MULTI-SPECTRAL IMAGING FOR ARTIFICIAL RIPENED BANANA DETECTION

*Narayan Vetrekar** *Raghavendra Ramachandra*† *Kiran B. Raja*† *R. S. Gad**

*Department of Electronics, Goa University, Taleigao Plateau, Goa, India
†Norwegian University of Science and Technology (NTNU), Gjøvik, Norway
Email: {elect.ntvetrekar; rsgad}@unigoa.ac.in, {raghavendra.ramachandra; kiran.raja}@ntnu.no

ABSTRACT

Ripening is a natural process that makes fruits edible and nutritious. With increasing demand, the practice to employ artificial ripening of fruits have been increased recently in the market chain to fulfill the needs of the consumer. Artificial ripening not only reduces the quality of fruits but also increases the health-related risk especially Calcium carbide(CaC_2), an artificial ripening agent, inherits the carcinogenic properties. Although the problem of detecting artificial ripening of fruits is important, the conventional methods based on chemical analysis are not feasible. In this paper, we present the use of multi-spectral imaging in eight narrow spectrum bands across VIS and NIR range to detect the artificial ripened banana. To present this approach, we introduce a newly constructed multi-spectral images collected from naturally and artificially ripened banana samples. The extensive experiments are performed on the large scale data set consists of 5760 banana samples by performing 10 fold cross-validation. The obtained average classification accuracy of 97.5% demonstrates the significance of multi-spectral imaging for differentiating natural and artificial ripened banana.

***Index Terms*—** Artificial Ripening, Multi-spectral Imaging, Banana, Feature Extraction, Classification

1. INTRODUCTION

Fruits are the natural sources of essential ingredients having tremendous nutrition value. Especially, the presence of antioxidant in fruits reduces the several diseases related to heart, brain disorder or cancer. Due to such benefits, its consumption has been increased in recent years for the development of healthy lifestyle in human being [1]. The nutritious values in the fruits are more significant when fruits are ripened naturally [2]. However, to fulfill the needs of consumer and for commercial benefits, nowadays fruits are deliberately being contaminated by the harmful chemicals to speed up the process of ripening and to extend the shelf life of fruits [3]. Scientifically, this process of ripening is mainly known as 'Artificial Ripening'.

The artificial ripening is stimulated by using the ripening agents such as acetylene, ethylene, etc.,[4] and its preference is becoming more prevalent in the commercial sector to make the fruits available for customers especially during off-season [5]. Further, the use of chemical ripening agents are permitted in many countries across worldwide within a permissible limit or many countries have their own specific rules and regulation regarding its usage [6, 7, 8]. But the high cost and limited availability of these chemicals, results in the use of other harmful chemical i.e. Calcium Carbide (CaC_2), to stimulate the artificial ripening of fruits. Although, the use of calcium carbide is prohibited in most of the countries [9] (For instance, India has banned the use of calcium carbide under Preservation of Food Adulteration (PFA) Act, 1955 [8]), it is still being used in the market chain due to low cost, easy availability and does not required any scientific knowledge or training (Such as there is no consistency in the amounts chemical use as well as the way it is used [10]). However, the use of Calcium Carbide adversely affects the quality of fruits, at the same time Calcium Carbide is a strong reactive chemical having carcinogenic properties, that are harmful to the human health [11]. Even though the problem of detecting artificially ripened fruits is a matter of concern due to the various health-related issues, it has not received significant interest from the research community to automate the process of detecting [6, 11].

1.1. Related works and Contribution

With limited pool of work in this direction, the available studies are based on invasive laboratory tests which are mainly based on the conventional techniques such as analytical, physical, chemical and most recent Deoxyribonucleic Acid (DNA) based molecular methods [12, 13, 14, 15]. These methods employ destructive and invasive approach, which requires the extracted juice or pulp of the fruits for the quality analysis. Even though these techniques are easy and more convenient, their industrial applicability is limited due to the high cost, complex experimental setup, time-consuming and requirement of special training on sample preparation [12]. Adding more to the limitations, these methods may not always provide quantitative and qualitative results [12], therefore, its utility is more restricted to laboratory analysis.

