Chemical Ripening and Contaminations Detection Using Neural Networks-based Image Features and Spectrometric Signatures

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Abstract. In this pandemic-prone era, health is of utmost concern for everyone and hence eating good quality fruits is very much essential for sound health. Unfortunately, nowadays it is quite very difficult to obtain naturally ripened fruits, due to existence of chemically ripened fruits being ripened using hazardous chemicals such as calcium carbide. However, most of the state-of-the art techniques are primarily focusing on identification of chemically ripened fruits with the help of computer vision-based approaches, which are less effective towards quantification of chemical contaminations present in the sample fruits. To solve these issues, a new framework for chemical ripening and contamination detection is presented, which employs both visual and IR spectrometric signatures in two different stages. The experiments conducted on both the GUI tool as well as hardware-based setups, clearly demonstrate the efficiency of the proposed framework in terms of detection confidence levels followed by the percentage of presence of chemicals in the sample fruit.

Key words: chemical ripening, arsenic contamination, visual features, IR spectral signatures.

1. Introduction

Nowadays health is of important concern for everyone, hence eating good quality fruits is a primary requirement for sound health. The fruits in general are plant products containing sugar, vitamin C and water along with minerals, cellulose, protein and photo chemicals that protect human body against various diseases [6]. In general, fruits obtain desirable flavor, quality, color and other textural changes during their natural ripening process. Unfortunately, nowadays it is quite very difficult to obtain naturally ripened fruits, due to existence of huge numbers of chemically ripened fruits in the markets, which are being ripened using hazardous chemicals such as calcium carbide (CaC_2). For example, nearly 80% fruits such as mango, papaya and banana are artificially ripened using different chemicals [16].

In general, though fruit ripening is a natural process, in order to speed up the rate of fruit ripening, most of the farmers and vendors use artificial ripening agents like calcium carbide. Specifically, calcium carbide is a dangerous, corrosive chemical and regular consumption of it leads to vomiting, diarrhoea, eye damage, ulcers, hypoxia and neurological disorders, and even to cancer due to the presence of arsenic as well as phosphorous poisoning traces. Due to these reasons, as per PFA (Prevention of Food

Adulteration) act in 1955, chemical ripening of fruits is strictly banned. Though calcium carbide is banned, still some traders are employing chemical ripening for profit purposes.

Spacial care must be paid to climacteric fruits. Climacteric fruits are those which, beginning from a certain developmental stage, continue to develop to full maturity, even when harvested. Specifically, in India, most of climacteric fruits, such as mango, banana and papaya are chemically ripened with industrial grade calcium carbide [16]. Specifically, in India, calcium carbide, a carcinogen, is widely used for artificial ripening of fruits such as banana as well as mango, which is illegal and strictly banned. Therefore, the identification of artificially ripened fruits followed by the quantification of CaC_2 contamination in such fruits is very important in order to safeguard the consumers from a series of health problems. Based on these aspects, a new framework is introduced in this paper, which makes use of both computer vision as well as Near-Infrared (NIR) spectrometric techniques for detecting the artificially ripened fruits, followed by the computation of chemical contaminations present in the sample fruits.

2. Related Work

In the existing literature, computer vision-based techniques are popularly utilized for quality determination and grading of fruits by means of automating the grading processes as well as minimizing the monotonous inspection tasks. Further, computer vision is also widely employed in the literature for defect detection, and classification of ripeness of fruits based on their appearance. For example, a comparative study of vitamins A, B, and C content in different types of tomatoes including ethylene and vine-ripened tomatoes is presented in [6]. Ahmad et al. [1] analysed the effect of ethylene towards the speed of ripening as well as the quality of banana fruit; however, they failed to accurately discriminate between ethylene vs. non-ethylene treated bananas. In [4], the authors employed acoustic responses, nuclear magnetic resonance and optical properties in order to estimate the firmness of fruits; yet, the presented method failed to predict the chemical ripening of fruits. In 2015, Bhosale et al. [3] presented a capacitive sensing system using color indexing and echo measurements, which can detect different ripening stages of papaya fruit. Recently, Pratim Ray et al. [15] introduced a monitoring tool for finding the ripening stage of banana fruit using color indices, which can also send the ripening information to the monitoring person present in a remote area with the help of a GSM module.

