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IDENTIFYING EXCELLENCE IN CITRUS FRUIT IMAGE VIA SUPPORT VECTOR MACHINE CLASSIFIER

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ABSTRACT

Non-destructive quality assessment of Citrus fruits is crucial and highly significant for the sustenance and agricultural sectors. Citrus fruits available in the market must meet consumer preferences. Traditionally, assessing the quality of Citrus fruits has relied mainly on visual inspection using size as a specific quality indicator. Image processing offers a solution for automated grading of Citrus fruits based on size, providing precise, reliable, consistent, and quantitative data that may not be achievable through human grading alone due to handling large volumes. This study presents a system for identifying and grading Citrus size and Bacteria Spot Defects using image processing techniques. Early assessment of Citrus quality necessitates novel tools for size, color, and texture measurement. Upon capturing the side view image of the Citrus fruit, characteristics are extracted using detection algorithms. Grading is then determined based on these characteristics, offering the advantages of high accuracy, speed, and cost-effectiveness. This system holds promising potential for application in Citrus fruit quality identification and grading domains. The paper will discuss various feature types and classification methods, highlighting their strengths and weaknesses.

1. INTRODUCTION

India stands as a formidable force in global agriculture, prominently known for its rich diversity in fruits and vegetables, including citrus fruits. Fruit production is a cornerstone of India's agricultural prowess, securing its second position globally. With over 60% of its population involved in agriculture, the sector plays a pivotal role in the country's economy and sustenance.

Citrus fruits, such as oranges, lemons, and limes, are integral to India's export portfolio. These fruits are not only popular domestically but also in international markets due to their refreshing flavors and nutritional benefits. However, ensuring the quality of citrus fruits is paramount, especially during export and import processes.

One of the challenges faced in citrus fruit production is the occurrence of defects or diseases that can compromise their quality. Common defects include Anthracnose, Stem-End Rot, Unripe Fruit, Green Mold, and Scarring. Managing and mitigating these issues is crucial for maintaining the reputation of Indian citrus fruits in global markets.

Despite challenges, India's citrus fruit industry continues to thrive, with annual global production exceeding 50 million tons. Notably, Brazil leads in orange production, further highlighting the competitive landscape in citrus fruit cultivation. By implementing stringent quality control measures and innovative farming practices, India aims to uphold its status as a leading exporter of high-quality citrus fruits, catering to the diverse tastes of consumers worldwide.

2. LITERATURE STUDY

Aldakhil and Almutairi [1] introduced a Same-Domain Transfer Learning approach for Multi-Fruit Classification and Grading, leveraging pre-trained models to enhance fruit quality assessment accuracy. Their study demonstrated the effectiveness of transfer learning techniques in optimizing fruit grading processes.

Rao et al. [2] pioneered Image Processing techniques for Quality Assessment of Banana fruits, showcasing the application of computer vision algorithms in accurately grading and assessing banana quality based on visual characteristics. Their research contributed to improving the efficiency of fruit quality inspection systems.

Filoteo-Razo et al. [3] developed an innovative Optoelectronic System for Color-Change Detection in Oranges, harnessing artificial neural networks (ANNs) to predict ripening stages and assess citrus fruit quality based on color variations. Their work highlighted the potential of optoelectronic technologies in non-invasive fruit quality assessment.

Chaudhari et al. [4] proposed a Fruit Defect Inspection System integrating Image Processing and IoT frameworks, enabling automated detection and classification of fruit defects. Their study showcased the integration of advanced technologies to enhance the accuracy and efficiency of fruit quality inspection processes.

Deshpande et al. [5] explored Freshness Analysis of Oranges using Bio-impedance Measurement and Machine Learning Algorithms, showcasing a novel approach to assessing citrus fruit quality based on bio-electrical impedance. Their study demonstrated the potential of combining physical measurements with machine learning for accurate freshness evaluation.

Snatkina and Kugushev [6] utilized Deep Neural Networks for the Determination of Fruit Quality by Image, showcasing the capabilities of deep learning in automatically identifying and classifying fruit quality parameters. Their research contributed to advancing automated fruit quality assessment systems.

