



# INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X

Impact factor: 4.295

(Volume 5, Issue 4)

Available online at: [www.ijariit.com](http://www.ijariit.com)

## Android application for detection of artificially ripened bananas

Subramanya G. C.

[subramanya1305@gmail.com](mailto:subramanya1305@gmail.com)

JSS Science and Technology University,  
Mysore, Karnataka

Neha Misba A. K.

[nehamisba100@gmail.com](mailto:nehamisba100@gmail.com)

JSS Science and Technology University,  
Mysore, Karnataka

Sumedha S.

[sumedhabhat5@gmail.com](mailto:sumedhabhat5@gmail.com)

JSS Science and Technology University,  
Mysore, Karnataka

Niharika U. H.

[niharikauh@gmail.com](mailto:niharikauh@gmail.com)

JSS Science and Technology University,  
Mysore, Karnataka

### ABSTRACT

*Health and nutrition are one of the leading concerns worldwide. To maintain good health people intake a lot of fruits which contain more amount of nutrition and helps them to remain fit. In order to achieve maximum fruit nutrition benefits, we must ensure that the fruits are not ripened by artificial means. The artificial ripening of fruits is by using calcium carbide (CaC<sub>2</sub>). Consumption of these types of ripened fruits leads to health problems. In this paper, we propose a method of digital image processing which helps in differentiating between artificially ripened and naturally ripened banana (Musa). This experiment includes sample images of more than 400 bananas of two different species each. Features like contrast, energy, homogeneity, dissimilarity, and correlation are considered for classification. An android application is developed which enables the user to identify the method used for ripening. Detection using this method provides 90% accuracy. This detection will help consumers in choosing the right fruits and creating awareness regarding the malnutrition caused due to artificial agents.*

**Keywords**— Artificial ripening, Natural ripening, Digital Image Processing, Android application, Discrete Wavelet Transform (DWT), Grey Level Co-occurrence Matrix (GLCM)

### 1. INTRODUCTION

Fruits are an important source for a supplementary diet. The quality of fruits is determined by a wide range of desirable characteristics such as a nutritional value, flavor, processing qualities and shelf life (Vishwas, 2009). Manipulating fruit yield and quality requires an understanding of the fundamental process that determines fruit set, maturation, and ripening (Mishra et al., 2015).

Ripening process is a combination of physiological, biochemical reactions leading to changes in the cosmetic as well as organoleptic qualities of the fruit. Fruit Ripening involves fruits to become more edible, provide a desirable flavor, color, quality and few other textural properties like change in shade, taste, succulence, consistency/smoothness, rigidity, flavor, and aroma (Downey, 1987). Ethylene is a natural plant hormone that is released upon maturity and it triggers the ripening process by inducing the synthesis of enzymes related to ripening. The consumption of fruits has increased in recent years due to the awareness of its benefits and their availability around the year.

Ripening of fruits is accompanied by a change of starch into sugar which is a change in chemical composition. The classification of fruits into non-climacteric and climacteric was done based on ripening behavior. Climacteric fruits are harvested in a fully mature state which is hard and green. Little quantity of ethylene stimulates the ripening process near consumption zones in a controlled environment of temperature and humidity. They include mango, guava, fig, apricot, banana, kiwi, apple, plum, pear, and passion fruit. The other categories of fruits are non-climacteric fruits. They are harvested only when they are completely ripened. They do not react to ethylene treatment as they emit a tiny amount of ethylene. They include orange, grapes, litchi, watermelon, and blackberry.

Fruit trade involves transporting climacteric fruits to distant places. These fruits liberate ethylene gas augmented with respiration rate during the process of ripening. It is difficult to handle the ripe fruits as they are squashy and flimsy and they usually cannot endure the rigors during transport. Therefore, to avoid spoilage of fruit over long distances, traders generally

harvest raw fruits and ripen them artificially at the destination market before the sale (WIKIPEDIA, n.d.). Considering the importance of artificial ripening in the supply chain of certain fruits, the Food Safety and Standards Authority of India (FSSAI) has permitted the use of ethylene gas in the concentration for artificial ripening of fruits and it is harmless because it is same as natural ripening. Another way of artificial ripening is by using calcium carbide.

Calcium carbide is widely used in different parts of the world (Taghadomi, 2015). Packets of calcium carbide powder are kept in the container of fruits which when comes in contact with moisture, acetylene gas is produced and acts as a ripening agent, which has fruit ripening characteristics similar to ethylene (Anjum et al., 2004). Artificial ripening is done to achieve faster and more uniform ripening.

