Sensor Applications

Multi-level Fusion of Multi-spectral Images to Detect the Artificially Ripened Banana

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Abstract—Automatic detection of artificially ripened fruits based on a non-destructive approach has recently gained significant attention. This work explores the inherent properties of multi-spectral imaging to distinguish between natural and artificially ripened bananas. The proposed method combines the prediction scores computed from the Support Vector Machine (SVM) on the individual and fused spectral bands images to detect the artificially ripened banana. Extensive analyses are performed on 5760 banana images captured in eight different spectrum bands covering Visible and Near-Infra-Red ranges. Obtained results indicate the average detection accuracy of $97.1 \pm 3.6\%$, thereby illustrating our proposed work's applicability.

Index Terms—Multi-spectral imaging, Artificial ripening, Feature extraction, Score fusion, Classification.

I. INTRODUCTION

Banana is one of the primarily consumed fruit worldwide due to its high nutritional and health benefits [1], [2]. The nutritional value of any fruit is high when it is allowed to ripen by its natural process. Essentially, ripening occurs due to the production of ethylene after harvesting and responds to an external ripening agent such as ethylene and acetylene [3], [4]. Now, with rising demand of banana in the consumer market, it is deliberately resorted to ripen artificially using industrial grade Calcium Carbide (CaC2). Calcium carbide is highly hazardous due to its carcinogenic properties and can cause sever effect on human health. Although, calcium carbide is banned in most of the countries, but the low cost and easy availability, the use of calcium carbide is enhanced in a market chain for the commercial benefits [5], [6]. With rising practice of artificial ripening of banana in market chain, the attention is required to distinguish natural and artificial ripened banana.

The simplest method that can be used to distinguish between natural and artificially ripened bananas is the visual inspection. However, the visual inspection limitations are that it is subjective and accuracy depends on human expertise. Besides visual inspection, previous work in this direction to detect artificially ripened fruits uses laboratory test methods that include analytical, physical, chemical and Deoxyribonucleic acid(DNA) [7], [8]. Even though laboratory-based approaches are convenient, it requires specialized training, especially to carry out the experimental sample preparation. Further, the requirement of a complex and costly experimental setup has reduced the applicability of these methods in an industrial setup. While we also note that laboratory techniques are destructive, they require pulp to be extracted from fruits, making such a method an invasive approach [9]. Apparently, these techniques will destroy fruits to measure required chemical functional groups in the operation process. As a result, it is non-conducive for wider applications. Alternatively, a non-destructive approach to detecting the artificially ripened banana is gaining more attention without damaging the fruit.

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The recent work has shown a preference for employing imaging technology across the spectrum in Visible (VIS) and Near-Infra-Red (NIR) wavelength range especially using multi-spectral imaging sensors [10]–[12].

In this work, we have employed a multi-spectral imaging sensor that acquires spectral band images in eight narrow spectrum bands in VIS and NIR range to distinguish between natural and artificial ripened bananas [13]. The eight narrow spectrum bands corresponds to $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $890nm$, $950nm$, $1000nm$ spanning between $530nm$ to $1000nm$ wavelength range. In general, multi-spectral imaging consists of acquiring complementary spatio-spectral details across the spectrum, which remain unique in terms of their characteristic features. Thus, to leverage the significant contribution of individual bands, we propose a method which extracts the features of individual eight spectral bands and a fused spectral band independently using the Local Phase Quantization (LPQ) method. We then employ the SVM classifier to obtain the prediction scores across individual and fused spectral bands. These scores are then processed using score level fusion to present the classification accuracy. We conduct experimental evaluations on 5760 sample multi-spectral banana images using the 10-fold cross-validation method. The main contribution of our work is as follows:

- Presents the multi-spectral imaging in eight narrow spectrum bands across VIS and NIR range to distinguish natural and artificially ripened bananas.
- Proposed method that combines scores obtained from the eight individual spectral bands and fused spectral bands using Support Vector Machine (SVM) algorithm for robust performance.
- Presents the evaluation results in the form of average classification accuracy based on our proposed method and compared across individual band performance to present the potential of the proposed approach.