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On the other hand, a nondestructive study based on using hyperspectral sensing and RGB imaging have also introduced in one of the very recent study to detect the artificial ripening of fruits [2]. The study has demonstrated the significance of hyperspectral and RGB imaging approach by employing the potential of Deep Learning (DL) to obtain robust performance. However, the use of RGB imaging allows extracting only the reflectance information which limits its use case in heterogeneous environmental condition. On the other hand, hyperspectral imaging provides reflectance and/or emittance information, but the drawback of using hyperspectral imaging is that it increases the redundancy in acquired information due to overlapping spectral bands, resulting in poor performance. Further, the high cost of hyper-spectral imaging makes its use case limited for quality analysis of fruits. Alternatively, the above problem can be addressed by employing intrinsic properties of the multi-spectral imaging sensor in discrete and disjoint wavelength range, which is one of our major contributions to detect artificial ripening of fruits in this paper.

The available previous approaches are based on destructive chemical analysis methods [12], with only one work based on hyperspectral and RGB imaging technique [2]. To best of our knowledge the potential of multi-spectral imaging sensor [16] has not been employed to distinguish natural and artificial ripening of fruits. Multi-spectral imaging extracts the spatial and spectral information in Visible (VIS) and Near-Infra-Red (NIR) wavelength range. In general, multi-spectral imaging obtains the inherent discriminative spectral band details in the discrete and disjoint manner for robust performance. Inspired from these arguments, in this paper, we employ the inherent properties of multi-spectral imaging sensor to classify naturally ripened fruit from artificially ripened fruit in a robust manner. The purpose of using multi-spectral imaging approach is to acquire the distinct intrinsic characteristic properties of natural and artificial ripened fruits, across the various spectrum bands. The difference in characteristic information results, mainly due to the difference in hormonal changes occurred when fruits are ripened naturally and artificially. Now to carry out this study of detecting artificial ripening of fruit, we have selected banana, the most popular and widely used fruit worldwide (The annual worldwide banana production is around 12 million tons [17]) for our experimental work. Further, to present our experimental evaluations, we introduce our newly constructed multi-spectral images for banana ripened with three different ripening processes including a natural ripening and two artificial ripening. Specifically, multi-spectral images are collected in eight narrow spectral bands such as $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $890nm$, $950nm$ and $1000nm$ across $530nm$ to $1000nm$ wavelength range. We present the extensive set of experimental results across individual spectral bands to obtain the classification accuracy, independently using six different state-of-the-art feature extraction methods such as Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), Local Phase Quantization (LPQ), GIST, and Binarized Statistical Image Features (BSIF) along with Support Vector Machine (SVM) Classifier. Moreover, to present the qualitative and quantitative analysis on the sample size of 5760 images, we have repeated the experiment for 10 different iterations of randomly selected training and testing banana samples such that the final average classification accuracy can be computed. In due course of this work, we have the number of contributions and are summarized as follows:

- Present the potential of multi-spectral imaging to differentiate between natural and artificial ripened banana using eight narrow spectral bands in VIS and NIR spectrum range. To best of our knowledge, this is the first study of its kind using inherent spatial and spectral information in eight spectrum bands to detect the artificial ripening of fruits.

- Introduces the newly constructed multi-spectral images for banana fruits ripened using three different methods: a natural ripened and two artificial ripened methods. The multi-spectral images of 5760 sample size are the first and largest dataset in this category of artificial ripening.

- Present quantitative and qualitative experimental average classification accuracy by repeating experiment 10 times using six different state-of-the-art feature descriptor techniques independently along with Support Vector Machine (SVM) classifier.