Banana, Mango, Sapota are some important fruit crops across the world. These fruits are made to ripen faster by treating with calcium carbide. Even though calcium carbide was banned by the Indian government, some traders still use it to ripen bananas, due to the high cost and scarce availability of ethylene gas.  $\text{CaC}_2$  contains the traces of arsenic and phosphorous which is a carcinogenic agent. The consumption of these fruits leads to various disorders like cancer, acute eyes burning, ulcers in mouth and stomach, etc. To create awareness and to solve this problem we proposed a method of Discrete Wavelet Transform (DWT) with GLCM (grey level co-occurrence matrix) to extract some features which helped us to set a threshold and classify artificially and naturally ripened fruits (A. Camargo et al., 2009). Also, an android application is developed which helps the user to identify the method used for ripening by clicking a picture of the fruit (Meier, 2009). We have developed a user interface through the application which gives information about the fruit.



**Fig. 1: Naturally ripened banana**



**Fig. 2: Artificially ripened banana**

## **2. BACKGROUND**

Banana is grown in about 120 countries. Total annual world production is estimated at 86 million tons of fruits. India leads the world in banana production with an annual output of about 14.2 million tons. (WIKIPEDIA, n.d.). Banana is artificially ripened due to following reasons:

- Transportation
- Long term availability

Detecting banana's ripened due to calcium carbide is necessary because the traces of toxic arsenic and phosphorous left behind on fruits by this chemical that is harmful to human health. The symptoms of arsenic or phosphorous poisoning include vomiting, diarrhea, burning sensation of chest and abdomen, weakness, irritation skin, ulcers on the skin, sore throat, cough and shortness of breath. It should be avoided completely during pregnancy.

### **2.1 Manual method to classify natural and artificially ripened bananas**

- Appearance: Naturally ripened bananas have black or brown stalk. The skin of it appears dark yellow with black and brown spots spread unevenly all over. Artificially ripened bananas, on the other hand, appear immaculate with lemon yellow skin. They also have a green stalk.
- Touch and feel: For artificially ripened bananas, some parts of the fruit will be very soft while others would be hard. This is because some parts come in contact with chemicals while others may not. (WIKIPEDIA, n.d.)
- Aroma and taste: Naturally ripened fruits generally have a better aroma and better taste compared to artificially ripened fruits. But this is a relative parameter and it cannot be considered as a standard for the detection of artificially ripened fruits.

Detection using these methods is not always feasible since it requires visual inspection by experts, a common man will not have knowledge regarding these features. (Mithun B.S et al., 2018)

### **2.2 Chemical tests to classify natural and artificially ripened bananas:**

Gas chromatography can be used to detect the presence of acetylene instead of ethylene in artificially ripened bananas, but this process is also not feasible since it requires the use of sophisticated instruments and the detection can be done only after it is completely ripened. (WIKIPEDIA, n.d.) The TTA (total titratable acidity) value is significantly lower in the naturally ripened samples in comparison with the artificially ripened ones, which could be used as the marker to identify artificially ripened banana. (Islam et al., 2018). In the tests we conducted for some samples of banana from day 0 of ripening to day 4 of ripening, we found that the total soluble solids (TSS), which was obtained by a refractometer in the laboratory, for artificially ripened banana is slightly higher than that of the naturally ripened banana of the same stage. Also, the firmness obtained by a firmness tester was higher for naturally ripened bananas. These were clear indications that ripening through artificial means aids the ripening process and hence the values obtained very higher for artificially ripened fruits in the initial stages of ripening. It was also observed that after day 4, banana samples ripened using calcium carbide ripen

completely and lose the qualities which make a fruit consumable. Whereas, naturally ripened bananas were still firm and were in a consumable state. Though these methods help in detection of artificially ripened fruits, these cannot be performed daily in real-time, which creates a need for robust, non-intrusive methods for detection of artificially ripened fruits.

### 3. THEORY BEHIND DISCRETE WAVELET TRANSFORM (DWT)

#### 3.1 Wavelet Transform

The wavelet transform is a waveform of finite duration with zero average value. The wavelet transform differs from the Fourier transform, whose basic function is sinusoid and spread theoretically from minus to plus infinity, but in the wavelet transform, the basis function is a small wave of varying frequency and limited period. These small waves are called wavelets (F. Arab et al., 2013).

The basis function (sinusoid function) in the Fourier transform is smooth and predictable, and it is good in describing constant frequency signals. However, wavelets in the wavelet transform are irregular, non-symmetrical, and have a limited duration. So, they are preferable in describing asymmetry within the signal. (Kamarul et al., 2007).

