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Post-Harvest on Citrus Fruit Analyzing the Disease Type in Early Stages Using the Image Processing

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Abstract— ***Image processing is a significant scientific tool for assessing food quality by using computer vision techniques. Plants are susceptible to diseases while practicing post-harvest technology. Detecting the diseases using the hyperspectral image segmentation technique by interpreting the external appearance and segmenting the diseased fruit is the current study. Particularly oranges the citrus fruits are highly vulnerable to post-harvest diseases such as brown rot, canker, scab, and greening due to high cold storage and also some of the pre-harvest factors. Classification of citrus typically orange fruit by identifying the disease by using the feature extraction by discovering different dimensions. Early detection of the diseases in the fruit prevents the fast spread and also reduces damage and financial loss. In the contemporary study on post-harvest disease detection in citrus fruits, a dataset of citrus diseased images is used and are easily classified with 79% of accuracy.***

Index Terms— ***Post-Harvest, Citrus fruit, Image Processing, Computer Vision, Classification, Segmentation and object Recognition***

I. INTRODUCTION

"Capture me anywhere any time" is the current state of art. Every moment is recorded in the digital form and shared across world. Hence, Digital image processing is the one of the prominent and exponentially growing research areas in the field of computer science. These images are processed and features are extracted with a minimal intrusion of humans.

Post-harvest protection of fruits is vital research in preserving the richness and nutrients of citrus fruits. Assessing and maintaining the quality of the citrus fruits using scientific tools is robust post harvesting technique. Predict the yield, size, shape, disease detection and ripeness of fruit is analyzed using the hyperspectral image detection. These images are studied to detect the type and intensity of diseases in citrus fruits.

Some of the disease wound infections, sour rot, brown rot, green mold and blue molds. Pre-harvest factors that influence post-harvest fruit growth are:

- Development and maturation
- Physical quality and pack out
- Susceptibility to physiological changes
- Pathological breakdown
- Assessment and inspection,
- Legal Conformity
- Market Value

The pre-harvest interdependent correlated factors that affect the post-harvest of the fruits are given as:

- Environment
- Root stock / scion
- Spacing and pruning
- Pest management
- Irrigation
- Nutrition

Sorting the citrus fruits by recognizing their features such as the texture, color and shape. The process involves consistent, effective, accurate and automated procedure is adapted for classifying the good quality products. In post-harvest quality control has a significant role in maintaining these features while packaging, shipping and while operations.

A. Pixel level intensities

Color variations are differentiated based on the locations at each pixel using the pixel level intensities.

B. Segmentation level intensities

Filtering the images using the three basic planes Red, Green and Blue determining the entire picture by partitioning into segments and extracting the features individually.

C. Conceptual level intensities

Specific feature extraction such as iris diaphragm, Finger impression, and recognizing the items in the image belongs to conceptual level intensities.

The current study focuses on developing a model for recognizing the early disease detection in citrus fruits by using segmentation level intensities. The paper extracts the features such as color and coarseness of a diseased fruits image by applying the linear and box filters using image segmentation. Later, the fruits are classified based on pixel level intensities and categorized as diseased and good fruit. In the current study diseases such as brown rot, green mold and blue molds are identified using the image segmentation. Early detection of the disease will condense the spread and thereby reduce the financial loss for the farmers.

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The paper is systematized as follows: Literature Review is described in Section 2. In Section 3, discusses the Research methodologies in disease detection in orange fruit images and results are represented in section 4 and section 5 is the conclusion.