In [7], the authors introduced threshold-based segmentation method using Haar features, to detect chemical ripening of banana fruits. Though the authors employed the third level of decompositions in wavelet domain for analysis of discriminatory behaviors, the proposed method suffered due to the variations in the features of ripened bananas. Thermal imaging framework for chemical ripening was proposed by Ansari in [2], which utilized infrared energy emitted by the sample fruit for pre-processing and segmentation followed by feature extraction stages. However, the performance of this method is slightly lower when compared to other methods due to the complex nature of neural network strategies used in the system. Further, Sukhesh et al. [9] introduced a cost effective device using sensors, which was capable of detecting nutrients and chemical contents in vegetables and fruits and of presenting it in the display on smart phones. Salunkhel and Aniket [17] presented a computer vision-based system, which could detect various ripening stages of Mango fruit using RGB and HSV features of images. The proposed system classified only the ripening stages of mango.

Veena and Bhat [5] designed a simple portable instrument for the detection of chemically ripened banana fruits using color-based features, which can also find out the specific ripening stage of the sample banana fruit. Therefore, this method performs better in terms of detecting chemical ripening, yet it suffers in case of complex banana structures. In [8], an IR-based sensor system was introduced, which can detect the presence of ethylene, so that different fruit ripening stages are clearly classified. Specifically, the authors used the thermal emission concept for estimating ethylene release during fruit ripening process. Although this method provides good reproducibility, yet it concentrates primarily on discrimination of fruit ripening stages to ensure food safety.

In the existing literature, only few efforts are made towards identifying the chemically ripened fruits by employing hybrid techniques including computer vision and sensor techniques [14]. For instance, Verma and Hegadi [20] presented a remote monitoring system for banana ripening process by employing wireless networks, which helps the user to monitor the ripening from a remote place. Recently, Srividya et al. [18] proposed an ethylene measurement system in order to predict correct stage of ripening of fruits using image-based features. In [13], the authors developed a mobile-based interface for detecting chemically ripened fruits, which performs histogram comparisons in order to obtain detection results. Although this method is easy to use, it still performs slightly low, due to the usage of mere surface features of the sample fruits. Recently, in [11] and [10], the authors employed NIR spectroscopic method as well as gold nano particle-based techniques in order to detect chemically ripened mango fruits. However, these techniques fail to quantify the presence of arsenic in the chemically contaminated fruit, which is yet to be explored in detail in the existing literature.

To summarize, most of the state-of-the art techniques are primarily focusing on detecting the stages of fruit ripening, as well as on the identification of chemically ripened fruits with the help of computer vision-based methods. From another perspective, image features are less effective in quantification of the exact amount of chemical contaminations present in the sample fruits. Due to these issues, *promising frameworks are very much essential, which employ both the image-based features and IR spectrometric signatures in order to detect artificial ripening of fruits followed by computation of chemical contaminations present in the sample fruits.*

3. Motivation and contributions

In this paper a new framework is introduced for detecting the man-made ripened fruits followed by the computation of chemical contaminations present in the fruit by employing both the spectrometric features as well as visual feature descriptors. Specifically, the new framework named ***Chemical Ripening and Contamination Detection (CRCD)*** is introduced, which first identifies the artificially ripened fruits and then quantifies the presence of chemical contaminations (in terms of presence of arsenic) in the given sample fruit. More specifically, the primary contributions of the proposed framework are as follows.

- A new *GUI-based Artificial ripening detector tool* for banana fruit is developed which is used to identify unnaturally ripened banana fruit by making use of edge and histogram-based visual feature descriptors. Further, the prototype of this GUI tool is also evaluated in a web-based portal and mobile-based interfaces in order to facilitate remote access, which is illustrated in detail in Section 7.
- A novel *arsenic contamination detection setup* is introduced which makes use of IR signature spectra of fruits for detecting chemically ripened fruits followed by Green Fluorescent Protein-based turbidity measurements for accurately quantifying the arsenic content present in the sample fruit, which is detailed in Sections 6.1 and 7.4.
- Further, chemical contamination rate of the given sample fruit is clearly indicated in terms of percentages in the *specially designed display panel fitted with aqua fruit chamber*, which in future can be employed effectively to protect customers from hazardous health issues. The setup of the aqua chamber and the panel is described in Sections 6.2, 6.3 and the detection results are described in Sections 7.3 and 7.4.

4. Methodology of the proposed framework

The block diagram for the proposed Chemical Ripening and Contamination Detection (CRCD) framework, is indicated in Fig. 1. It is implemented in two different modules, namely the image processing module and the arsenic detection module, which are detailed as follows.