In rest of the paper, Section II present the detailed description of our proposed approach, Section III describe the database employed in this work in eight narrow spectrum bands spanning from VIS to NIR wavelength range, Section IV presents the experimental results

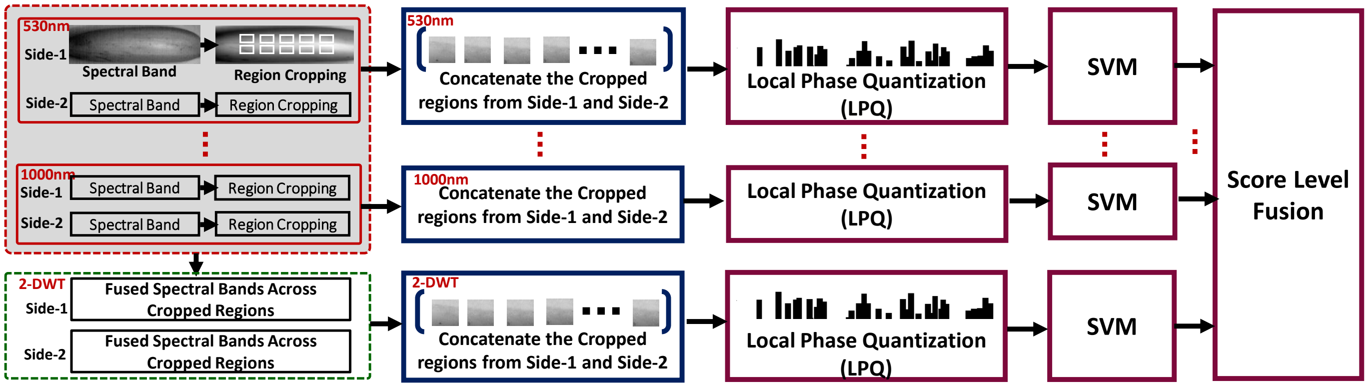

Fig. 1: Proposed Approach of score level fusion to distinguish natural and artificially ripened banana.

along with discussion and final conclusion is presented in Section V.

II. PROPOSED APPROACH

The conceptual representation of our proposed work is illustrated in Figure 1. The proposed approach presents the detection of artificial ripened banana by performing the multi-level fusion of individual spectral bands and fused spectral bands.

Let the individual spectral band be represented as $z_\lambda = \{z_1, z_2, z_3, \ldots, z_8\}$ Where λ represents images corresponding to the eight individual bands in VIS and NIR range. The individual band images contain not only bananas but also unwanted background information, which needs to be discarded before processing with the proposed method. Therefore, considering complementary image details across the individual spectral bands, we cropped 10 different regions from the banana samples and let this be represented as $r_{\lambda k}$ using equation 1.

$$r_{\lambda k} = \{r_{\lambda 1}, r_{\lambda 2}, \ldots, r_{\lambda 10}\} \tag{1}$$

Where k represents 10 cropped regions of bands. We then combined these 10 regions by concatenation method to simplify our algorithm and is given by equation 2.

$$s_\lambda(x, y) = [r_{\lambda 1}(m, n) \,||\, r_{\lambda 2}(m, n) \,||\, \ldots, || \, r_{\lambda 10}(m, n)] \tag{2}$$

where, $s_\lambda(x, y)$ represents the single matrix after concatenation having dimension $(x, y) \geq (m, n)$. Now, the multi-spectral banana database consists of images acquired on two different sides of banana [13]. Hence, to further simplify our approach, we then combine these two sides of data by using equation 3.

$$w_\lambda(u, v) = \left[w_\lambda^{s1}(u, v) \,||\, w_\lambda^{s2}(u, v)\right] \tag{3}$$

