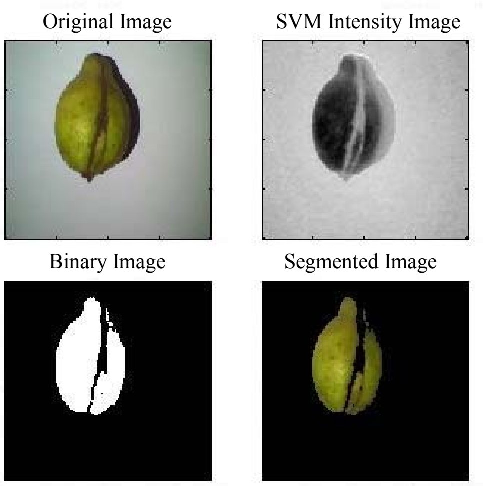


Fig. 1. The Segmentation Process

pre-assigned by human expert to each sample. A human perception of maturity of a guava sample is based on its color. Hence, we have based our feature space on the apparent color of our specimen. Every classification problem is based mathematically, but many decision-making problems are too complex to be perceived quantitively because of their continuous-valued nature. Fuzzy set theory induces a nature of vagueness to the crisp logic, to induce flexibility in decisions that greatly affects complex decision-making problems.

### *A. Feature Space*

The dataset is not publicly available. The image acquisition stage is carried out by capturing snapshots of each fruit in white light upon a plain white surface.

The natural bruises borne by various specimens are crucial to be dealt with prior to the classification step. We selected 180 foreground pixels and 492 background pixels from the dataset. We train support vectors to differentiate the concerning fruit from unwanted vestiges. The support vectors are trained upon triplets of RGB pixels that are acquired from samples. The positive class pixels belong to the portion we wish to process further, i.e. the specific part of the fruit that possesses the ripeness color, whereas the negative class pixels are smidgens of bruises, background, shadows, and unwanted part of fruit. The optimal hyperplane (1) is trained upon $l$ number of labeled pixels $(x_i, d_i)$, where $i = 1, ...., l$ and $x_i \in \mathrm{R}^n$ is the RGB pixel, $d_i \in \{-1, +1\}$ are the class labels, and $\mathbf{w}$ and $b$ are optimum weight and bias values respectively.

$$\mathbf{w}x + b = 0 \tag{1}$$

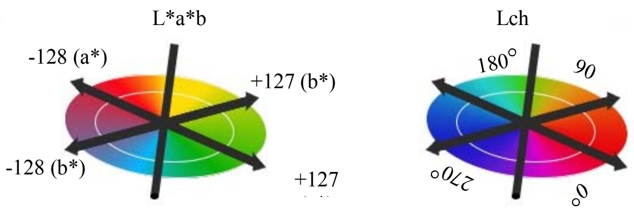


Fig. 2. The Cartesian L*a*b domain and Cylindrical Lch domain

Fig. 3. The representative color selection based on most redundant hue

Each of the pixels from the test image is then classified, by being evaluated upon the hyperplane. The SVM classified image contains classified values for each pixel, which is further normalized to form an intensity image. Otsu thresholding transforms the image into a crisp binary mask, where the desirable part is white and the undesirable part is black. We then apply this mask over the original image, simply by pixel replacement. The pixels belonging to the white part are replaced by corresponding pixels of the image whereas black pixels stay as it is, liberating the raw image from background, shadows and unwanted bruises and discolorations. The results of our segmentation method can be seen in Fig 1, the 'SVM Intensity Image' is the plot of SVM classified pixels, the 'Binary Image' is the Otsu thresholding of the intensity image and the 'Segmented Image' is the result of pixel replacement that is achieved by mapping only the black pixels of binary image over the RGB planes of the original image.

To formulate the feature space, we first convert the RGB image into CIE L*a*b space. This conversion is viable for our further preference of feature impression that is acquiring the consistent hue of the sample as the representative trait. The transformed L*a*b coordinates can be manipulated to acquire the respective value of hue and saturation by converting Cartesian coordinates $a$ and $b$ into cylindrical coordinates as can be seen in (3) and (4).

$$\vec{Y} = a + jb \tag{2}$$

$$H = \arctan\left(\frac{b}{a}\right) \tag{3}$$

$$C = \sqrt{a^2 + b^2} \tag{4}$$

where $\vec{Y}$ is the Cartesian component of an RGB pixel converted into L*a*b domain and $j = \sqrt{-1}$ in (2), $H$ and $C$ in (3) and (4) are hue and saturation (chroma) respectively. The cylindrical system can be viewed in Fig 2. Within each sample, we select the most redundant hue. The theoretical instinct behind such a specification is that the hue is the purest color of an object. Every specimen per class possesses a different ripeness stage, that is evident from its apparent color. The most redundant hue of the fruit implies the dominant color possessed by the fruit surface. The most redundant hue, along with its corresponding saturation and lightness value is the set of attributes that we have deemed plausible for classification.