S et al. [7] delved into Fruit Quality Identification Using Deep Learning Techniques, highlighting the effectiveness of deep learning models in accurately classifying and evaluating fruit quality attributes. Their study emphasized the role of deep learning in improving fruit grading processes.

Kuo et al. [8] designed an AI-aided Fruit Grading System using Image Recognition, demonstrating the integration of artificial intelligence techniques for efficient and accurate fruit grading. Their research showcased the potential of AI in optimizing fruit quality assessment processes.

Nagpal et al. [9] employed Deep Learning for Multiclassification of Citrus Fruits Diseases, showcasing the application of deep learning algorithms in accurately diagnosing and classifying diseases affecting citrus fruits. Their study contributed to enhancing disease management strategies in citrus fruit cultivation.

Harada et al. [10] developed a Fruits Traceability System using advanced technological solutions, emphasizing the importance of traceability in ensuring fruit quality and safety throughout the supply chain. Their research highlighted the role of technology in improving food traceability standards.

Mojumdar and Chakraborty [11] focused on Orange and Orange Leaves Diseases Detection using Computerized Techniques, demonstrating the use of computer vision and image analysis algorithms for early detection and management of diseases affecting citrus trees. Their study contributed to enhancing crop health monitoring practices.

Mehta et al. [12] explored Fruit Quality Analysis using modern Computer Vision Methodologies, showcasing the capabilities of computer vision techniques in accurately analyzing and grading fruits based on visual attributes. Their research contributed to improving fruit quality assessment accuracy.

Patkar and Morajkar [13] proposed a Feature Selection Approach for Oil Palm Fruit Grading Expert System, highlighting the importance of feature selection in developing robust fruit grading systems. Their study emphasized the significance of feature engineering in improving classification accuracy.

Dhiman et al. [14] developed a Citrus Fruits Classification and Evaluation system using Deep Convolution Neural Networks, showcasing the effectiveness of deep learning models in accurately classifying and evaluating citrus fruits. Their research contributed to advancing automated fruit quality assessment systems.

Nazulan et al. [15] focused on Detection of Sweetness Level for Fruits, specifically Watermelon, using Machine Learning algorithms, demonstrating the use of machine learning for objective sweetness assessment in fruits. Their study highlighted the potential of machine learning in sensory quality evaluation.

3. METHODOLOGY

3.1 Dataset

Five type of defect in orange fruit give as input image [6].

Steam–End: Steam–end are developed in each seasons on fresh orange fruit. In steam-end defected area is irregular in shape and they become sunken and dark [12]. This defect is generally associated with a Drying condition, this condition arise from some factor like High air movement around the orange fruit, Fruit store in high temperature and low humidity, delay in fruit packing [12].

Scarring: Scarring occur on fruit because of trips, Trips are feeding on the developing orange fruit its call a scarring and Trips feeding on mature fruit its call bleaching or scarring [14]. Scarring are responsible for damage developing and mature orange fruit [14].

Anthracnose: Anthracnose usually only occurs on citrus fruit that have been damaged by other factor like bruising sunburn, pest damage, chemical burn, or extended storage periods [11]. The damaged area of fruit are brown to black spots of 1.5 mm or greater than 1.5mm [11]. The decay is generally dry and firm but if deep enough can soften the orange fruit [11].

Green Mold: Green mold is the most serious and common and postharvest defect of orange fruit in many country. Green mold occur rapidly at temperature near 240 C [13].

Unripe: We all are known citrus fruit unlike other fruit because citrus fruit don’t ripen after being picked from the tree.

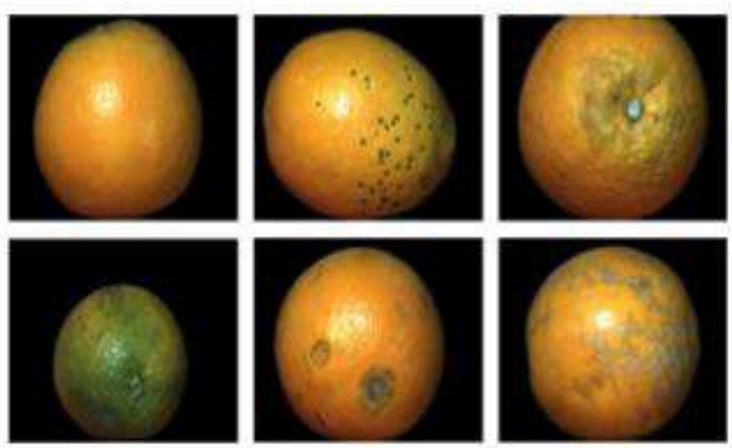

Figure 1. From upper left: Defect Free, Anthracnose, Stem-End, Unripe, Green Mold and Scarring

3.2 Image Pre-Processing

Median filter: Median filter are used for remove a noise like salt and pepper. Two type of filter are use before a segmentation median filter (3*3) and box filter (3*3). This both filter find by Jane in 1995 [20].