Where $w_\lambda^{s1}(u, v)$ and $w_\lambda^{s2}(u, v)$ represents the data belongs to side-1 and side-2 respectively. Further, to effectively combine the contribution of individual spectral bands in our proposed approach, we also employed the fusion of all eight bands to enhance the performance accuracy of our approach. To carry out the fusion, we used 2-Discrete Wavelet Transform Average fusion (2-DWT) [13]. Therefore, referring to equation 1, we performed average wavelet fusion of bands independently on 10 different banana regions. After performing fusion, we followed a similar procedure to combine 10 regions and two sides of banana samples, as carried out for individual bands using equation 2 and 3 respectively. Let the data matrix obtained after average wavelet fusion is represented by $D_f(u, v)$.

Leveraging the characteristic features of the individual and fused spectral bands is essential for robust detection performance analysis. Hence, we employed LPQ feature extraction algorithm on $w_\lambda(u, v)$ (individual bands) and $D_f(u, v)$ (fused bands). LPQ is a well-known, proven texture descriptor method that extracts the information embedded at the local and global levels. Further, feature extraction not only extracts the dominant features but also discards the unwanted common information, thereby reducing the dimensionality of data during the processing without compromising the integrity of the data. The LPQ histogram features obtained for individual and fused bands were then classified with SVM to obtain the prediction scores independently. The obtained scores were then combined at score level fusion using a simple sum rule to compute the final prediction output in our proposed algorithm, as illustrated using equation 4.

$$\Psi = \psi_{(\lambda=1)} + \psi_{(\lambda=2)} + \ldots + \psi_{(\lambda=8)} + \psi_f \tag{4}$$

where, $\psi_{(\lambda=1,\ldots,8)}$ are the prediction score Where $\psi_{(\lambda=1,\ldots,8)}$ are the prediction score corresponding to individual bands and ψ_f corresponds to the prediction score on fused bands, obtained using the SVM.

III. MULTI-SPECTRAL DATABASE

This section of paper describe the details related the database employed in this work. The database consist of banana image collected with eight bands using multi-spectral imaging sensor in VIS and NIR wavelength range [10]. The banana sample images belongs to eight bands consists of 530nm, 590nm, 650nm, 710nm, 770nm, 890nm, 950nm and 1000nm spanned from 530nm to 1000nm range.

Table 1: Summary presenting the number of multi-spectral sample images for banana belongs to a natural ripening and two artificial ripening categories

Banana	Ripening Category	Number of Days	Samples	Bands	Sides	Total
30	3	2	2	8	2	5760

The database consist of a total 5760 samples of banana images collected for three different categories of ripening: a natural ripening (labeled as 'Nat-Ripe') and two artificial ripening (labeled as 'Art-Ripe-Gas' and 'Art-Ripe-Sol'). Natural ripened banana were subjected to ripen without any chemical treatment. Artificial ripening category,

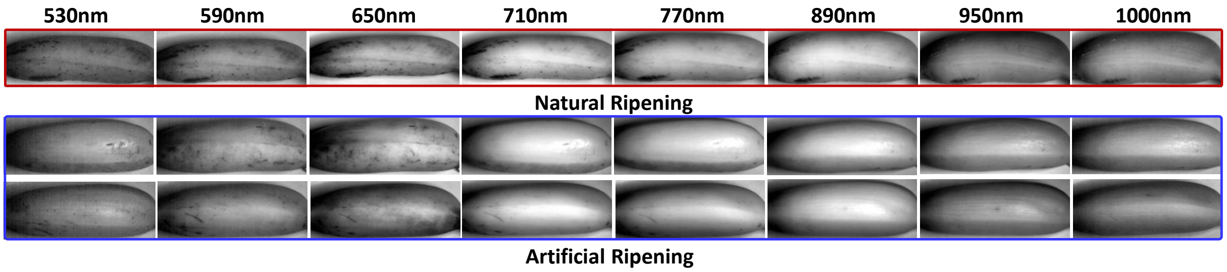

Fig. 2: Sample banana images corresponds to eight narrow bands in VIS and NIR wavelength range: (a) Row1 illustrates images corresponds to natural ripened category (labeled as 'Nat-Ripe'), (b) Row2 and Row3 illustrates images corresponds to artificial ripened category (labeled as 'Art-Ripe-Sol' and 'Art-Ripe-Gas' respectively)