Rest of the paper is organized as follows: Section 2 describes the detail description of sample data collected for naturally and artificially ripened banana using multi-spectral imaging sensor, Section 3 presents the methodology employed in the experimental evaluation of this work, Section 4 present the experimental evaluation protocol along with classification accuracy and Section 5 summarizes the final conclusion.

2. DATABASE

In this section of the paper, we present in detail the description of our multi-spectral fruit database collected for the banana in this work. The data was acquired using our in-house, custom-built multi-spectral imaging sensor [16] in eight narrow spectrum bands corresponds to $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $890nm$, $950nm$ and $1000nm$ wavelengths spanning from Visible (VIS) to Near-Infra-Red (NIR) range. The database comprises of 30 bananas to obtain a total of 5760 sample images. Now, considering the scope of this work to detect the artificial ripening of fruits, we have collected multi-spectral sample images for banana under three different categories of the ripening process. Out of three, the first one consists of sample images correspond to the natural ripening and the remaining two consists of sample images corresponds to two different artificial ripening process.

Table 1: Summary describing the numbers of sample images

Database	Banana	Number of Days	Samples	Bands	Sides	Total Images
Nat-Ripe	30	2	2	8	2	1920
Art-Ripe-Sol	30	2	2	8	2	1920
Art-Ripe-Gas	30	2	2	8	2	1920

In the case of natural ripening, the collected banana samples from the field are allowed to ripen naturally in normal environmental condition (without using any chemical process). For simplicity in this paper, the sample images collected in this category of the data is labeled with the acronym 'Nat-Ripe'. In the case of artificial ripening, we performed two different methods of ripening which are mainly employed in the market chain by using Calcium Carbide (CaC_2) chemical. In the first case of the artificial ripening process, we used acetylene gas (which is an artificial ripening agent), released due to the chemical reaction which takes place when CaC_2 is in contact with water. The experiment is performed in an airtight container such that the acetylene gas released after the chemical reaction is trapped to stimulate proper artificial ripening process. The sample images collected after this process of ripening is labeled by acronym 'Art-Ripe-Gas' for simplicity. In a similar line with the previous process of artificial ripening, instead of acetylene gas, we used the chemical solution (obtained after mixing CaC_2 with water) as a ripening agent for this experiment. Specifically, we placed the samples of banana in the chemical solution for approximately about 10 seconds and then these samples were placed in the airtight container for ripening. The sample multi-spectral images collected for this set of experiment is labeled as 'Art-Ripe-Sol'

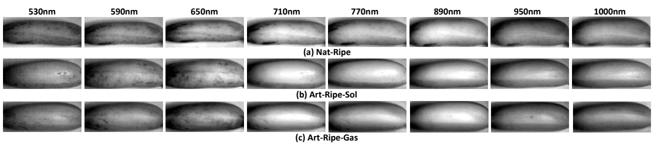

Fig. 1: Sample multi-spectral images collected in eight narrow band images for natural and artificial ripened Banana fruits

We have used two different sides of the banana to collect multi-spectral images and for each side, two sample images are collected. The entire experiment of data collection using multi-spectral imaging is repeated for two days. Under each category of ripening, we have obtained a total of 1920 sample images, which corresponds to 30 Banana $\times$ 2 Days of sample collection $\times$ 2 Samples $\times$ 2 Sides of Banana $\times$ 8 Bands = 1920. Table 1 represent the summary of the total number of sample images collected under each category of ripening. Further, the sample spectral band images collected is then processed for histogram equalization to enhance the contrast uniformly across each of the spectral band images before feature extraction. Figure 1 illustrates the sample preprocessed images collected using multi-spectral imaging sensor corresponds to 'Nat-Ripe', 'Art-Ripe-Gas','and 'Art-Ripe-Sol'.