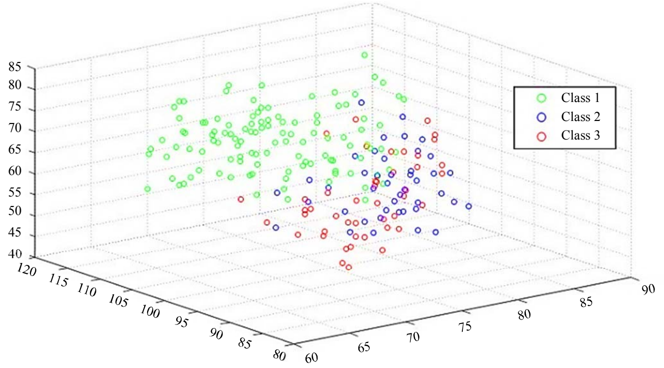


Fig. 4. Inseparability of the dataset

The result of our operation can be seen in Fig 3.

## *B. Mamdani Fuzzy Inference system(FIS)*

Fuzzy sets proposed in [8] describes the theory of fuzzy sets and membership functions. By constructing the fuzzy inference system (FIS), we fuzzify the thresholds of interclass attribute divisions, that ensures a flexibility of decisions which is lacked by various classification methods.

The input sample is represented by a unique value of hue, saturation, and lightness. The system is trained upon these values. There are certain specifications required to construct the FIS. Training of the system is achieved by extracting feature information from the sample space and infusing the parameters desired by the FIS, that are membership functions and fuzzy rules.

Fuzzy inference of a crisp value is a nonlinear relationship that contains various degrees of membership values of each linguistic variable and logical set of rules. The steps that construct a fuzzy system can be witnessed in following stages:

- Definition of input and output traits.
- Construction of Fuzzy membership functions based upon the respective fuzzy sets of the input traits.
- Fuzzy rule specification based upon heuristic and unique combinations of each membership functions.
- Specification of a Defuzzification method

In a simple problem, assigning the membership functions, and specifying rules can be achieved heuristically by human knowledge and preference of conditions. Parameters of the membership functions can be specified manually if certain ranges of the input traits are choice dependent or the class can be predicted by a noncomplex combination of conditions. However, considering a problem with intricate database, manual analysis is quite hectic due to its continuous-valued nature and extreme inseparability. To visualize and comprehend the complexity of our dataset, the inseparability can be visualized in Fig 4. As per class, there exist certain unique ranges of feature values that may tend to overlap. Lightness may appear identical throughout each class. It may not seem to be a significant trait, but can be considered for increased efficiency and plausible feature length. While considering the problem of color based classification, the true information lies within the hue and saturation of the concerning object. Each class contains different

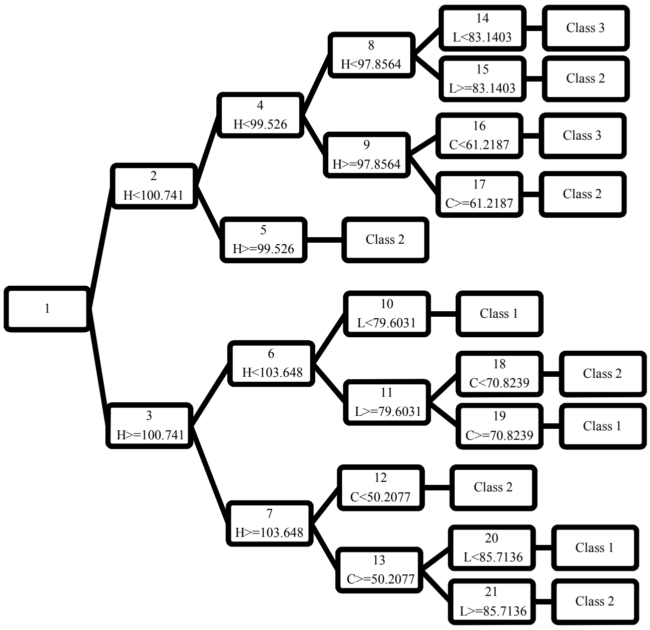


Fig. 5. Classification tree

ranges of hue and saturation values, hence implying different colors within each class that could be possessed by the target sample. To approach from numeric database to fuzzy terminology is a challenging task. To transform our continuous valued dataset for acquisition of range based rules, we have constructed a classification tree to partition our data into ranges of attributes for respective class.