II. LITERATURE REVIEW

Table 1: Review on Image Processing in Citrus Fruits

(Lee & Archibald, 2011)	Maturity date evaluation and surface detection using the Color scale and Color mapping methods on Tomato plant
(Bouganis & Shanahan, 2007)	Complex and irregular shapes are recognized at an industrial level project using the intelligent system and identify the defected regions.
(Mohanaiah, Satyanarayana, & Gurukumar, 2013)	Entropy, angular moments, correlation and inverse difference moments are extracted using Gray level co-occurrence matrix (GLCM) for high dimensional images.
(Kwok, Ha, Liu, & Fang, 2009)	Swarm optimization and Gamma correction methods of Artificial Intelligence are built for preserving the image intensity in multi-object images.
(Ngan & Pang, 2009)	Initially regularity measures are obtained, later patterned measures and finally hash function is applied for image periodicity
(Celebi, Kingravi, & Aslandogan, 2007)	Noise removal using the cosine function is applied on images for efficient comparison and classification in disease detection.
(Zaragoza, 2010)	Degrading pre harvest protection methods, degreasing the uncertainties in citrus fruit detection and coloration in orange are studied for preserving the fruit quality.
(Jose Antonio, Cynthia, Li, & Encarnacion, 2017)	Pre-harvest-treatment, segmentation, homography and classify the fruits are the various stages involved in inspection of the fruit and this stage analysis has a high-performance rate.
(Sergio, Won Suk, Nuria, Francisco, & Jose, 2016)	Early detection of diseases such as canker, black spot, decay in citrus fruits by automated techniques of internal and external examination is observed by Sergio and Cubero
(Ahmad & Kamran, 2020)	Linear discriminant analysis and quadratic discriminant analysis methods are used for classifying the elongation, roughness and irregular shapes in carrots

III. RESEARCH METHODOLOGY

Initial step of methodology is the preprocessing by using the filters, later feature extraction and detection by depicting the texture and color, and finally classifying the image by categorizing into diseased and a good fruit. The methodology adopted for the current study in classifying the diseased fruit and a good fruit involves the following steps as shown in figure 1.

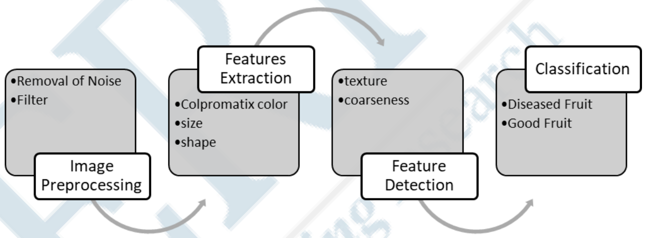

Figure 1: Methodology involved in classification of diseased and good citrus fruits

A. Image Preprocessing

A linear or a point filter is used as a preprocessing step. The process involves a scalar is multiplied to the pixel value of an input image. Such a value is represented as scalar constant. K is the scalar, L is the changing contrast f(i,j) is the input image pixel coordinate and g(i,j) is the output image pixel coordinates. The linear filter equation 1 is given as below and the respective images are displayed in figure 2:

$$g(i,j) = K \times f(i,j) + L \qquad (1)$$

Table 2: K and L for linear filters

K = 0.5	L = 0
K = 1	L = 10
K = 0.8	L = 15

Figure 2: Linear Filters with different K and L values

A Box Filter averages out the pixel value as the kernel matrix in 2 and is user for blurring the image is denoted as follows and the image is shown in figure 3:

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$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix} \quad (2)$$

Figure 3: Box filter for the image applying kernel matrix

B. Feature Extraction

Tuning the variables by applying advanced filters such as Gaussian Blurred that removes the high frequency components and is a low pass filter and the equation 3 gives the formula. This holds the information on intensity and reduces the component noise.

$$f(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}} \quad (3)$$

Pixel f(i,j) is the input image, σ is the standard deviation in the equation 3. The output image is displayed in the figure 4.