3. METHODOLOGY

This section of our paper describes in detail the methodology employed to detect artificially ripened banana. Figure 2 demonstrates the methodology employed in this work. In general, for a given spectral band image of banana corresponds to two different sides, we first crop the 10 different regions independently for two sides of the same banana sample, which we combined together using concatenation technique before performing any feature extraction method. Finally, extracted features are learned in Support Vector Machine (SVM) classifier to detect the artificial ripening.

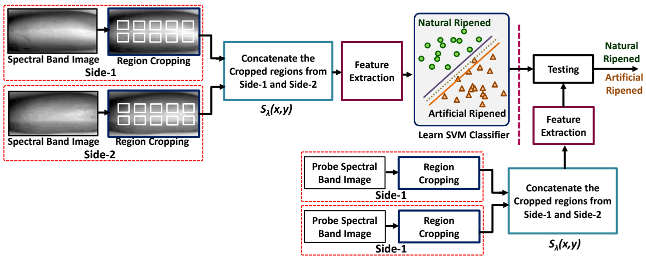

Fig. 2: Methodology employed to differentiate natural and artificial ripened banana using state-of-the-art-feature extractor and classification methods (Side-1 corresponds to the upper side and side-2 corresponds to lower side of a banana sample (Refer Section 2))

Let the spectral band image M_λ be represented by the Equation 1

$$M_\lambda = \{M_1, M_2, M_3, \ldots, M_8,\} \tag{1}$$

where, λ represents the individual eight spectral bands corresponds to $530nm$, $590nm$, $650nm$, $710nm$, $770nm$, $890nm$, $950nm$ and $1000nm$ in the VIS and NIR ($530nm$ - $1000nm$) wavelength range. Now considering the fact that multi-spectral imaging extracts the inherent discriminative features across the electromagnetic spectrum in the form of reflectance and/or emittance, it is our assertion that the characteristic information obtained across individual spectral bands will be different for natural and artificial ripened fruits. Thus to detect the artificial ripening samples, we have considered the cropped regions corresponding to different regions of Banana samples, which can be illustrated by Equation 2

$$m_{\lambda i} = \{m_{\lambda 1}, m_{\lambda 2}, \ldots, m_{\lambda 10}\} \tag{2}$$

where, $i = \{1, 2, 3, \ldots, 10\}$ represents the 10 cropped region corresponds to sample spectral band image M_λ. The size of each cropped region is 151×151 and to reduce the computational complexities, we concatenate these 10 regions to a size of 151×1510. The Equation 3 represents the concatenation of 10 regions to form single matrix.

$$C_\lambda(p, q) = [m_{\lambda 1}(r, s) \,||\, m_{\lambda 2}(r, s) \,||\, \ldots, || \, m_{\lambda 10}(r, s)] \tag{3}$$

where, (r, s) and (p, q) represents the dimensions of individual cropped region and concatenated regions respectively.

Further, to simplify our approach, we have combined the cropped regions of both the sides of Banana samples to form a final feature matrix before processing it for feature extraction (Figure 3). Now, if $c^{'}_{\lambda}(p,q)$ and $c^{''}_{\lambda}(p,q)$ be the individual concatenated regions (Obtained using Equation 3) corresponding to $side-1$ and $side-2$ of banana sample respectively, then the final concatenated feature matrix $S_{\lambda}(x,y)$ can be represented using Equation 4.

$$S_{\lambda}(x,y) = \left[c^{'}_{\lambda}(p,q) \, || \, c^{''}_{\lambda}(p,q) \right] \tag{4}$$

where, (x,y) represents the final feature matrix of size 151×3020, which will be processed for feature extraction and clas-
s

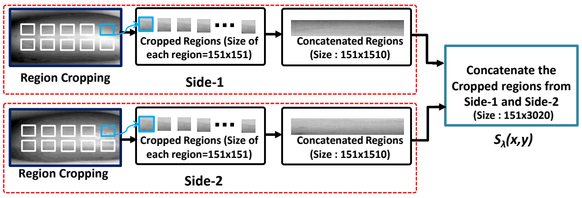

Fig. 3: Detail representation of combining feature matrix corresponds to two different sides of a banana

Now, to extract the characteristics feature information, we have employed six different state-of-the-art local and global feature descriptor methods such as Local Binary Pattern (LBP) [18], Histogram of Oriented Gradients (HOG) [19], Local Phase Quantization (LPQ) [20], GIST [21], Log-Gabor (LG) [22] and Binarized Statistical Image Features (BSIF) [23] independently along with Support Vector Machine (SVM) Classifier.