The wavelet transform is based on the use of basis functions given as

$$\Phi^{a,b}(x) = \frac{1}{\sqrt{a}} \Phi\left(\frac{x-b}{a}\right) \tag{1}$$

Where “a” governs the scale and “b” the translation

In the case of two dimensions, it is represented by:

$$\Phi^{a,b}(x,y) = \frac{1}{\sqrt{a_1 a_2}} \Phi\left(\frac{x-b_1}{a_1}, \frac{y-b_2}{a_2}\right) \tag{2}$$

In the case of three dimensions, it can be represented as:

$$\Phi^{a,b}(x,y,z) = \frac{1}{\sqrt{a_1 a_2 a_3}} \Phi\left(\frac{x-b_1}{a_1}, \frac{y-b_2}{a_2}, \frac{z-b_3}{a_3}\right) \tag{3}$$

#### 3.2 1D DWT

Figure 3 shows the simplest 1D DWT scheme. The left half of figure 3 is the forward 1D DWT called the decomposition or analysis part, and the right half is the inverse 2D DWT called the reconstruction or synthesis part. In the decomposition part, the input signal is filtered by low pass and high pass filters (decomposition filters) and then downsampled by a factor of two to output the downsampled signal in the wavelet domain known as the wavelet coefficients (Dipalee et al., 2015). As illustrated in the Figure, the input to a decomposition stage (analysis filter bank)  $f(n)$  is processed through two paths. In the upper path,  $f(n)$  is passed high-pass filter ( $H_0 e^{j\omega}$ ) and decimated by a factor of two. The two outputs after low and high pass filters are  $f_0(n)$  and  $f_1(n)$ , respectively.

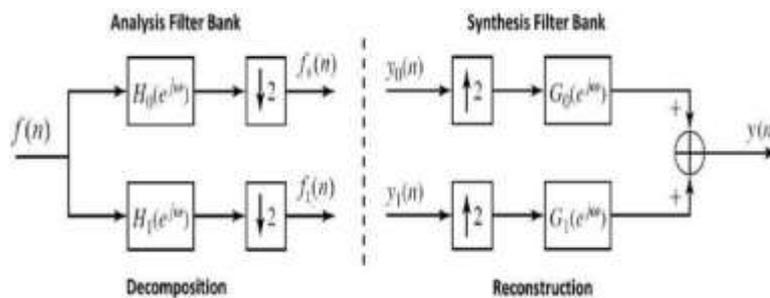


Fig. 3: A two-channel filter bank

In the reconstruction part (which is called synthesis filter bank), there are two inputs  $y_0(n)$  and  $y_1(n)$  and one single output  $y(n)$ , where the input signals  $y_0(n)$  and  $y_1(n)$  are upsampled by a factor of two and then filtered using a low-pass filter ( $G_0 e^{j\omega}$ ) and high-pass filter ( $G_1 e^{j\omega}$ ), respectively. By summing the two filtered signals, the output  $y(n)$  can be obtained.

The forward DWT coefficients for sequence  $f(n)$  (where,  $n = 0, 1, 2, M$ ) are defined by

$$W_\phi(j_0, k) = \frac{1}{\sqrt{M}} \sum_n f(n) \phi_{j_0, k}(n) \tag{4}$$

$$W_\psi(j, k) = \frac{1}{\sqrt{M}} \sum_n f(n) \psi_{j, k}(n) \quad \text{for } j \geq j_0 \tag{5}$$

The  $\phi_{j_0, k}(n)$  and  $\psi_{j, k}(n)$  in these equations are scaling and wavelet functions, respectively. The inverse DWT is

$$f(n) = \frac{1}{\sqrt{M}} \sum_k W_\phi(j_0, k) \phi_{j_0, k}(n) + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{\infty} \sum_n W_\psi(j, k) \psi_{j, k}(n) \tag{6}$$

#### 3.3 2D DWT

The 1D DWT illustrated in the previous section can be extended to the 2D image of ( $M \times N$ ) dimensions. When the 2D DWT is applied on an image, first 1D filtering is applied along rows of the image and then along columns or vice versa as shown in Figure. The output from this decomposition is four sub-components LL, HL, LH, and HH, where **L** refers to low pass filter and **H** refers to high pass filter, and this case is considered one level decomposition.