In the first module of the proposed CRCD framework the captured images of sample fruit undergo the first stages of processing. The Near Infra-Red (NIR) camera is employed to capture the images of the sample fruits in different directions and views, including front and top views. Specifically, in the first stage, convolutional neural network (CNN) based classification algorithms are used to train both ripened and unripened categories of input banana images. More specifically, visual feature descriptors of input images including shape, edge and color features (weighted at the ratio 25:25:50) are extracted and classified by employing Inception v3 algorithm [19], which is one of the widely-used image recognition models. Initially, the pre-trained neural network extracts

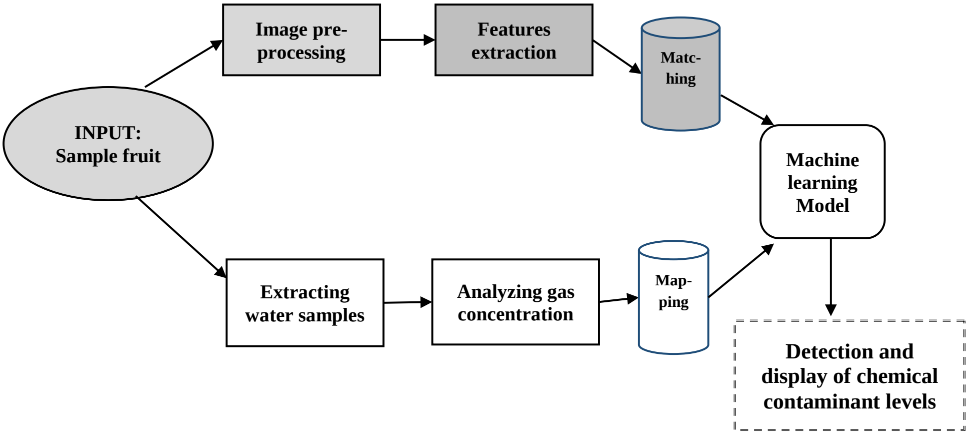


Fig. 1. Block diagram of the proposed CRCD framework.

the visual features using CNN including fully-connected and softmax layers. Then, the resultant features are combined to form a feature database named the Visual Features Database in order to proceed with testing stage.

In the testing stage, initially visual features of query banana image are compared with the corresponding features of the training database. The results of the comparison are represented in terms of confidence level metrics. In the proposed framework, 75% of the samples are utilized for the training stage after random selection whereas the remaining 25% of the samples are included in the testing part of the database.

In the second module, Green Fluorescent Protein (GFP) [12] based arsenic gas setup incubated with a water sample is utilized, in which the fluorescence is detected optically and quantified, so that the concentration of arsenic in the water samples can be measured. Precisely, the intensity of the fluorescence is a function of the amount of bacteria present in the water sample, which is further quantified to measure the turbidity of the water sample. The turbidity measurement enables us to determine chemical contaminations of the sample fruit in terms of arsenic gas contaminations. The resultant turbidity values are mapped and analyzed with standard metric values of normal water, in order to identify whether the fruit is a naturally or chemically ripened one. The comparison results are combined using the machine learning model and displayed in the LCD display panel mounted at the front display panel in the setup framework.

These processes are discussed in detail in the further Sections.

Fig. 2. (**a**) Sample snapshots of naturally ripened bananas and (**b**) sample snapshots of artificially ripened bananas.

5. Data bases

5.1. Banana fruits database creation

For experimental purpose, 500 banana images from 10 bananas of type Elaichi (species name: *Musa acuminata*) are captured under different scenarios including ripened, unripened, individual and group basis of fruits. Specifically, the banana dataset includes snapshot of bananas, which are captured using Canon 700D DSLR camera with the resolution of 4898×3265 pixels. Initially, few samples of unripened bananas are treated for artificial ripening with the help of calcium carbide. Precisely, the sample bananas are kept in an air tight container inside a dark room with the presence of calcium carbide for 8-10 hours, in order to make them ripen at a faster rate. The rest of the bananas are allowed to undergo natural ripening stages for a waiting period of 24 to 30 hours. Fig. 2a represents the snapshots of bananas, which were allowed to complete their ripening stages at normal conditions, whereas Fig. 2b indicates the sample snapshots of bananas, which were treated with calcium carbide for completing their ripening stage, respectively.