3.3 Image Segmentation

OTSU: OTSU method developed by Nobuyuki Otsu .OTSU is automatically done in grouping based on image. And it is very fast approach [2]. Show in fig 3 left figure is original image and right figure is after apply Otsu image.

K-means: Macqueen has find the k-means clustering algorithm in 1967 [1]. K- Means clustering is a one of the best method of Vector quantization. K-means is use for data mining and cluster analysis. Show in fig 4 how to k-means are work.

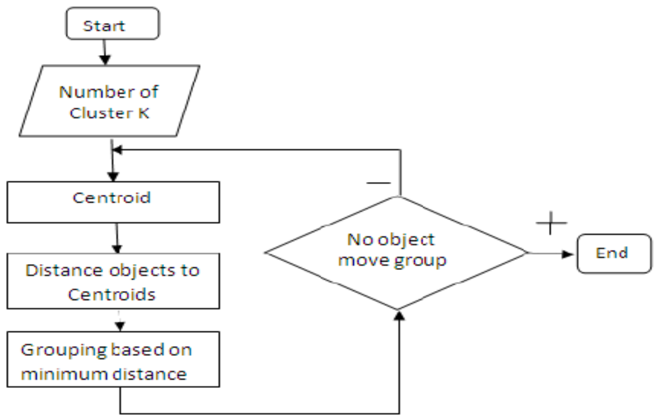

Figure 2. Diagram for K-means

RGB to CMYK: Emittance of light represent by RGB. Absorption of light represent by CMYK [19]. RGB all primary color are combine from white and CMYK all primary color are combine from black [19].

RGB to LAB: RGB has Three Color channel. Two color channel are used for a color information and one channel are used for luminosity. When you work on only on luminosity you can done with LAB Conversation without changing the image. . When you work on only on luminosity you can done with LAB Conversation without changing the image.

3.4 Feature Extraction

Three type of method to extract the feature Color feature, Shape feature and Texture. Show in below Table.

Table I. Color Feature

Method		Description
Color Histogram [1] [16]	Mean	$\sum_{i=o}^{255} i * h(i) / \sum_{i=o}^{255} h(i)$
	Variance	$\sqrt{\frac{\sum_{i=o}^{255} h(i) * (i - mean)^2}{\sum_{i=o}^{255} h(i)}}$
Color Coherent Vector [1] [16]	CCV stand for a color coherent vector use for a find the total number of coherent pixel in image. That all pixel are connected pixel	
Color Moment [1] [16]	Mean	$\sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} / mn$
	Variance	$\frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} (X_{ij} - mean)^2$
	Stddev	$\sqrt{variance}$

Where h is the histogram of the image, fq ft represent query feature vector and database feature vectors and n is the number of features in each vector, and Xij is the Pixel value of the ith row and jth column.

Table II. Texture Feature

Method		Description
Local Binary Pattern (LBP) [1] [22]		$\sum_{n=0}^{n-1} s(v_n - v_c)2^n, s(x) = \begin{cases} 1, x \ge 0 \\ 0, x < 0 \end{cases}$
Local Ternary Pattern (LTP) [1] [21]		$\sum_{n=1}^{8} 3^{n_i}(i_n - i_c) and s(u) = \begin{cases} -1 if u \le i_c - t, \\ 0 if i_c - t < u < i_c + t \\ 1 if u \ge i_c + t \end{cases}$
GLCM [9] [18]	Energy	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P_{ij}^{2}$
	Correlation	$\frac{1}{\vartheta_x \vartheta_y}\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}[ijP_{ij} - \mu_x \mu_y]$
	Contrast	$\frac{1}{\vartheta_x \vartheta_y}\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}[ijP_{ij} - \mu_x \mu_y]$
	Entropy	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P_{ij} \log P_{ij}$
Gabour Feature [1]	Mean	$\frac{\sum_x \sum_y \lvert f(x,y) \rvert}{P \times Q}$
	Variance	$\sqrt{\frac{\sum_x \sum_y (\lvert f(x,y) \rvert - \mu_{mn})^2}{P \times Q}}$