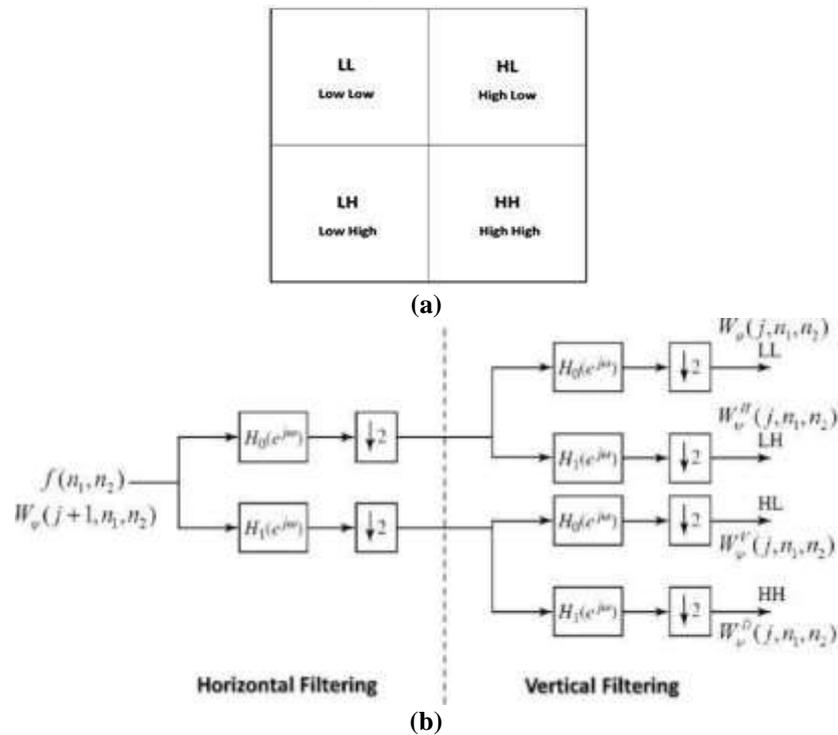


Fig. 4. Decomposition of image into four sub-bands: (a) sub-bands for 1-level decomposition; (b) basic scheme

In order to obtain a multi-level wavelet decomposition of an image, the above scheme of figure 4(b) is applied again to the LL sub-component to produce four sub-components. This operation can be repeated many times according to the required wavelet decomposition level. Fig 5 shows the cascaded filter banks that achieve two-level wavelet decomposition.

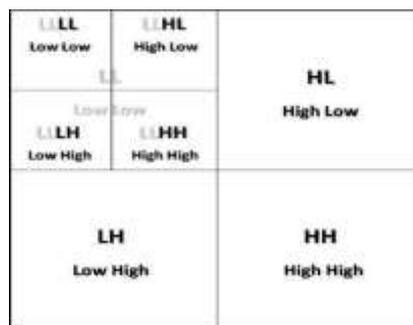


Fig. 5. Sub-bands for two-level decomposition

### 3.4 Wavelet Transform Matrix

An  $N \times N$  ( $N$  is even) wavelet transform matrix is created from two blocks of size  $(N/2) \times N$ . The first half of the matrix represents the LPF and the second half represents the HPF. The first half is constructed with LPF coefficients which are placed in order in the first row. Each subsequent row is obtained by rotating the previous row to the right by two units with cyclic rotation (wrap around) at the ends. In a similar manner, second half of the matrix is constructed with HPF coefficients. In order to transform a data vector with more than  $N$  coefficients using the transform matrix, zeros are appended to make the filter length equal to that of the data length. The LPF block when multiplied with an  $N$ -coefficient vector produces  $N/2$  smooth or average coefficients and the HPF block when multiplied with the same vector produces  $N/2$  detail coefficients. The detail coefficients, when combined with the average coefficients, reproduces the original vector. For a comparatively smoother data, the detail coefficients would be near zero. (Lianhe et al., 2012).

### 3.5 Haar Transform Matrix

The  $2 \times 2$  Haar transform matrix is given by

$$W = \begin{bmatrix} h_0 & h_1 \\ g_0 & g_1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

The first row of the matrix represents the LPF and the second row represents the HPF. To transform a signal with 8 coefficients, the wavelet transform matrix used is

$$W = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix}$$

### 3.6 Wavelet Transform on Two Dimensional Data

Two-dimensional data such as an image can be analyzed by performing a two-dimensional transform on the image (F.Tabassum et al., 2015). The wavelet transform matrix has to be applied to each of the rows and columns of the image. For an image A of size  $N \times N$ , the two-dimensional transform is obtained as WAWT where W is the wavelet transform matrix. If H represents the LPF part of W and G represents the HPF part, then

$$WAW^T = \begin{bmatrix} H \\ G \end{bmatrix} A \begin{bmatrix} H^T \\ G^T \end{bmatrix} = \begin{bmatrix} HAH^T & HAG^T \\ GAH^T & GAG^T \end{bmatrix}$$