The construction of the classification tree is based upon the algorithm of Classification and Regression Trees (CART) [9]. CART constructs a tree by the aid of impurity measure known as Gini's diversity index(GDI) for each node that can be seen in (5).

$$I = 1 - \sum_i p^2(i) \tag{5}$$

where $I$ is the GDI, summation is performed over classes, $i \in \{1,2,3\}$ is the class label, and $p(i)$ is the probability calculated at each node for every attribute. Splitting criterion results in splitting the database into attribute based branches having respective class at the leaf node. The tree for our database can be seen in Fig 5. By constructing a classification tree, we have acquired ranges of attributes conditioned for different classes. These ranges will further act as aid in constructing the membership functions and the branches will serve as fuzzy rules of our inference system. The classification tree is constructed upon training dataset. Excessive pruning may overlook certain decision rules or unique ranges; therefore, the tree must not be very detailed or harshly pruned.

### *1) Fuzzy Sets*

Fuzzy system works in a logical fashion based upon fuzzy rules. These rules are specified on fuzzy sets. A linguistic variable which is basically the fuzzified input feature possesses some fuzzy sets, that are basically territories divided along the

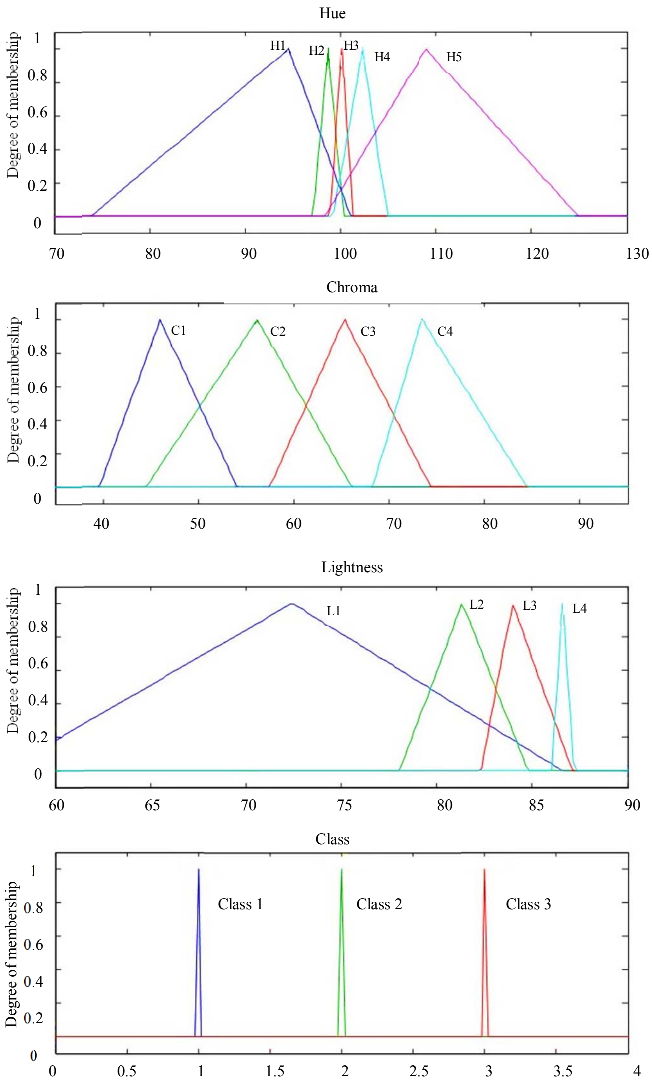


Fig. 6. The membership functions

crisp values of the feature with fuzzy boundaries. An exemplary fuzzy rule constructed upon fuzzy sets can be seen in (6), where $A_1$, $B_1$ and $C_1$ are the fuzzy sets of linguistic variables $A$, $B$, and C.