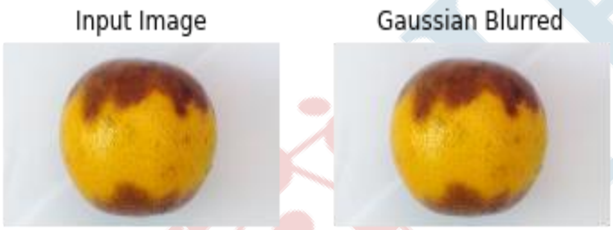

Figure 4: Gaussian Filter output

Histogram equalizer is applied for improving the contrast of the original image. It accomplishes this by effectively spreading out the most frequent intensity values, by stretching out the intensity range of the image.

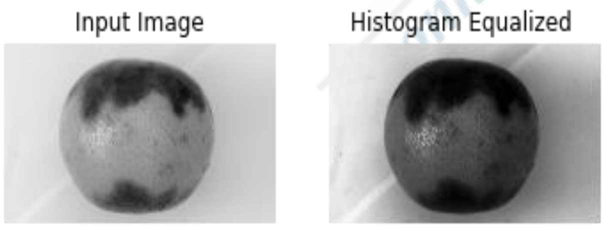

Figure 5: Histogram Equilizer output

C. Feature Detection

Kmeans clustering is applied to arrange the color intensities and color shades applied on the image. The output is displayed in the figure 6.

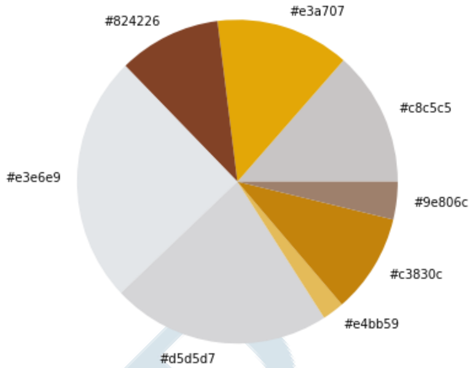

Figure 6: Pie chart with color intensities and hex codes

The output in the figure 6 arranges the array of RGB values in the form of a pie chart taking into account 8 colors occurred in the image. The 8 color intensities are represented in the Pie chart with their respective hex codes.

In edge detection applying the Laplace second order difference between the current pixel and neighbouring pixel will result in noise removal. If the magnitude is large then consider the pixel is noisy is computed using the equation 4.

$$W = \left[c_{i+m,\,j+n}\right]; -1 \le m,n \le 1; \quad (4)$$

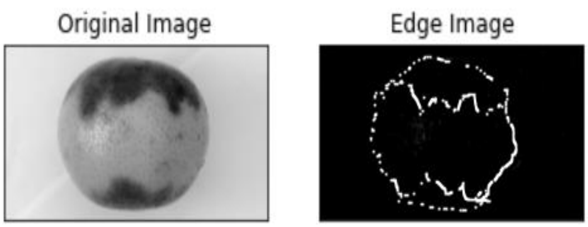

Figure 7: Laplace Second Order for edge detection

D. Classification

Stacked sparse layered architecture learns the intrinsic characteristics layer by layer and hence the efficiency of the model is improved.

Features of stacked sparse auto-encoder (SSAE) model are listed as below:

- Transformation of data to sparse representation in order to reduce the dimensionality
- Eigen dimensions are structured in to sparse dimensions for optimizing the deep network.
- Automatic learning is designed for hidden layer nodes to extract feature information
- Sparse constraint implementation improves the training speed.
- High dimensional image classification preserves the factors of original image

The added sparse constraint of the hidden layer at specified sparsity for the activation function is 0. The activation

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function given in equation 5 for the j^{th} node at l layer is given below as $a_j^{(l)}$:

$$a_j^{(l)} = f(\sum_i^{s_{l-1}} W_{ji}^{(t-1)} * \alpha_i^{(t-1)} + b^{(l-1)}) \quad (5)$$

Stacked sparse auto-encoder model SSAE depth model optimizes kernel parameters to classify images by detecting the disease as shown below in the figure 8.