Hence, there are four blocks in the wavelet transform. The first block T HAH is an approximation of the entire image.  $HAG^T$ ,  $GAH^T$ , and  $GAG^T$  hold differences in the vertical, horizontal and diagonal directions respectively. A two-dimensional transform can also be done by performing two separate one-dimensional transforms. First, filter the image along the x-dimension using low pass and high pass analysis filters and downsample the result by two. Place the output coefficients of LPF on left part of the matrix and those of HPF on the right. Because of downsampling by two, the total size of the transformed image is same as the original image. Consequently, filter the sub-image along y-dimension and downsample the result by two. The image is now split into four bands denoted by LL, HL, LH, and HH after first-level decomposition. This process of filtering the image or 2D data is called pyramidal decomposition. Inverse transform can be obtained using inverse of the transform matrix. For orthogonal transform matrices, inverse is just the transpose. That is, and  $W^{-1} = W^T$

### 3.7 GLCM (Grey Level Co-occurrence Matrix)

The Gray Level Co-occurrence Matrix (GLCM) and associated texture feature calculations are image analysis techniques. Given an image composed of pixels each with an intensity (a specific gray level), the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity (a.k.a. image texture) at the pixel of interest. (P. Mohanaiah et al., 2013).

## 4. METHODOLOGY

### 4.1 Sample preparation

We considered two different banana species i.e., Grand Nain as banana type 1 and elaiichi as banana type 2 each of 400 samples out of which 200 fruit samples are not treated with any ripening agent hence these are considered as naturally ripened fruits. The other 200 samples are treated with calcium carbide hence considered as artificially ripened fruits. A total of 800 banana samples two-dimensional for experimentation. And images were captured using an android camera for different ripening stages continuously and processing is partly done for every ripening stages.

### 4.2 Image Acquisition

At first a total of 800 banana images have been taken with a resolution of 1080\*1920 pixels using android Mi A1 phone. The images are captured between 9 AM to 12 PM under the natural light. A white background is used so that segmentation can be done easily. Then each ripening stage of this calcium carbide treated and non - treated bananas is observed and the sample images of all these samples are taken using the same technique.

### 4.3 Discrete Wavelet Transform

The image is transformed using discrete HAAR wavelet transform with level 2 decomposition. The transformed image is then reconstructed and given as input to the GLCM algorithm.

### 4.4 Algorithm for GLCM

- Quantize the image data. Each sample on the echogram is treated as a single image pixel and the value of the sample is the intensity of that pixel. These intensities are then further quantized into a specified number of discrete gray levels as specified under Quantization.
- Create the GLCM. It will be a square matrix  $N \times N$  in size here N is the Number of levels specified under Quantization.

The matrix is created as follows:

- Let s be the sample under consideration for the calculation.
- Let W be the set of samples surrounding sample s which fall within a window centered upon sample s of the size specified under Window Size.
- Considering only the samples in the set W, define each element  $i, j$  of the GLCM as the number of times two samples of intensities i and j occur in specified Spatial relationship (where i and j are intensities between 0 and Number of levels-1).
- The sum of all the elements  $i, j$  of the GLCM will be the total number of times the specified spatial relationship occurs in W.
- Make the GLCM symmetric:
  - Make a transposed copy of the GLCM
  - Add this copy to the GLCM itself

This produces a symmetric matrix in which the relationship i to j is indistinguishable for the relationship j to i (for any two intensities i and j). As a consequence the sum of all the elements  $i, j$  of the GLCM will now be twice the total number of times the specified spatial relationship occurs in W (once where the sample with intensity i is the reference sample and once where the sample with intensity j is the reference sample), and for any given i, the sum of all the elements  $i, j$  with the considered i value will be the total number of times a sample of intensity i appears in the specified spatial relationship with another sample.

5. CALCULATIONS

Divide each element by the sum of all elements. The elements of the GLCM may now be considered probabilities of finding the relationship i, j (or j, i) in W. (A. Averbuch et al., 1996)

To calculate the selected feature, we use only the values in the GLCM. The following formulae are used:

Energy feature:

$$\text{Energy} = \sum_{i,j=0}^{N-1} (P_{ij})^2 \tag{7}$$

Contrast feature:

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2 \tag{8}$$

Homogeneity feature:

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{9}$$

Correlation feature:

$$\text{Correlation} = \sum_{i,j=0}^{N-1} \frac{P_{ij}(i-\mu)(j-\mu)}{\sigma^2} \tag{10}$$

$P_{ij}$  = Element i,j of the normalized symmetrical GLCM.