4. EXPERIMENTS AND RESULTS

In this section, we present in detail the experimental evaluation protocol and related experimental results to detect the artificial ripening of banana using six different state-of-the-art feature extraction methods such as LBP, HOG, LPQ, GIST, LG, BSIF independently along with SVM classifier. Basically, we crop the regions corresponds to two different sides of banana sample independently and then the concatenated feature matrix corresponding to these two sides are processed for feature extraction followed by SVM classifier. The experimental results in the form of classification accuracy across individual spectral bands are obtained using newly constructed multi-spectral images of 5760 samples collected for banana fruit. We present the average classification accuracy by repeating the experiment for 10 different iterations of a random selection of training and testing set in a disjoint manner to present the significance of multi-spectral imaging in detecting artificial ripening of banana fruit.

4.1. Experimental Protocol

To carry out the experimental evaluation results, we partition the banana samples into two disjoint sets comprising of training and testing set. The training set consists of a total of 30 bananas, in which 15 bananas including there samples correspond to natural ripened data ('Nat-Ripe') and the remaining 15 bananas including there samples corresponds to artificial ripened data (Either 'Art-Ripe-Gas' or 'Art-Ripe-Sol'). In the similar line, testing set consist of a total of 30 bananas, in which 15 bananas including there samples corresponds to natural ripened data ('Nat-Ripe') and the remaining 15 bananas including there samples corresponds to artificial ripened data (Either 'Art-Ripe-Gas' or 'Art-Ripe-Sol'). Samples for the training and testing set is selected randomly in a disjoint manner to obtain the classification accuracy. Further, we present two sets of experimental evaluation results to obtain accuracy independently across individual spectral bands to detect the artificial ripening of banana. The two sets of evaluation includes:(1) Nat-Ripe v/s Art-Ripe-Gas and (2) Nat-Ripe v/s Art-Ripe-Sol. Further, the details related to each of these evaluations are discussed in more details in the following sections.

Table 2: Average classification accuracy obtained across individual spectral bands for Nat-Ripe v/s Art-Ripe-Gas evaluation

Algorithms	Spectral Bands							
	530nm	590nm	650nm	710nm	770nm	890nm	950nm	1000nm
LBP-SVM	60.6±6.6	61.1±9.6	74.0±5.7	89.0±5.7	79.0±6.4	87.4±3.7	74.1±6.6	74.0±9.6
HOG-SVM	72.9±8.6	77.6±6.1	79.1±6.1	87.2±5.1	85.0±3.8	89.5±5.1	80.8±7.3	70.0±8.0
LPQ-SVM	90.8±3.8	85.6±5.8	83.5±5.5	92.5±3.6	90.7±6.3	91.1±6.6	80.4±8.8	82.0±5.4
GIST-SVM	68.0±8.6	71.7±9.6	72.5±6.0	72.5±6.0	70.0±8.9	83.8±6.3	76.5±9.1	75.5±9.1
LG-SVM	90.0±5.5	86.9±7.1	89.0±6.3	88.1±6.0	93.9±5.4	87.0±9.9	87.5±8.4	90.5±6.1
BSIF-SVM	85.2±9.4	82.7±8.6	87.5±7.8	**94.7±6.8**	93.9±6.6	93.7±5.1	87.5±9.5	88.7±6.3