5.2. Mango fruits database creation

To evaluate the performance of the proposed framework towards mango fruits, a mango fruit dataset consisting of images was generated for both training and testing purposes. Precisely, 60 mangoes belonging to four different varieties: Alphonso, Badam, Mallika and Neelam are considered. One set of mango fruits are allowed to ripen naturally while the other set of mangoes were artificially ripened using artificial ripening agents like calcium carbide. Fig. 3 shows sample snapshots of mango images in various views.

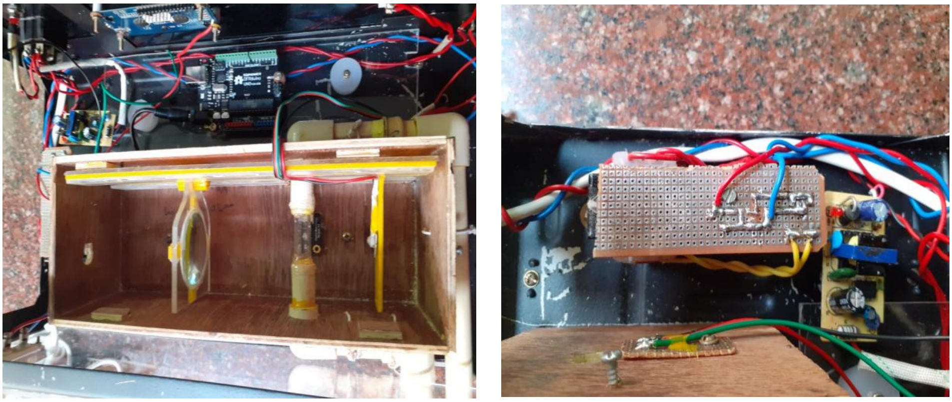
Fig. 3. Sample snapshots of mango images in various views.

Further, nearly 950 fruit images were generated for both training and testing datasets, which were labeled separately as naturally ripened mango fruits as well as artificially ripened fruits.

6. Experimental setup

6.1. Arsenic contamination detection setup

The basic principle of this setup is based on a fluorescent method, where GMO bacteria-based Green Fluorescent Protein-based bacterial biosensor (GFP) [12] is used to detect the presence of arsenic in the test water sample. Then the optical detection of fluorescence used to quantify the result in terms of the concentration of arsenic. Specifically, a vial containing the test water sample is placed on a socket and a fluorescent excitation LED light is passed through it, which also includes $\lambda = 488\,\mathrm{nm}$ needed for enhanced GFP (eGFP). More specifically, the GFP absorbs blue light ($\lambda = 475\,\mathrm{nm}$) and emits green light ($\lambda = 504\,\mathrm{nm}$) which is detected by a photosensor in order to deal with the intensity loss. Then the eGFP fluorescence signal reaches the photosensor with the help of a long-pass filter. Precisely, the intensity of the fluorescence can be indicated as a function of the number of bacteria present in the sample. More precisely, the number of bacteria can be quantified indirectly by measuring the turbidity of the sample [12]. A red LED is placed in-line with the photosensor so that the transmittance can be measured and converted into turbidity. The measurement of turbidity makes it possible to normalize the results with respect to the density of bacteria. Specifically, the measurement of turbidity can be employed in order to determine the concentration of arsenic present in the water sample and thereby chemical contaminations in the fruit can be detected. More specifically, the transmission results are compared against a standard curve of water containing known



(a) **(b)**

Fig. 4. (**a**) Snapshot of the GPF setup including sample water vial, lens and filters. (**b**) Snapshot of the setup including the GFP and the Arduino board connectivity.

arsenic concentrations, in order to exactly determine the concentration of arsenic in the sample. In Fig. 4a the GFP-based arsenic detection setup including sample water vial, lens and filters are shown, whereas Fig. 4b illustrates the Arduino board connectivity at the back side of the GFP setup.

6.2. Aqua-fruit chamber setup

In the proposed CRCD framework, in order to obtain a water sample of test fruit, the aqua-fruit chamber setup is employed, which is shown in Fig. 5. Precisely, in this setup, the sample fruit is dipped in water, which is circulated continuously with the help of a water regulatory pump with a push button (On/Off switch) mount assembly. After dipping the fruit in water for specific amount of time, the water samples of input fruit is collected in the vial shown in Fig. 5 for further processing. More precisely, Fig. 5a shows the water pump mount assembly and Fig. 5b indicates the push button setup in the proposed framework.