N= Number of gray levels in the image as specified by Number of levels in under Quantization on the GLCM texture page of the Variable Properties dialog box.

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij} \tag{11}$$

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij} (i - \mu)^2 \tag{12}$$

$\sigma^2$  = the variance of the intensities of all reference pixels in the relationships that contributed to the GLCM, calculated using (12).

6. ANDROID APPLICATION DEVELOPMENT

The client is the android application which calls the inbuilt camera function, which enables the user to capture the image of the fruit. Usually in android phones, the captures image will be in JPEG (Joint Photographic Expert Group) or PNG (Portable Network Graphics) format which does not require any type of image encoding before sending it to the backend or server (Gong, Lei et al., 2008). The captured image is sent for processing in the backend. The python code runs in the backend which preprocesses the image, extracts GLCM features and based on the preset threshold decides whether the image is artificially ripened or naturally ripened. The Result is sent back to the client to be displayed on mobile screen.

7. FLOW CHART

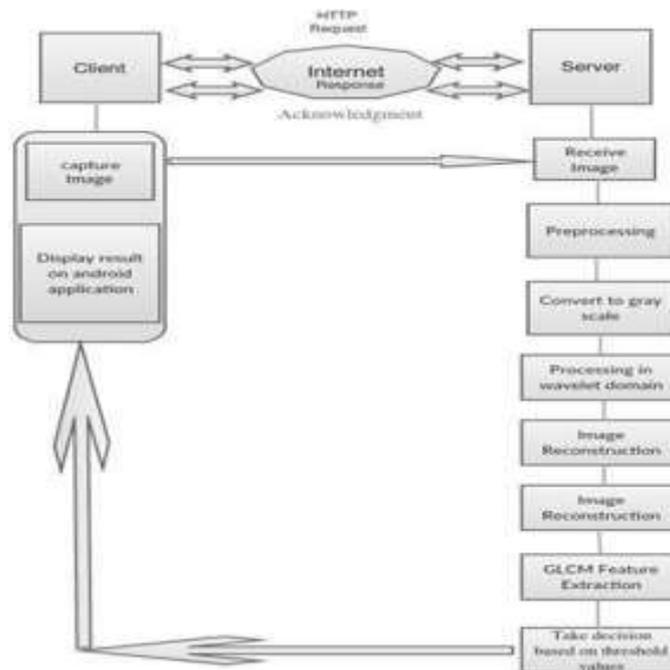


Fig. 6. The overall flow of the program and application

8. RESULT

Table 1: Banana Type 1 artificially ripened (Calcium Carbide)

Samples	Contrast	Dissimilarity	Homogeneity	Energy	Correlation
1	3745.626	15.062	0.9017	0.8701	0.2902
2	4201.476	16.960	0.8909	0.8579	0.2815
3	3917.581	15.757	0.8979	0.8662	0.2774

4	3273.216	13.171	0.9027	0.8699	0.4150
5	2614.822	10.476	0.9295	0.8982	0.3904
6	3273.231	13.166	0.9070	0.8734	0.3842
7	2893.575	11.636	0.9157	0.8835	0.4189
8	3793.669	15.227	0.9024	0.8717	0.2559
9	3989.281	16.026	0.8942	0.8635	0.2947
10	4464.818	17.966	0.8844	0.8519	0.2649

**Table 2: Banana type 1 Naturally Ripened**

Samples	Contrast	Dissimilarity	Homogeneity	Energy	Correlation
1	6474.936	26.124	0.7949	0.7215	0.4611
2	6113.094	24.723	0.8060	0.7422	0.4576
3	6203.457	24.933	0.8116	0.7396	0.4431
4	5187.914	20.913	0.8625	0.8243	0.2814
5	5784.258	23.305	0.8479	0.8110	0.2712
6	5100.125	20.608	0.8657	0.8338	0.2788
7	5727.231	22.872	0.8353	0.7676	0.4069
8	5697.607	23.006	0.8482	0.8107	0.2981
9	4612.570	18.547	0.8590	0.8047	0.4578
10	5189.921	20.870	0.8447	0.7884	0.4312