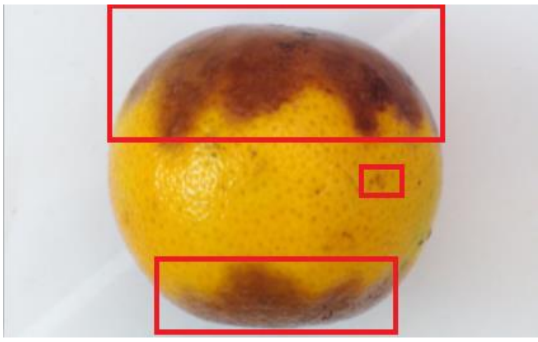

Figure 8: Model extracting the features using SSAE

The feature extraction process is start with Color Space model. The color descriptors, RGB colormap features are extracted using color descriptors as mean and standard deviations of 3 channels. A tractable a Colpromatix color space code for Gray and RGB color space models is derived from a grayscale image by mapping each intensity to a color according to channel intensity.

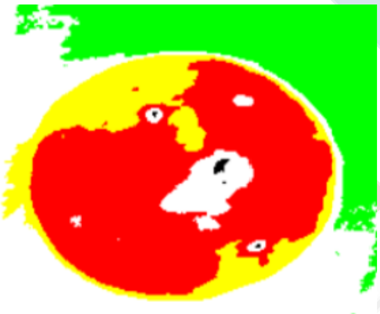

Figure 9: Colpromatix output

IV. RESULTS AND DISCUSS ION

Implemented model is verified by experimental analysis that effect multiple block rotation and is reconstructed on various images.

Table 3: Classification Accuracy

Fruit	
Diseased	83%
Good	81%

To examine the model accuracy various images of with different scales were tested for identifying the diseased and good fruit. The output is depicted in figure 10.

Figure 10: Diseased and Good Fruit detection

Diseases recognized in the study are Brown Rot, Blue molds and Green Molds. The diseased fruits are identified using the red colored rectangular snips and good fruits are identified using the green rectangular snips as shown in the Figure 10.

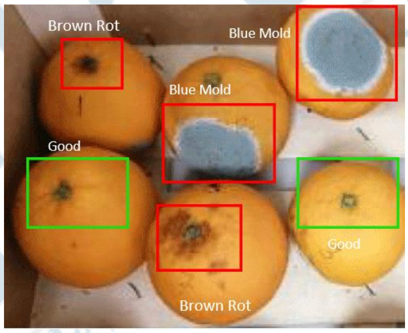

Figure 11: Detection of Brown Rot and Blue Molds

The accuracy of disease detection is depicted in the table 4. Brown Rot are easily detected by noticing color intensities with an accuracy of 80%. Blue and Green molds are detected with an accuracy of 79 and 78% respectively.

Table 4: Accuracy of Disease Detection

Disease	Accuracy
Brown Rot	80%
Blue Mold	79%
Green Mold	78%

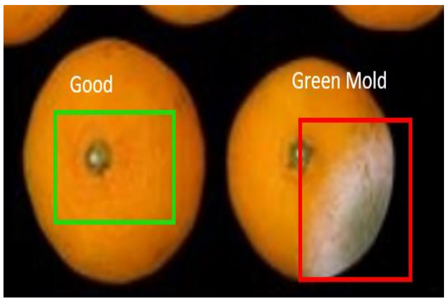

Figure 12: Detection of Green Molds

The disease detection of green molds and blue molds is represented in the figure 11 and 12.

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V. CONCLUSION

Citrus fruit image processing approaches used in the field of agriculture and food industry for fruit disease classification is implemented in the research study. The process involves in identifying the diseased fruit and a good fruit using the image segmentation with an average accuracy of 82% The proposed feature extraction method of Colpromatix color space model process and analyze the disease locations effectively for the diseases Brown rot, blue molds and green molds with an average accuracy of 79%. Stacked Sparse Auto encoder model depicts the pixel intensity feature extraction with high efficient values compared to the other methods in classifying the diseased fruits and good fruits.

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