i.e. 'Art-Ripe-Gas' stimulated to ripen banana using acetylene gas released from the mixture of CaC_2 and water. In contrast, the other artificial ripening category, i.e. 'Art-Ripe-Sol' stimulated to ripen using a liquid mixture of CaC_2 and water. The chemical reaction performed to stimulate the artificial ripening in as follows:

$$CaC_2 + 2\,H_2O \longrightarrow C_2H_2 + Ca(OH)_2 \tag{5}$$

Under each category of ripening, the database consists of sample images from two sides of banana i.e. upper and lower side of banana, with a total of 1920 images. Multi-spectral data of 1920 images comprises of 30 Banana of one category of ripening $\times$ 2 Days of Acquisition $\times$ 2 Sample Images $\times$ 2 Sides of Banana $\times$ 8 Spectral Bands that corresponds = 1920 Images in each category of ripening. Now, 1920 $\times$ 3 Categories of ripening corresponds to a total of 5760 sample images. The detail summary of database used in this work is presented in Table 1 and the sample images corresponding to multi-spectral banana database is illustrated in Figure 2.

Table 2: Summary of data partition consisting samples belongs to training and testing set for the experimental evaluation

Ripening Category	Data Partition	Training	Testing
Nat-Ripe	Banana	15	15
	Number of Days	2	2
	Samples	2	2
	Bands	8	8
	Sides	2	2
	Cropped Regions	10	10
	Total	2400	2400
Nat-Ripe-Sol or Nat-Ripe-Gas	Banana	15	15
	Number of Days	2	2
	Samples	2	2
	Bands	8	8
	Sides	2	2
	Cropped Regions	10	10
	Total	2400	2400

IV. EXPERIMENTS AND RESULTS

This section presents the experimental evaluation protocol and corresponding results based on the proposed approach to distinguish natural and artificial ripened banana. The proposed approach in this paper combines scores obtained from the eight individual bands and fused spectral bands using SVM algorithm for the performance analysis. The experiments present results on a multi-spectral fruit database [10] that consist of 5760 samples of banana images collected for three different categories of ripening: a natural ripening and two artificial ripening (The details are described in Section III). For experimental evaluation, we present results in this section in the form of average classification accuracy using 10 fold cross-validation method for random selection of training and testing sample set in disjoint manner. Further, to present the significance of our proposed approach, we compare the classification accuracy of proposed approach with respect to the performance of individual spectral bands in this work.

In the evaluation protocol, the training and testing set consist of randomly selected 50% samples from each data category. Specifically, the training set consists of 15 banana from the category of 'Nat-Ripe' and 15 banana from the category of 'Art-Ripe-Sol' or 'Art-Ripe-Gas' including their sample images that corresponds to a total of 2400 images. Similarly, the testing set consists of 15 banana from the category of 'Nat-Ripe' and 15 banana from the category of 'Art-Ripe-Sol' or 'Art-Ripe-Gas' including their sample images that corresponds to a total of 2400. The detailed summary of data partition for the experimental analysis is shown in Table 2.