**Table 3: Banana type 2 artificially ripened (Calcium Carbide)**

Samples	Contrast	Dissimilarity	Homogeneity	Energy	Correlation
1	4413.435	17.751	0.8908	0.8639	0.1945
2	2032.518	8.109	0.9402	0.9023	0.5315
3	2982.502	11.908	0.9137	0.8676	0.4879
4	2322.872	9.258	0.9324	0.8932	0.5134
5	3317.065	13.222	0.9024	0.8404	0.5362
6	2859.823	11.431	0.9131	0.8632	0.5349
7	2976.481	11.883	0.9113	0.8638	0.5032
8	3648.111	14.608	0.8953	0.8440	0.4612
9	3987.924	15.999	0.8998	0.8712	0.2288
10	3503.449	13.999	0.8952	0.8392	0.5089

**Table 4: Banana type 2 naturally ripened**

Samples	Contrast	Dissimilarity	Homogeneity	Energy	Correlation
1	5002.681	20.121	0.8723	0.8365	0.2665
2	4854.840	19.537	0.8755	0.8359	0.2718
3	5056.741	20.249	0.8518	0.7946	0.4212
4	5535.139	22.268	0.8621	0.8270	0.2402
5	5001.082	19.999	0.8745	0.8325	0.2361
6	5129.071	20.566	0.8710	0.8317	0.2303
7	5002.686	20.131	0.8734	0.8389	0.2641
8	5138.321	20.590	0.8463	0.7833	0.4439
9	5001.231	19.989	0.8756	0.8354	0.2410
10	5212.246	20.764	0.8558	0.7917	0.3942



Original Image



Transformed Image

**Fig. 7: Banana type 1 CaC<sub>2</sub>**

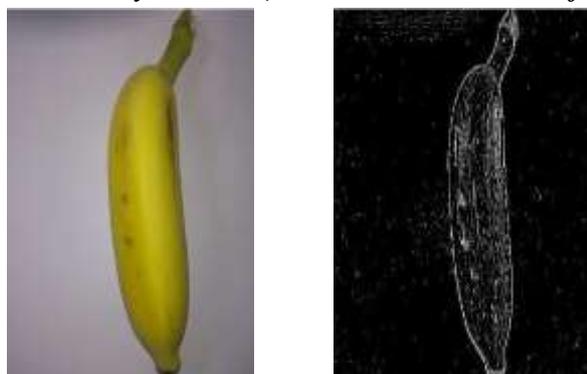


Original Image



Transformed Image

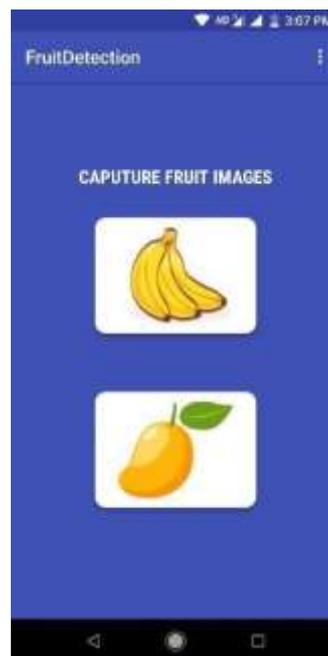
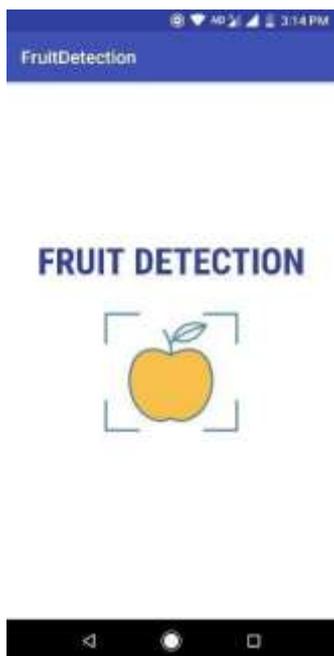
**Fig. 8: Banana type 1 Natural**



Original Image Transformed Image  
**Fig. 9: Banana type 2 CaC<sub>2</sub>**



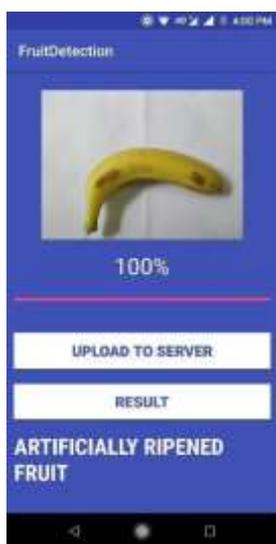
Original Image Transformed Image  
**Fig. 10: Banana type 2 Natural**