$$If\ A = A_1\ AND\ B = B_1\ Then\ C = C_1 \tag{6}$$

The specification of fuzzy sets in our problem cannot be done by manual analysis due to the problem of linear inseparability and continuous valued data points on a minute scale. The construction of the classification tree has rendered out some conditional thresholds for every input trait, that can be seen in Fig 5. We have declared our fuzzy sets for each linguistic variable as proportioned by the automatically generated classification tree. The linguistic variables for our problem are in the manner of Hue $\supseteq$ {$H_1$, $H_2$, $H_3$, $H_4$, $H_5$}, Chroma $\supseteq$ {$C_1$, $C_2$, $C_3$, $C_4$}, Lightness $\supseteq$ {$L_1$, $L_2$, $L_3$, $L_4$} and Class $\supseteq$ {Class1, Class2, Class3}

*2) Fuzzy Membership Function*

Table 1 The Fuzzy Rules

| Sno | Hue | Chroma | Lightness | Class |
|---|---|---|---|---|
| 1 | 1 | - | 1 | 3 |
| 2 | 1 | - | 2 | 3 |
| 3 | 1 | - | 3 | 2 |
| 4 | 1 | - | 4 | 2 |
| 5 | 2 | 1 | - | 3 |
| 6 | 2 | 2 | - | 3 |
| 7 | 2 | 3 | - | 2 |
| 8 | 2 | 4 | - | 2 |
| 9 | 3 | - | - | 2 |
| 10 | 4 | - | 1 | 1 |
| 11 | 4 | 1 | 2 | 2 |
| 12 | 4 | 1 | 3 | 2 |
| 13 | 4 | 1 | 4 | 2 |
| 14 | 4 | 2 | 2 | 2 |
| 15 | 4 | 2 | 3 | 2 |
| 16 | 4 | 2 | 4 | 2 |
| 17 | 4 | 3 | 2 | 2 |
| 18 | 4 | 3 | 3 | 2 |
| 19 | 4 | 3 | 4 | 2 |
| 20 | 4 | 4 | 2 | 1 |
| 21 | 4 | 4 | 3 | 1 |
| 22 | 4 | 4 | 4 | 1 |
| 23 | 5 | 1 | - | 2 |
| 24 | 5 | 2 | 1 | 1 |
| 25 | 5 | 2 | 2 | 1 |
| 26 | 5 | 2 | 3 | 1 |
| 27 | 5 | 3 | 1 | 1 |
| 28 | 5 | 3 | 2 | 1 |
| 29 | 5 | 3 | 3 | 1 |
| 30 | 5 | 4 | 1 | 1 |
| 31 | 5 | 4 | 2 | 1 |
| 32 | 5 | 4 | 3 | 1 |
| 33 | 5 | 2 | 4 | 2 |
| 34 | 5 | 3 | 4 | 2 |
| 35 | 5 | 4 | 4 | 2 |

In order to fuzzify a crisp value, membership functions for each feature and class are acquired. Membership functions are constructed upon fuzzy sets of values specifying the membership values for each set. Representation of membership functions is quite variable such as triangular, trapezoidal, Gaussian etc. In this paper, we have preferred triangular membership approach due to simplicity and easier

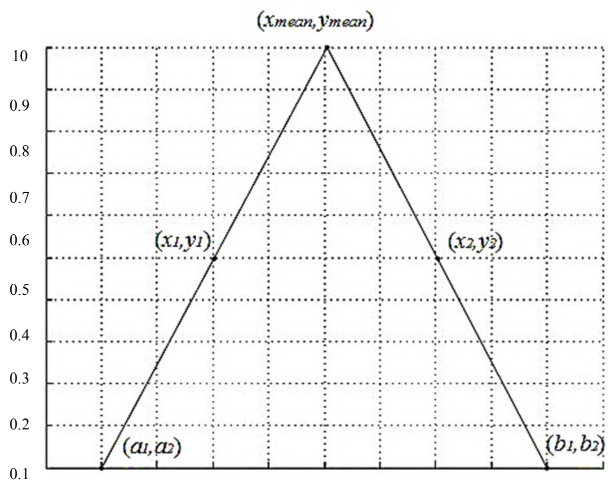


Fig. 7. Parametric estimation of the Triangular membership function.

comprehension. Gaussian membership function can also be used but we did not consider it because of the fact that Gaussian is symmetric around its mean with a certain standard deviation. Whereas witnessing our triangular functions in Fig 6, they have different slopes and are not necessarily symmetric around their mean. That is why it is advisable to use triangular membership function so that the nature of the certain range is not overruled.

