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NON-DESTRUCTIVE CLASSIFICATION OF FRUITS BASED ON COLOR BY USING MACHINE LEARNING TECHNIQUES

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***Abstract*:** Inclusion of computer vision and image processing technique in agriculture field providing a user friendly environment in quality testing and grading of fruit before placing it in market. Automated quality testing and grading of fruits influenced with the extracted quality parameters of fruit image and number of dataset used in training phase of machine. Color, size, texture and surface defect are the basic parameters in quality measure of fruits in agriculture field. This paper focused on classification accuracy based on extracted color and geometric features of fruit mango (magniferia Indica) and used sample size in training phase of machine learning algorithm. In this study maturity of mango is predicted with extracted color features by using a combination of RGB, HSI, HSV color model and classification is done using Naïvebayes and BPNN machine learning algorithms. This complete method passes from three phases 1) image pre-processing 2) feature extraction and 3) classification. The experimental results illustrate the usefulness of these measures by providing the prior information in classification. BPNN results are satisfactory in both cases of used features like i) color features ii) color and geometric features.

Index Terms*: *Classification, Machine Learning, BPNN, Naiv bayes, computer vision.

1.INTRODUCTION

Mango (Mangifera indica L.) called king of fruits in India is one of the most important fruits of the world, found mostly in tropical and subtropical regions (Nandi et al. 2014). Due to its high nutritious value, delicious taste and excellent flavor , low calories, it has very high demand in the world .As India is one of the largest producer and exporter of mangoes in the world that helps in increasing Nation economy. The main mango producing state in India is Uttar Pradesh producing 23.86% of complete India. In India quality testing and grading is mostly done manually. But from last decay automation in agriculture industries is playing a vital role in grading of fruit. In agriculture industries machine learning technique is providing the satisfactory results in increasing grading quality and decreasing task completion time (J. Jhawar ., 2015).

In automation technique data classification accuracy depends on collected data samples and training given to machine. Generally, there are different techniques used to train the reference samples to the grading system and then classify the new sample base on the training stage which are; statistical classification, neural network classification, fuzzy logic classification and then neural-fuzzy classification. 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

The Cape gooseberry (Physalis peruviana L.), known as the goldenberry in English-speaking countries and as aguaymanto in Peru, is a plant native to the South American

Andes Salazar et al. (2008); Luchese et al. (2015). This plant has attracted the interest of functional food markets (emerging markets of growing economic importance) due to its medicinal, nutritious, and pharmaceutical properties.

Because the food industry needs to provide fruits ´ with a high and consistent quality, it is necessary to improve their production methods to ensure that only high-quality fruits are retained during manufacturing and commercialization Benedito et al. (2006). An important step in ensuring a high quality for fresh fruits such as the Cape gooseberry is sorting, which is currently based on the visual inspection of color, size, and shape parameters Zhang et al. (2014).

However, the visual inspection process suffers from certain disadvantages: it is subjective, variable, tedious, laborious, inconsistent and easily influenced by the environment Arakeri and Laksmana (2016). Consequently, there is growing interest in reducing the subjectivity of visual inspection using innovative and non-contact measurements such as artificial vision systems, which can measure the entire surface of a sample; as a result, these types of systems are more representative than colorimeters, which are based on point-to-point measurements .

Computer vision systems (CVSs) are currently employed for the classification of horticultural products and for monitoring such products for defects and bruising Romano et al. (2012). At present, the development of CVSs is focused on defining new methods for the evaluation of color and shape parameters. In this context, color is of special interest because it constitutes an important sensory attribute providing necessary quality information for human perception. In particular, consumers tend to prefer products exhibiting a uniform appearance and vivid colors. Moreover, color has been closely associated with various quality factors (ripeness, variety, and desirability) and food safety. Therefore, color is an essential classification element for most food products.

Each color that humans can recognize in an image is formed from a combination of the three socalled primary colors, red, green, and blue, which can be arranged within a color space to facilitate the specification of colors in a standardized and widely accepted form. In essence, a color space is the specification of a three-dimensional coordinate system and a subspace of this system in which a single point represents each color. Nevertheless, there is more than one color space, and each color space can be classified into one of three spaces according to Wu and Sun Wu and Sun (2013): hardware-orientated spaces, human-orientated spaces, and instrumental spaces.