**Fig. 11: User Interface of Android application**



**Fig. 12: Banana type 1 Android Application results**



**Fig. 13: Banana type 2 Android Application results**

**9. CONCLUSION**

The image processing assisted method for differentiating artificially and naturally ripened bananas was developed successfully with the efficiency of 90%. According to the survey, it was revealed that the bananas treated with ethylene are same as naturally ripened bananas. Also considering the harmful effects of the byproducts obtained when fruit is treated with calcium carbide we came up with a methodology to detect calcium carbide treated fruits using smartphones. The proposed method converts the image into wavelet domain and various features were extracted from the GLCM matrix. Considerable differences in the contrast feature were seen. We have considered 400 samples for each in which 300 samples were used for setting the threshold for the contrast value. The other 100 samples were used for testing. An android app was developed and server client concept was used for

clicking the picture of banana, uploading to server and getting the results on phone display. And because of higher efficiency this method helps people to be fit by consuming healthy fruits.

## 10. REFERENCES

- [1] A.Averbuch, D. Lazar and M. Israeli, 1996. Image compression using wavelet transform and multi resolution decomposition, in IEEE Transactions on Image Processing, 5, 4-15, doi: 10.1109/83.481666.
- [2] A Camargo, & J S Smith., 2009. An image-processing based algorithm to automatically identify plant disease visual symptoms. Biosystems Engineering, 102, 9-21.
- [3] Anjum, Muhammad Akbar, and Hakoomat Ali., 2004. Effect of various calcium salts on ripening of mango fruits. Journal of Research Science 15, 45-52.
- [4] Dipalee Gupta, Siddhartha Choubey., 2015. Discrete Wavelet Transform for Image Processing. International Journal of Emerging Technology and Advanced Engineering ISSN 2250-2459, ISO 9001:2008 Certified Journal.
- [5] Downey, G., 1987. Review and assessment of food and nutrition policies. Food, Health and the Consumer, 121- 212.
- [6] F. Arab, S. M. Daud and S. Z. Hashim., 2013. Discrete Wavelet Transform Domain Techniques. International Conference on Informatics and Creative Multimedia, Kuala Lumpur, 340-34 doi: 10.1109/ICICM.2013.
- [7] F. Tabassum, M. I. Islam and M. R. Amin., 2015. A simplified image compression technique based on Haar Wavelet Transform. International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, 1-9.doi: 10.1109/ICEEICT.2015.7307490.
- [8] Gong, Lei, and Cong Zhou. 2008. Development and Research of Mobile Termination Application Based on Android Computer and modernization.
- [9] Islam, Md & YousufImtia z, Mollik&Alam, Sabrina &Nowshad, Farrhin & Shadman, Swarit Ahmed & Khan, MohidusSamad., 2018. Artificial Ripening on Banana (MusaSpp.) Samples: Analyzing Ripening Agents and Change in Nutritional Parameters. Cogent Food & Agriculture. 10.1080/23311932.2018.1477232.
- [10]Kamarul Hawari Gha zali; Mohd.Marzuki, Mustafa ;AiniHussain., 2007. Feature Extraction Technique using Discrete Wavelet Transform for Image Classification. 5th Student Conference on Research and Development, INSPEC Accession Number: 9940176.
- [11]LianheZhi, Wei Liu, Qi Liu., 2012. Matrix Operation of Discrete Wavelet Transform. International Conference on Industrial Control and Electronics Engineering, INSPEC Accession Number: 13057542.
- [12]Meier, Reto., 2009. Android™ Application Development. Framework, 318.
- [13]Mishra, A., Asthana, P., &Khanna, P., 2014. The Quality identification of Fruits in Image Processing Using Matlab. International Journal of Research in Engineering and Technology, 3, 92-95.
- [14]Mithun B.S., SujitShinde, Karan Bhavsar, ArijitChowdhury, ShaliniMukhopadhyay, Kavya Gupta, BrojeshwarBhowmick, Sanjay Kimbahune., 2018. Non-destructive method to detect artificially ripened banana using hyperspectral sensing and RGB imaging. Proc.SPIE 10665, Sensing for Agriculture and Food Quality and Safety X, 106650T.
- [15]P. Mohanaiah, P. Sathyanarayana, L. GuruKumar., 2013. Image Texture Feature Extraction Using GLCM Approach. International Journal of Scientific and Research Publications, 3 ,ISSN 2250-3153.
- [16]Taghadomi-Saberi S., 2015. Determination of Cherry Color Parameters during Ripening by Artificial Neural Network Assisted Image Processing Technique. Journal of Agricultural Science and Technology, 17, 589- 600.
- [17]Vishwas A., 2010. Ripening of fleshy fruit : molecular insight and the role of ethylene. Biotechnology advances 28, 94-107.