Since the target maturity grades are merely Raw, Ripe, and Overripe, the memberships functions are supervised to follow these classes, rather breaking into irrelevant sets, that may cause complexity. The feature space is comprised of three characteristics of the sample; Hue, Chroma, and Lightness value. Each attribute comprises of unique membership functions according to the respective fuzzy sets.

The membership functions can be seen in Fig.6. Every node splitting in Fig.5 defines a certain threshold level for a certain attribute, and the range of values within these thresholds of a concerning attribute becomes the subset of that attribute. In each attribute, we divided the range according to the threshold specified by the classification tree. To specify the perimeters of membership functions, we concatenated the data points along threshold of each attribute. The ranges can be witnessed in node splitting shown in Fig. 5. To specify a starting and an ending point of a membership function, consider a hypothetical crisp range of attribute value $X=\{x_1<x_{mean}<x_2\}$, where $x_1$ and $x_2$ are acquired from the classification tree. A triangular membership function in Fig.7 that is to be constructed upon the range of *X* is comprised of two lines having different gradients, and some specific valued points such as $(y_1, y_2)=0.5$, $(a_2, b_2)=0$, $y_{mean}=1$, $x_{\text{mean}}$ is the average of the range *X,* and $x_1$ and $x_2$ are respectively the starting and ending of the range.

The parametric estimation can be acquired by modified form of slope point formula for hypothetical $a_1$ and $b_1$ values which can be visualized in (7) and (8).

$$a_1=\frac{(x_{mean}-x_1)}{(y_{mean}-y_1)}(a_2-y_1)+x_1 \tag{7}$$

$$b_1=\frac{(x_{mean}-x_2)}{(y_{mean}-y_2)}(b_2-y_2)+x_2 \tag{8}$$

where $a_1$ and $b_1$ denotes the *x*- axis components of starting and ending points of the membership function. The output is the class label we desire, and we specified it to be discrete natured in (9):

$$\begin{aligned} Class1&=(a_1,x_{mean},b_1)=(1,1,1)\\ Class2&=(a_1,x_{mean},b_1)=(2,2,2)\\ Class3&=(a_1,x_{mean},b_1)=(3,3,3) \end{aligned} \tag{9}$$

#### 3) Fuzzy Rule Implication

Fuzzy rules are conditional statement, that are combination of membership functions that are mimicked after human perception of decision making under certain circumstances. The fuzzy rule implication caters the problem by its logical nature, rather than numerically which implies an efficient classification. Furthermore, the logical operation of AND, that in terms of set theory is *intersection*, is used. The fuzzy rules can be viewed in Table 1. These rules are perceived upon the branches of our classification tree in Fig.5.

#### 4) Defuzzification

A crisp valued attribute vector, after being translated through its linguistic variables and evaluated through fuzzy rules is further aggregated and defuzzied into a crisp valued class label. The outcome of a fuzzy rule is the logical outcome of two or more fuzzy membership functions, that needs to be converted into a precise value. Defuzzification method must be selected heuristically, by analyzing the membership functions of output. There are many methods of defuzzification [10] including bisector, max membership principle, weighted-average method, center of sums, and most popular Centroid method. We have preferred the very fast and efficient method of Mean-Max (middle of maxima) that can be seen in Fig 8. It reveals crisp label as output through the formula (10),

$$c=\frac{a+b}{2} \tag{10}$$

where *c* is the crisp output, whereas *a* and *b* are the points of the plateau region of the output fuzzy sets. Centroid is the most celebrated method of defuzzification, but in our case, it resulted in degrading the accuracy, as it is more suitable for such a decision surface that has overlap in membership functions.

## III. RESULTS

In this paper, we have achieved a color based fuzzy classification method of differentiating three different maturity stages of 200 guava samples. The FIS based classification has proved to be quite efficient, yielding 93.4% accuracy. The results are compared with a Naive Bayesian network and multi-class SVM network. We have also estimated the true positive rate (TPR) (11) and false positive rate(FPR) (12) along with *Precision* (13) of the system.