4.2. Evaluation-1: Nat-Ripe v/s Art-Ripe-Gas

In this section of experiment, we present the qualitative and quantitative results to detect artificial ripening when the samples of banana are artificially ripened using acetylene gas released from the chemical reaction takes place when CaC_2 comes in contact with water. Table 2 presents the average classification accuracy along with standard deviation, computed after repeating the experiment in 10 different trials, for random selection of training and the testing samples. Figure 4 present graphically the results in the form of mean and variance plot across individual spectral bands using state-of-the-art feature extraction and classification methods. Overall, reasonable classification accuracy can be observed across individual spectrum band to detect the artificial ripening of banana based on multi-spectral imaging. The major observations for this set of the experiment can be summarized as follows:

- The highest classification accuracy of 94.7% along with 6.8% standard deviation is obtained using BSIF-SVM approach for $710nm$ spectrum band, while the lowest classification accuracy of 60.6% along with 6.6% standard deviation is observed for LBP-SVM methodology.
- Amongst the six different feature descriptor methods employed in this work, BSIF, LG, LPQ have indicated

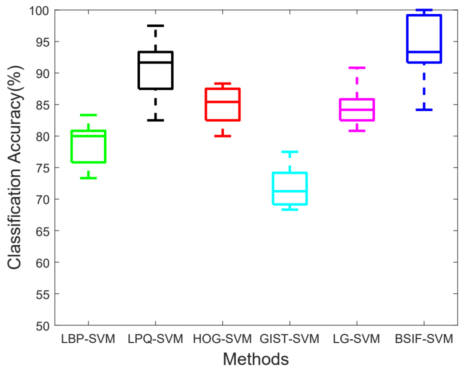

Fig. 4: Classification accuracy to detect artificial ripened banana samples across individual spectral bands for Nat-Ripe v/s Art-Ripe-Gas experimental evaluation(Results related to best Performing $770nm$ bands are demonstrated for simplicity)

above 80% classification accuracy compared to the other local and global feature extractor methods such as LBP, HOG, GIST. The same can be observed from the mean and variance plot illustrated in Figure 4.

- In the case of individual spectral bands, almost all the bands have demonstrated better performance accuracy using state-of-the-art methods. Specifically, the bands such as $710nm$, $770nm$ and $890nm$ have shown consistently highest classification accuracy, demonstrating the significance of these spectral bands in extracting discriminative feature information for robust performance.
- Further, the individual spectrum bands such as $530nm$, $590nm$ and $1000nm$ performs slightly poor as compared to other bands. The reason could be due to the lower sensor response and lower transmission of optical filters, resulting in poor Signal-To-Noise (SNR), thereby degrading the overall accuracy of these bands. However, with the use of robust feature descriptor methods such as BSIF, LG, LPQ, its accuracy towards detecting artificial ripening of fruits can be improved (As can be seen from Table 2).

Table 3: Average classification accuracy obtained across individual spectral bands for Nat-Ripe v/s Art-Ripe-Sol evaluation

Algorithms	Spectral Bands							
	530nm	590nm	650nm	710nm	770nm	890nm	950nm	1000nm
LBP-SVM	82.5±6.1	83.6±8.2	90.0±6.6	93.9±3.7	90.8±7.4	92.5±5.3	87.4±5.6	85.9±6.6
HOG-SVM	70.0±9.6	73.5±8.7	86.5±6.5	89.0±4.5	93.1±4.6	90.6±6.7	82.5±7.0	82.5±7.7
LPQ-SVM	89.7±6.9	89.4±7.5	90.4±4.9	94.0±5.1	**97.5±3.3**	92.3±6.5	87.0±7.5	91.0±4.4
GIST-SVM	77.5±12.0	80.4±7.5	80.5±4.7	77.4±8.9	82.1±5.3	77.3±8.5	78.3±6.3	83.4±10.0
LG-SVM	84.0±6.7	83.6±6.6	78.0±10.3	82.8±7.2	84.5±7.8	92.6±4.1	89.0±7.8	84.5±7.1
BSIF-SVM	91.5±7.6	91.6±6.0	90.7±4.9	94.0±7.1	96.3±5.7	90.0±8.7	87.4±7.8	92.8±5.6