6.3. Display panel setup

Fig. 6a shows the front view of the display panel setup, which is used to display the results of the experiments in terms of chemical contamination measurements. Specifically, the display panel is fixed inside a metallic compartment in order to avoid external damages due to dust, heat and water. The display panel is also equipped with a power button, pump regulatory switch and LED switches shown in Fig. 6a. Fig. 6b. indicates the side

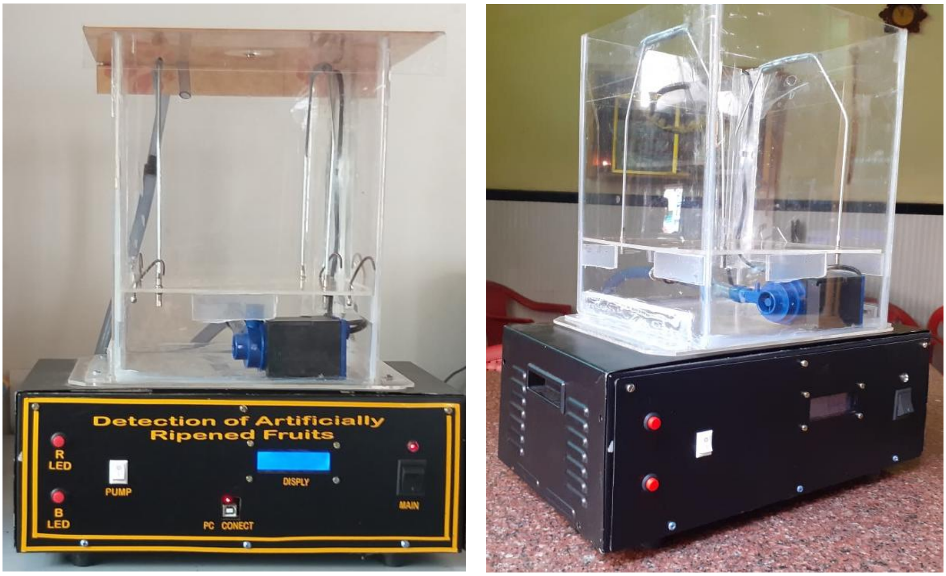
(a) (b)

Fig. 5. (**a**) Aqua-chamber setup with pump mount. (**b**) Push button assembly.

view of the display panel along with the aqua chamber setup mounted on it, in which slight air ventilation is also provided for experimentation purpose. More specifically, in the proposed framework, standard HD44780 LCD is used as the display panel for displaying the outputs, which is 16 characters wide with 2 rows, and displays white text on blue background. It includes a connection port of 0.1 inch pitch, single row for easy bread-boarding and wiring and also all the pins are documented on the back of the LCD to assist in wiring it up to other modules of the setup.

6.4. Main controller setup

The main controller of the experimental setup acts like a heart of the system and consists of an Arduino board. This controller interacts with all the modules of the setup including the display panel, the GFP setup, the aqua chamber and the sensor camera module. Therefore, the connectivity of the Arduino plays a major role in determining the performance of the proposed research work. Fig. 7 shows the main controller setup including the connectivity of the Arduino board with the display panel, the aqua fruit chamber and the GFP setup. Further, in the proposed CRCD framework, ArduCam MT9 MP-CMOS infrared camera module with adapter board is utilized to capture the images of sample fruits in terms of different views and various dimensions. Precisely, this camera module is placed inside an outer cabinet in order to enable clear capturing. The resolution of the camera is 1280×1024 SXGA at 30 fps, whereas the ADC is 10 bits.



(a) **(b)**

Fig. 6. (**a**) Front view of the display panel. (**b**) Side view of the display panel along with the aqua chamber setup.

7. Methods and results

7.1. Chemical ripening detection using visual features

In this section, the chemical ripening detection results computed using image processing module of proposed CRCD framework are discussed in detail. Precisely, Fig. 8 shows the snapshot of the GUI named *Artificial Ripening Detector for Banana Fruit* which supports both the web portal interface as well as the mobile application interface for its processing. More precisely, Fig. 8 shows the web portal, used in proposed system, for uploading the banana pictures for processing.