$$TPR=\frac{TP}{TP+FN} \tag{11}$$

$$FPR=\frac{FP}{FP+TN} \tag{12}$$

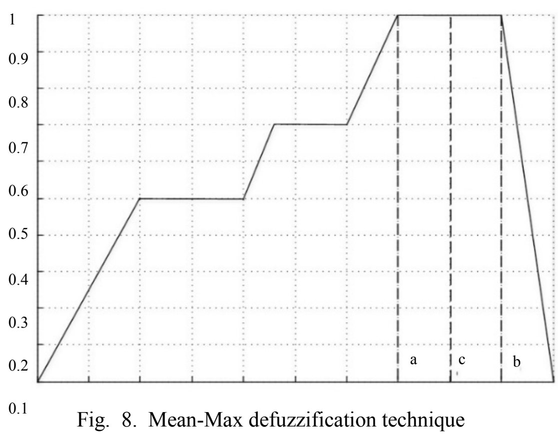


Fig. 8. Mean-Max defuzzification technique

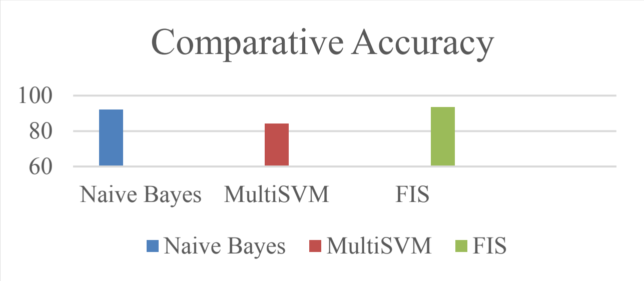


Fig. 9 Comparative Accuracy Chart

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

where *TP* is true positive, *FP* is false positive, *TN* is true negative, and *FN* is False negative.

Naive Bayes classifier [11] is based on Bayesian learning. It is conceptually perceived that attribute values are conditionally independent whilst given a target value. The system has achieved classification accuracy of 92.1%. The formula for Naive Bayes can be seen in (14).

$$\upsilon_{NB} = argmax\, \mathrm{P}(\upsilon_j)\prod_i \mathrm{P}(a_i \mid \upsilon_j) \tag{14}$$

where $\upsilon_{\mathrm{NB}}$ is the most probable hypothesis given by the Naive Bayes classifier, and $\mathrm{P}(a_i \mid \upsilon_j)$ is the conditional probability of individual attribute $a_i$, where $i \in \{1,\ldots,n\}$ and $\upsilon_{\mathrm{j}}$ is the instance being evaluated. Provided a training set, the learner predicts or classifies on given instance, that is the specific values possessed by each attribute. Ideally Naive Bayesian is suitable for a discrete valued attribute space, but in case of a continuous valued dataset, it groups the attribute into sub-ranges.

Multiclass SVM [12] is also the part of our comparative experimentation. The multi-class SVM is trained by one-verses-all technique that constructs *k* separate binary classifiers for *k*-class classification. The binary classifier that gives the maximum output value during the testing specifies the output class label. The modified decision surface in (1) for *k* number of classes can be seen in (15), where $n = \{1,2,....,k\}$.

Table 2: The performance evaluation Table.

| Method | Class | TP | FP | Precision | Accuracy |
|---|---|---|---|---|---|
| FIS | Class 1 | 0.9796 | 0.037 | 0.9796 | 93.421% |
| | Class 2 | 0.7857 | 0.0161 | 0.9167 | |
| | Class 3 | 0.9231 | 0.0476 | 0.8 | |
| Naive Bayes | Class 1 | 0.9388 | 0 | 1 | 92.12 % |
| | Class 2 | 0.9286 | 0.0645 | 0.7647 | |
| | Class 3 | 0.8462 | 0.0317 | 0.8462 | |
| MultiSVM | Class 1 | 0.9388 | 0 | 1 | 84.21% |
| | Class 2 | 0.8571 | 0.1452 | 0.5714 | |
| | Class 3 | 0.4615 | 0.0476 | 0.6667 | |

$$f(x) = argmax_n \left[ (\omega_n \bullet x) + b_n \right] \tag{15}$$

An estimation of 84.2% classification accuracy is achieved by this method. The accuracy comparison of all networks can be viewed in Fig 9. The comparative result of FIS can be viewed in Table 2.

## IV. Conclusion

We proposed a novel approach for fruit ripeness estimation using FIS. The proposed method was tested on dataset of 200 guava images. The segmented guava samples were assigned representative colors based on the most apparent Hue along with the corresponding saturation and lightness value. The data is then partitioned as a classification tree. The fuzzy classification is performed by FIS system, that is based on the classification tree. The rules are also specified by the classification tree, as well as the fuzzy sets for each linguistic variable. The results are quite satisfactory with an accuracy of 93.4%. We have also conducted a comparative study for our system by achieving 92.1% accuracy over a Naive Bayesian network and 84.2% accuracy over training MultiSVM system, regardless our approach proved to be the most efficient.

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