Machine vision has been mainly used for the quality determination and grading of fruits and vegetables. It has the prospective to automate manual grading processes and minimizes monotonous inspection tasks. Computer vision is also used for defect detection, classification and finding out the ripeness of fruits based on their appearance. This work summarize the review of the various work using different image processing based classification techniques like histogram based method, Fuzzy logic technique, artificial neural network technique(ANN), support vector machine (SVM), Histogram method, RGB color space method, Color mapping technique

2.METHODOLOGY AND DATA COLLECTION

Methodology of this experiment is displayed in figure 1. MATLAB 2017 b is used for image feature extraction and classification. Rest part of this section includes data collection and image pre-processing phase for accurate dataclassification.

Data collection

In this experiment total 1640 mango images are collected from a mango orchid in the same environment between May 2018 and June 2018. Mango data was collected in three stages of mango that was unripe, ripe and over ripe. The camera was placed at a distance of 30 cm from the sample. An individual sample image is captured two times in two directions for accurate maturity prediction. Collected data set samples are displayed.

Collected data set is divided in 80:20. 80% of dataset is used in training phase of machine and 20% is used in the testing phase of machine. In this study we also compared classification accuracy by varying number of samples used intraining phase of machine.

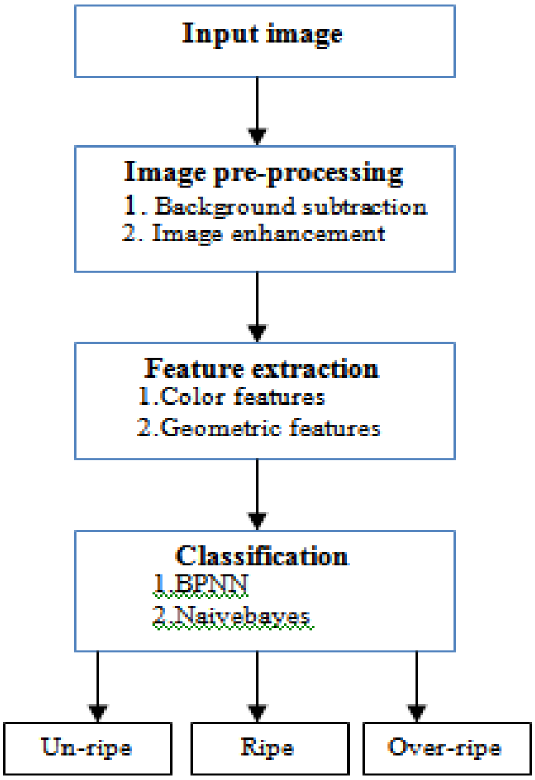

Figure 1: Methodology of classification

Image pre-processing

Image pre-processing is an essential part in image processing technique used to eliminate unessential information like brightness effects, illumination problem due to low contrast from image. Poor contrast images effects the segmentation accuracy. In contrast enhancement mean and median filter is used displayed in figure2.

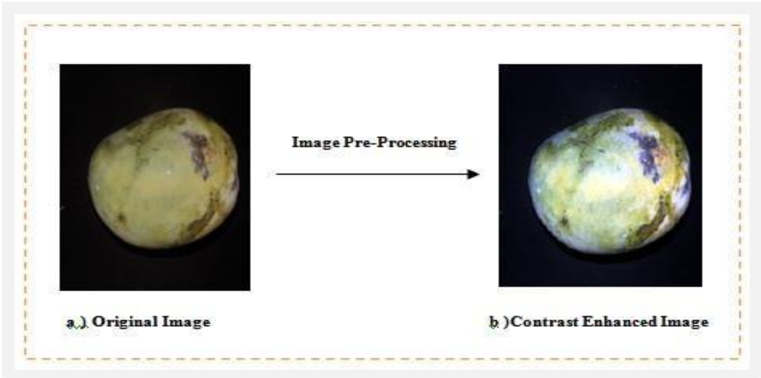

Fig 2 Image Processing

Feature extraction

Results given by machine depend on information input to the machine. In image processing field extracted features from image are used as an input to the machine on the basis of this input machine will produce result. Essential feature extraction with accuracy will affect classification accuracy of machine learning algorithm. In this way a code book is created in the form of color features.

Extracted color features

In maturity prediction of any fruit extracted color features play the vital role. RGB color model is widely used by various researchers in color feature extraction (Jhawar et al., 2015). But this model is affected with light. To increase maturity prediction accuracy a combination of RGB, HSV, HSI and L*a*b color model is used. In this red, green and blue color mean, hue, saturation and value mean, hue ,saturation and intensity mean and L, a and b mean is evaluated in used different color space. RGB color space intensity is used in training phase and HSV, HSI, Lab color space intensity is used in the validation phase of classification.