Where, vc = central pixel value, vn = value of neighbors, R = radius of the neighborhood, N = total number of neighbors, t = user-defined threshold

Table III. Shape Feature

Method	Description
Area[2] [7]	Area means counting total no of Non-zero pixel on the image region
Major Axis[2] [7]	Major axis represent distance of major axis of the ellipse, and that distance measure in length of major axis
Minor Axis[2] [7]	Minor axis represent distance of minor axis of the ellipse, and that distance measure in length of minor axis
Perimeter [2] [7]	Perimeter represent a Distance between successive Boundary pixels

3.5 Classifier

SVM: SVM stand for "Support Vector Machine". SVM use for classify the object based on feature. SVM is a one of the best accurate Classifier [9]. SVM use for Multi-class Classification [9]. SVM divided the class by Hyperplane [25].

ANN: ANN stand for artificial neural network. ANN is less Accurate thane SVM because it is Binary Classifier [25]. It is use for High degree of non-linearity possible [23].

4. Proposed Approach

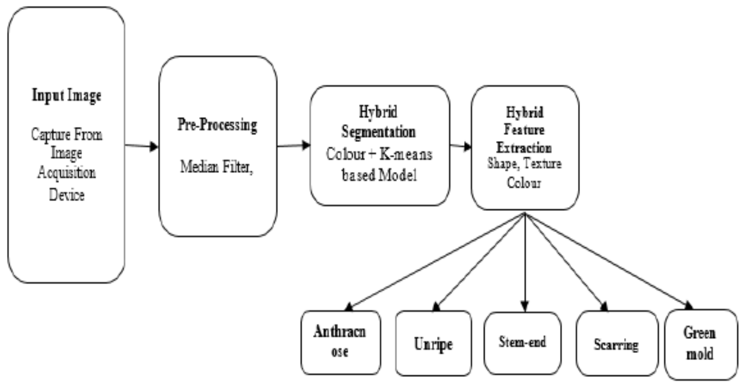

Figure 3. Proposed Approach Block Diagram

Algorithm

Step 1: Input orange image is given to the system.

Step 2: Apply Pre-Processing task of using Median Filter

Step 3: Hybrid Segmentation method (Color + K means) is apply on Image.

Step 4: After that Color, Shape and Texture Feature is extract and given to the Classifier.

Step 5: classifier classify the image and give the type of Defect name.