4.3. Evaluation-2: Nat-Ripe v/s Art-Ripe-Sol

In this section of the paper, we present the classification accuracy to detect artificial ripening of banana, when the ripening is carried out by placing banana samples for approximately about 10 seconds using chemical solution prepared by the mixture of CaC_2 with water (Details are given in the Section 2). Figure 5 demonstrate the graphical representation of classification accuracy and Table 3 presents the experimental results corresponds to individual spectral bands to present the significance of multi-spectral imaging for detecting artificial ripening of banana samples. Compared to the previous evaluation, this set of the experimental results have provided the improvement in detection accuracy using state-of-the-art feature extraction and classification methods. However, based on the experimental results obtained in this section of experiment, the specific observations can be summarized as follows:

- The highest classification accuracy of 97.5% along with 3.3% standard deviation is obtained using LPQ-SVM approach for $770nm$ spectrum band, while the lowest classification accuracy of 70.0% along with 9.6% standard deviation is observed for HOG-SVM methodology. This indicates that the artificially ripened banana using chemical solution inherits more unique discriminative features information than one performed with acetylene gas, resulting in better performance of Nat-Ripe v/s Art-Ripe-Sol compared to Nat-Ripe v/s Art-Ripe-Gas.
- In similar line with above experimental results, BSIF-SVM, LG-SVM, and LPQ-SVM have consistently indicated the highest average classification accuracy, while the individual spectrum bands such as $710nm$, $770nm$ and $890nm$ still show the outstanding results.

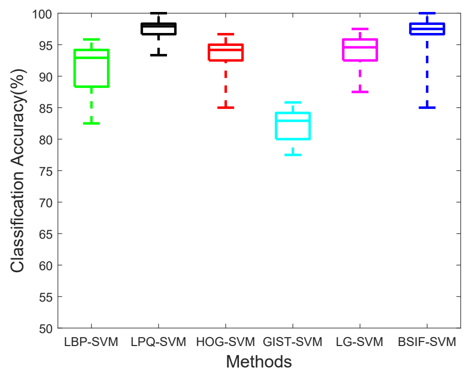

Fig. 5: Classification accuracy to detect artificial ripened banana samples across individual spectral bands for Nat-Ripe v/s Art-Ripe-Sol experimental evaluation (Results related to best Performing $770nm$ bands are demonstrated for simplicity)

To summarize, the extensive experimental results across individual spectrum band obtained with two experimental evaluations to demonstrate the potential of multi-spectral imaging in detecting the artificial ripening of banana. Further, with various feature descriptor performing consistently better across all the bands indicates the significance of these approach for improved classification accuracy.

5. CONCLUSION

Artificial ripening is a complex problem in various countries, where vendors apply unregulated ripening methods such as the use of Calcium carbide (CaC_2) in a market chain to satisfy customer needs. The problem of detecting artificial ripening is a challenging task, we have presented in this paper, the potential of multi-spectral imaging to differentiate natural and artificial ripened banana thereby extracting inherent spatial and spectral details of banana in eight spectrum band spanning from $530nm$ to $1000nm$ range for robust performance. We have introduced a newly constructed multi-spectral image data acquired to detect the artificial ripening of banana. To best of our knowledge data collected for the sample size of 5760 is the first and largest data collected in multi-spectral imaging with eight bands. Using the sample data, we have computed extensive experimental evaluation results by repeating the experiments for 10 different trials of a random selection of training and testing set to obtain average classification accuracy. The results obtained across individual spectral bands demonstrated the highest average classification accuracy of 97.5% using state-of-the-art methods, presenting the significance of employing multi-spectral imaging to detect artificial ripening of banana.

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