Image/Features	'HSV Intensity'	'HSI Intensity'	'RGB Intensity'	'LAB Intensity'
1.	0.287996379	0.24201104	32.28347778	6.61815229
2.	0.287590326	0.24631231	37.89229329	7.48424944
3.	0.287888894	0.24480399	49.20707194	9.97510529
4.	0.311031273	0.25739145	43.29288737	9.07360827
5.	0.28627501	0.24397714	38.98487854	7.98475633
6.	0.283191489	0.24385057	53.0754954	10.3671674
7.	0.302024461	0.252434	47.05983988	9.95536775
8.	0.287996379	0.24201104	32.28347778	6.61815229
9.	0.317861021	0.26965052	41.20815023	7.59829585
10.	0.284667161	0.23658692	34.52958679	6.86825127
11.	0.296919919	0.2537069	36.10286967	7.16811781
12.	0.275976049	0.23705536	44.71295675	8.31060667
13.	0.290475981	0.24321492	42.10635376	8.15619098
14.	0.283267248	0.24133717	52.02966309	9.84842122
15.	0.304775752	0.25943191	59.04716492	11.5060198
16.	0.287996379	0.24201104	32.28347778	6.61815229

17.	0.287590326	0.24631231	37.89229329	7.48424944
18.	0.302024461	0.252434	47.05983988	9.95536775
19.	0.296919919	0.2537069	36.10286967	7.16811781
20.	0.290475981	0.24321492	42.10635376	8.15619098
21.	0.317988094	0.26900545	47.77317301	8.65030307
22.	0.271884934	0.23874715	54.64713033	10.0920659
23.	0.290312287	0.24157788	35.7071991	7.68849539

Table 1: Extracted color features

Geometric feature extraction

In quality testing and grading of any fruit geometric features are considered as the basic input. In this study 3 geometric features are extracted for evaluating the size of mango in enhancing classification accuracy. Extracted geometric features are:

1. Area
2. Filled area
3. Perimeter
4. Major axis
5. Minor axis
6. Orientation

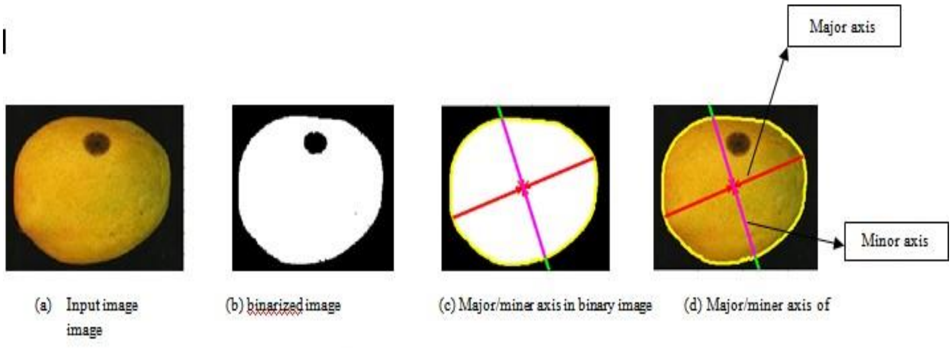

Fig 2: Geometric features extraction

Fig3GeometricFeatures

3.CLASSIFICATION RESULTS

In this research Naïve bayes and BPNN classifiers are used for classification of mangoes based on extracted color and geometric features. Classification measurement units are accuracy, sensitivity, specificity, precision and missed classification.

$$\text{Accuracy} = \frac{\textit{Number of corrected predictions}}{\textit{Total number of predictions}}$$

$$\text{Precision} = \frac{\textit{True positive}}{\textit{True positive + false positive}}$$

$$\text{Recall} = \frac{\textit{True positive}}{\textit{True positive + false negative}}$$

$$\text{Sensitivity} = \frac{\textit{True positive}}{\textit{True positive + False negative}}$$

Classification results for training dataset

BPNN classifier results in training phase of machine are good and acceptable for ripe and over-ripe mangoes as compared to Naïve bayes classifier, in both cases of used features. Training dataset classification accuracy by Naïvebayes is 79.6178% and 84.0764% for un-ripe, ripe and over-ripe class respectively by using color and geometric features in classification displayed in figure 4, 66.4013. %, 75.3185% and 85.9873% for un-ripe, ripe and over-ripe class respectively by using color features only, displayed in figure 4. Classification accuracy by BPNN is 91.0032%, 91.3217% and 99.6815 % for un-ripe, ripe and over-ripe mangoes respectively in case of color and geometric features, displayed in figure 5. Classification accuracy by BPNN is 89.3412%, 86.0034% and 93.8726 % for un-ripe, ripe and over-ripe class of mango respectively in case of color features displayed in figure 4.