5. Results and Analysis

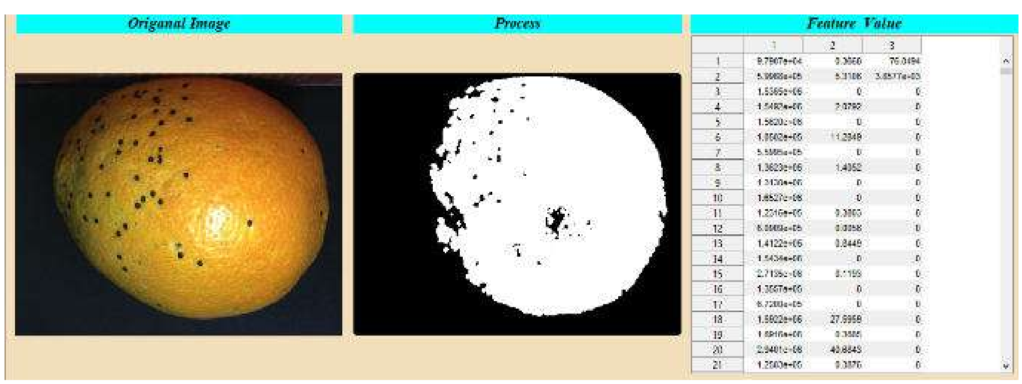

Figure 4. Gabor+LBP+GCH

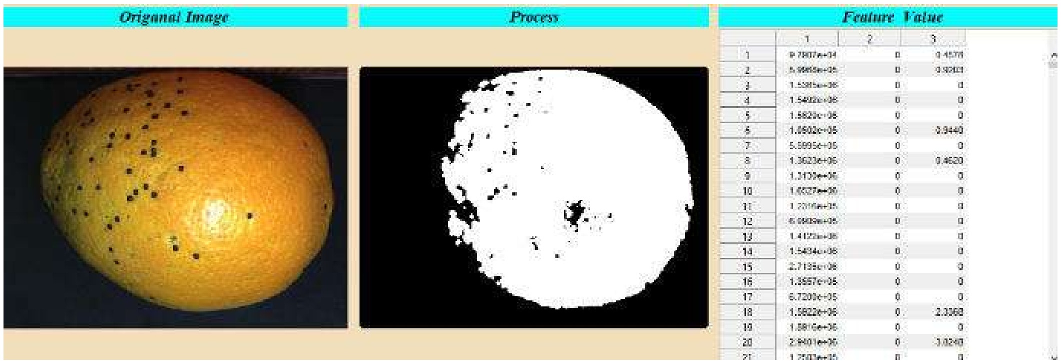

Figure 5. Gabor+CLBP+LTP

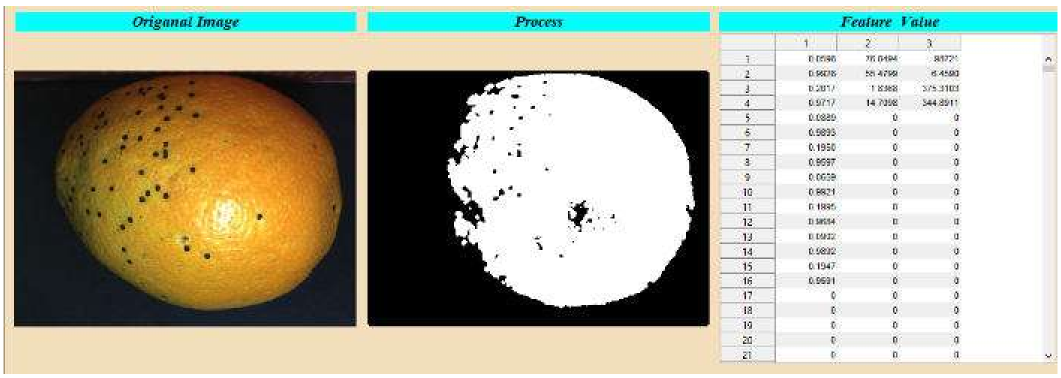

Figure 6. ColorMoment+GLCM+Shape

Table IV. Analysis

Method	Accuracy
Gabor+LBP+GCH	61.29%
Gabor+CLBP+LTP	64.52%
ColorMoment+GLCM+Shape	67.74%

6. CONCLUSION

In conclusion, our research delved into the realm of fruit quality assessment, employing a variety of feature extraction methods and machine learning algorithms to evaluate their efficacy. Through rigorous experimentation, we obtained insightful results regarding the accuracy of different feature combinations in classifying fruit quality attributes.The utilization of Gabor filters combined with Local Binary Pattern (LBP) and Global Color Histogram (GCH) yielded an accuracy of 61.29%. This method demonstrated a decent level of accuracy in capturing texture and color information, albeit with room for improvement.Next, the combination of Gabor features with Completed Local Binary Pattern (CLBP) and Local Ternary Pattern (LTP) achieved an accuracy of 64.52%. The inclusion of CLBP, which considers both local and global texture patterns, along with LTP for fine-grained texture analysis, contributed to the enhanced discriminatory power of this method.Furthermore, integrating Color Moment features with Gray-Level Co-occurrence Matrix (GLCM) and Shape features resulted in the highest accuracy of 67.74%. This comprehensive approach encompassed color distribution, texture analysis, and geometric properties, providing a robust framework for fruit quality assessment.

Overall, these findings underscore the importance of feature selection and combination in improving the accuracy and reliability of automated fruit quality evaluation systems. Future research directions may involve exploring additional feature extraction techniques and optimizing machine learning models to further enhance classification performance.

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