A. Evaluation

Considering the three categories of data in the multi-spectral banana database, we present two experimental evaluations. Evaluation 1 is based on 'Nat-Ripe' and 'Art-Ripe-Gas' data to detect the artificial ripened banana when the samples were resorted to ripen using the acetylene gas released as a result of chemical reaction between calcium carbide and water. Evaluation 2 is based on 'Nat-Ripe' and 'Art-Ripe-Sol' data when banana samples were ripened using the liquid mixture prepared from calcium carbide and water. Table 3 shows the average classification accuracy and Figure 3 illustrates the mean-variance plot for both the evaluation 1 & 2. The proposed method presents an outstanding performance for both the evaluations, as compared to the performance obtained for the individual spectral band using an SVM classifier. Specifically, the highest average classification accuracy of $95.0 \pm 5.2\%$ is obtained for evaluation 1, while the highest accuracy of $97.1 \pm 3.6\%$ is obtained for evaluation 2, presenting the robustness of our proposed method. It is observed that the performance accuracy of proposed approach with evaluation 2 is better than the evaluation 1, which implies the presence of significant discriminative information across the individual spectral bands (as can be seen from

Table 3: Average classification accuracy (%) along with standard deviation obtained across individual bands and proposed approach for Evaluation 1 ('Nat-Ripe' & 'Nat-Ripe-Gas') and Evaluation 2 ('Nat-Ripe' & 'Nat-Ripe-Sol')

Results	Spectral Bands								Proposed
	530nm	590nm	650nm	710nm	770nm	890nm	950nm	1000nm	
Evaluation 1	78.8±9.2	78.2±7.6	72.2±9.8	77.7±9.9	82.8±6.9	87.2±6.0	82.8±7.9	80.2±7.5	**95.0±5.2**
Evaluation 2	74.4±7.2	74.4±7.6	73.2±9.8	80.2±8.6	93.2±3.6	88.0±7.2	85.2±8.7	91.8±5.9	**97.1±3.6**

the classification accuracy from both the evaluation in Table 3) when samples of banana ripened with chemical solutions prepared from calcium carbide and water. Further, we also note that the individual bands show consistently good performance, signifying the potential of multi-spectral imaging for the detection of artificial ripening of bananas. More importantly, bands such as 770*nm*, 890*nm*, 950*nm*, 1000*nm*, which are in NIR region, present better results than the other bands, as can also be seen from Figure 3. Better accuracy in these bands could be due to the presence of unique complementary detail in the form of reflectance and emittance, as compared to other bands which fall in the visible section of the spectrum that can deliver only the reflectance details.

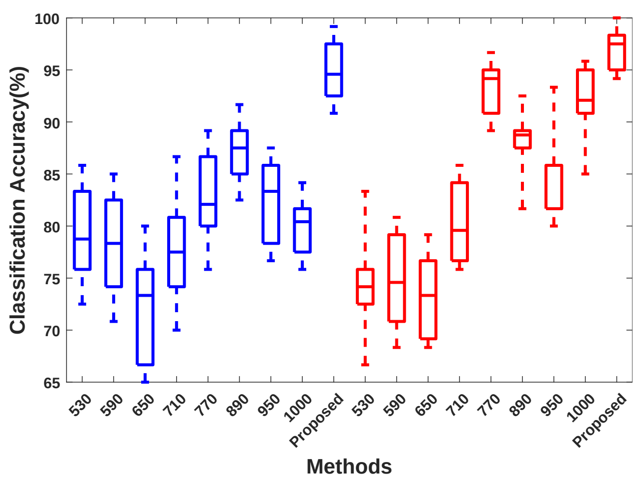

Fig. 3: Classification accuracy to detect artificial ripened banana samples across individual spectral bands and based proposed approach. For simplicity, Evaluation 1 & 2 are shown with blue and red color.

To summarize, our proposed approach based on score level fusion produces outstanding performance in distinguishing natural and artificially ripened bananas. Further, multi-spectral imaging has demonstrated its preference as a non-invasive and non-destructive approach to detect artificially ripened bananas.