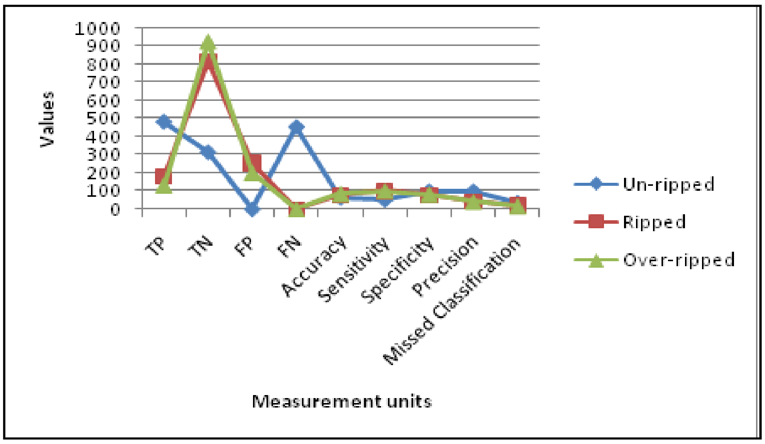

Figure 4: Naïve bayes classifier results based on color feature

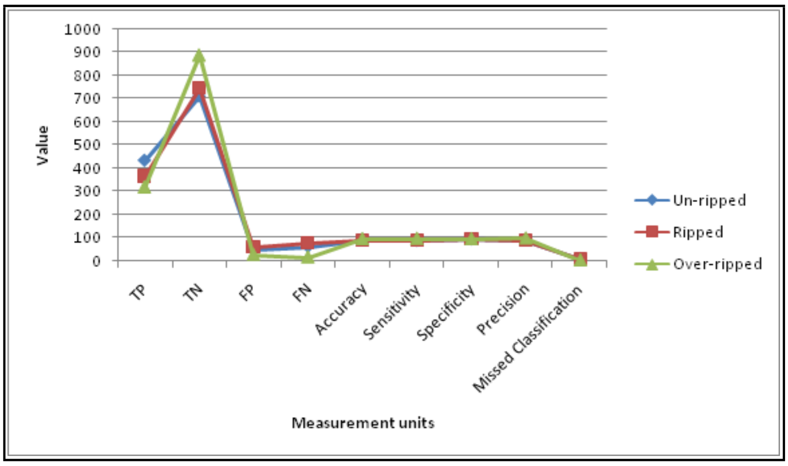

Figure 5: BPNN classifier results based on color features

Classifier results for testing dataset

Testing dataset classification accuracy by Naïve bayes is 62.5995 %, 71.8833% and 83.8196% for un-ripe, ripe and over-ripe class respectively in case of color and geometric features used as an input, displayed in figure 6, 61.2307%, 72.0342% and 82.6784% for un-ripe, ripe and over-ripe class respectively displayed in figure 8. Classification accuracy by BPNN is 92.4578%, 92.7089% and 99.0634 % for un-ripe, ripe and over-ripe class respectively in case of color and geometric features, displayed in figure 7, accuracy is 90.3209%, 89.6743% and 97.5698 % for un-ripe, ripe and over-ripe class respectively in case of color and geometric features , displayed in figure 8