V. CONCLUSION

Detecting artificially ripened fruits is challenging, and the presently available laboratory methods are destructive. Further, we have proposed a robust approach that combines the SVM prediction scores obtained from the individual spectral bands and fused spectral bands using the sum rule. This work presents a non-destructive approach based on a multi-spectral imaging sensor to distinguish between natural and artificial ripened bananas. The work was performed on a multi-spectral fruit database of 5760 banana images acquired in eight bands spanned across VIS and NIR ranges. The experimental results were obtained based on the proposed approach and compared against individual spectral-band performance. Using 10 fold cross-validation, the proposed method computed the highest average classification of 97.1 ± 3.6% compared to the individual bands. The outstanding performance of the proposed method demonstrated the potential use of inherent properties of multi-spectral imaging sensors as a non-invasive tool in detecting the artificially ripened banana.

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REFERENCES

[1] V. Vivek, L.Cristina, and B. Steffany, "Global market report: Bananas," 2020.

[2] M. M. H. Adeyemi, M. Bawa, and B. Muktar, "Evaluation of the effect of calcium carbide on induce ripening of banana, pawpaw and mango cultivated within kaduna metropolis, nigeria"," *Journal Of Chemical Society Of Nigeria*, vol. 43, 2018.

[3] S. Maduwanthi and R. Marapana, "Induced ripening agents and their effect on fruit quality of banana," *International journal of food science*, vol. 2019, 2019.

[4] B. Mithun, S. Shinde, K. Bhavsar, A. Chowdhury, S. Mukhopadhyay, K. Gupta, B. Bhowmick, and S. Kimbahune, "Non-destructive method to detect artificially ripened banana using hyperspectral sensing and rgb imaging," in *Sensing for Agriculture and Food Quality and Safety X*, vol. 10665. International Society for Optics and Photonics, 2018, p. 106650T.

[5] G. P. A. T. FOOD, "The prevention of food adulteration act, 1954 (37 of 1954)[act as on date-modified up to 1995]."

[6] M. N. Islam, M. Y. Imtiaz, S. S. Alam, F. Nowshad, S. A. Shadman, and M. S. Khan, "Artificial ripening on banana (musa spp.) samples: Analyzing ripening agents and change in nutritional parameters," *Cogent Food & Agriculture*, vol. 4, no. 1, p. 1477232, 2018.

[7] S. Bansal, A. Singh, M. Mangal, A. K. Mangal, and S. Kumar, "Food adulteration: Sources, health risks, and detection methods," *Critical Reviews in Food Science and Nutrition*, vol. 57, no. 6, pp. 1174–1189, 2017.

[8] M. Mangal, S. Bansal, and M. Sharma, "Macro and micromorphological characterization of different aspergillus isolates," *Legume Research - An International Journal*, vol. 37, p. 372, 08 2014.

[9] A. Lakade, K. Sundar, and P. Shetty, "Gold nanoparticle-based method for detection of calcium carbide in artificially ripened mangoes (magnifera indica)," *Food Additives and Contaminants: Part A*, vol. 35, 03 2018.

[10] N. Vetrekar, R. Ramachandra, K. B. Raja, and R. S. Gad, "Multi-spectral imaging for artificial ripened banana detection," in *2019 8th European Workshop on Visual Information Processing (EUVIP)*, 2019, pp. 187–192.

[11] N. Vetrekar, A. Prabhu, A. Naik, R. Ramachandra, K. Raja, A. Desai, and R. Gad, "Collaborative representation of convolutional neural network features to detect artificial ripening of banana using multi-spectral imaging," *Journal of Food Processing and Preservation*, 07 2022.

[12] J.-L. Li, D.-W. Sun, and J.-H. Cheng, "Recent advances in nondestructive analytical techniques for determining the total soluble solids in fruits: a review," *Comprehensive Reviews in Food Science and Food Safety*, vol. 15, no. 5, pp. 897–911, 2016.

[13] N. Vetrekar, R. Ramachandra, K. B. Raja, and R. S. Gad, "Multi-spectral imaging to detect artificial ripening of banana: A comprehensive empirical study," in *2019 IEEE International Conference on Imaging Systems and Techniques (IST)*. IEEE Press, 2019, p. 1–6.