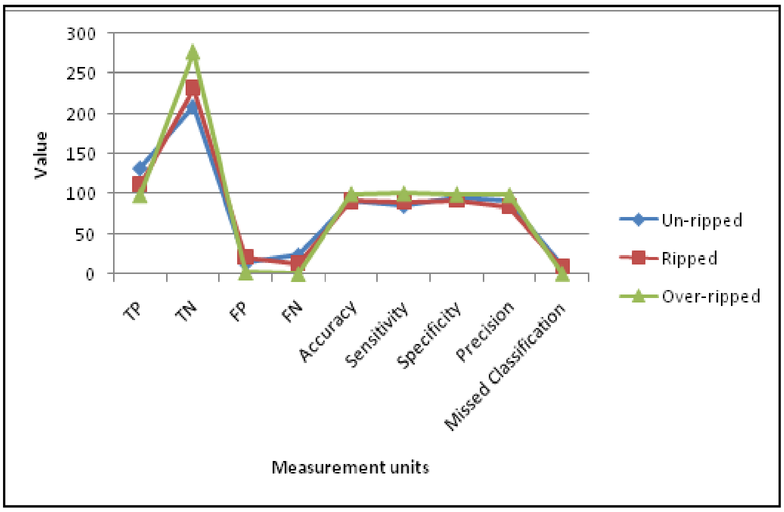

Figure 6: Naivebayes classifier results based on samples

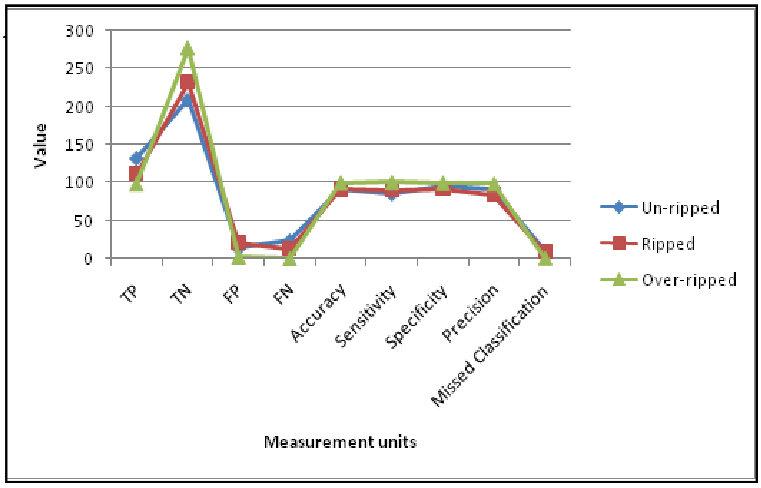

Figure 7: BPNN classifier results based on color features

Machine learning algorithms classification accuracy based on used samples in training phase of machine displayed in figure 8 and figure9. In used dataset 1312 used in training phase and 382 used in testing phases. After the training of machine above 700 samples classification accuracy of bothclassifiers is coming stable and satisfactory up to a label.

4.VALIDATION USING PATTERN RECOGNITION TOOL IN MATLAB

In validation we used Pattern Reorganization App of neural network. Dataset is divided in 70:15:15 in training, testing and validation. Mean square error in training, testing and validation phase is 4.5825e-4, 7.43639e-4 and 4.90390e-4 respectively. Best validation performance is .00085014 at epoch 1000 displayed in figure 13.Regression graph of data classification is displayed in figure 9.

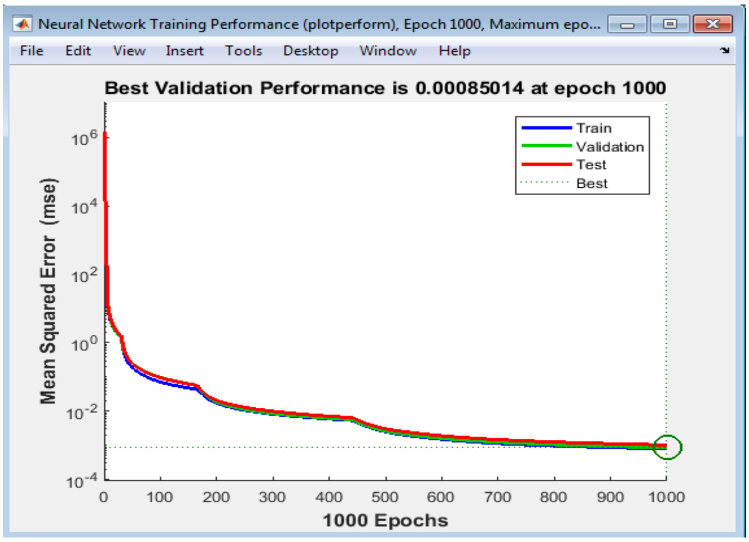

Figure 9: Neural network training performance graph

5.CONCLUSION AND FUTURE WORK

This study concluded that results provided by BPNN are satisfactory and acceptable in comparison of Naïve bayes in both case of used features. Classification accuracy is also influenced with the used training samples in machine learning algorithms. BPNN is considered the best classifier which confirmed by zero differences between results obtained in the test series. Classification accuracy is up to 99.08% in over-ripe class that is considered the poor quality class of mangoes. In case of un-ripe (average quality class) and ripe (good quality class) of mangoes this classification accuracy is switching between 91.05% and 90.34%.In future we will work on to improve these class classification accuracy. One more problem phased in this study is the variation of classification accuracy in retraining neural network again and again. In future we will also try to resolve this problem by using some optimizing algorithms with BPNN.

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