Once the sample fruit image is uploaded in to the server, the proposed CRCD framework proceeds with the next step, in which checking of the input image for ripened banana/unripened banana is implemented. In the proposed framework, it employs an Artificial Neural Network (ANN), trained with more than 600 images of ripened and unripened bananas, in order to proceed with the decision process in terms of probability scores. Specifically, if the probability score for ripened banana is more than 0.9, then

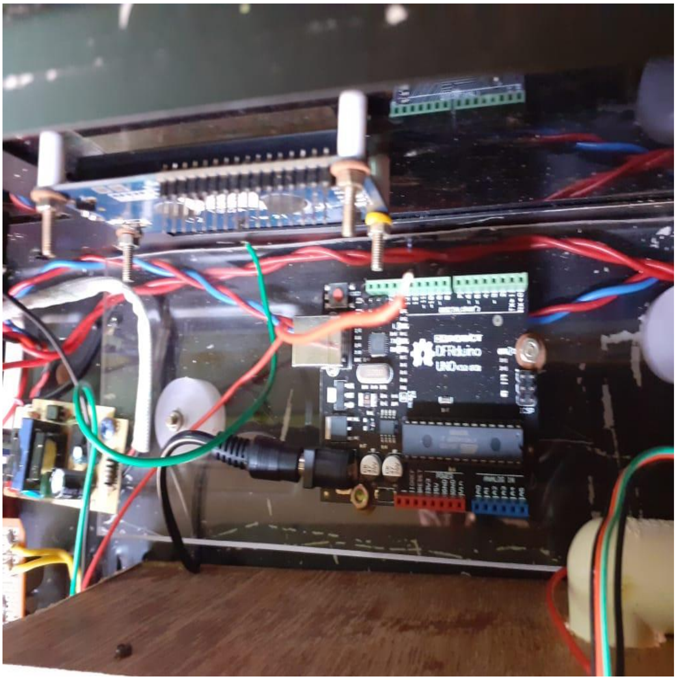


Fig. 7. Connectivity of the Arduino with the display panel, the aqua chamber and the GFP setup.

the system displays the result, as shown in Fig. 9, and proceeds for further processing. Otherwise, it displays an error message.

Fig. 10 indicates the various steps involved in the proposed CRCD framework, including gray scale conversion, noise reduction followed by the edge as well as shape detection functionalities. Specifically, in the proposed CRCD framework, Canny edge detection algorithm is employed for extracting the features. After this step, two histograms are calculated from sample fruit image namely, luminance and RGB curves. More specifically, in Fig. 11 the first histogram corresponding to the luminance values as well as the second histogram representing the RGB curves for the input image are shown. Then the resultant histograms are compared along with the respective feature descriptors of input images stored in the database. Precisely, in the proposed framework, after the forming of the histograms, the resultant graphs of input fruit image are compared against the database images. More precisely, an ANN, which is trained using the histograms having

Fig. 8. Snapshot of the web portal GUI for uploading the sample fruit image.

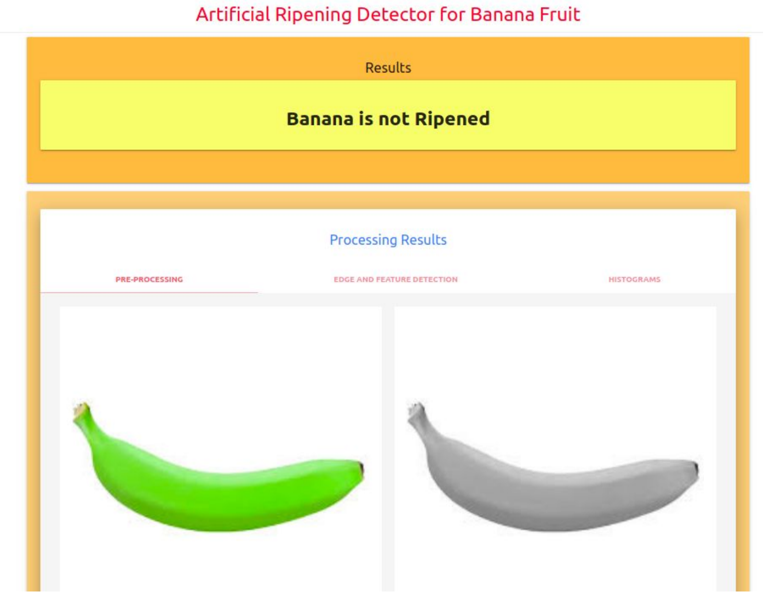


Fig. 9. Ripened vs. unripened: detecting unripened fruits.

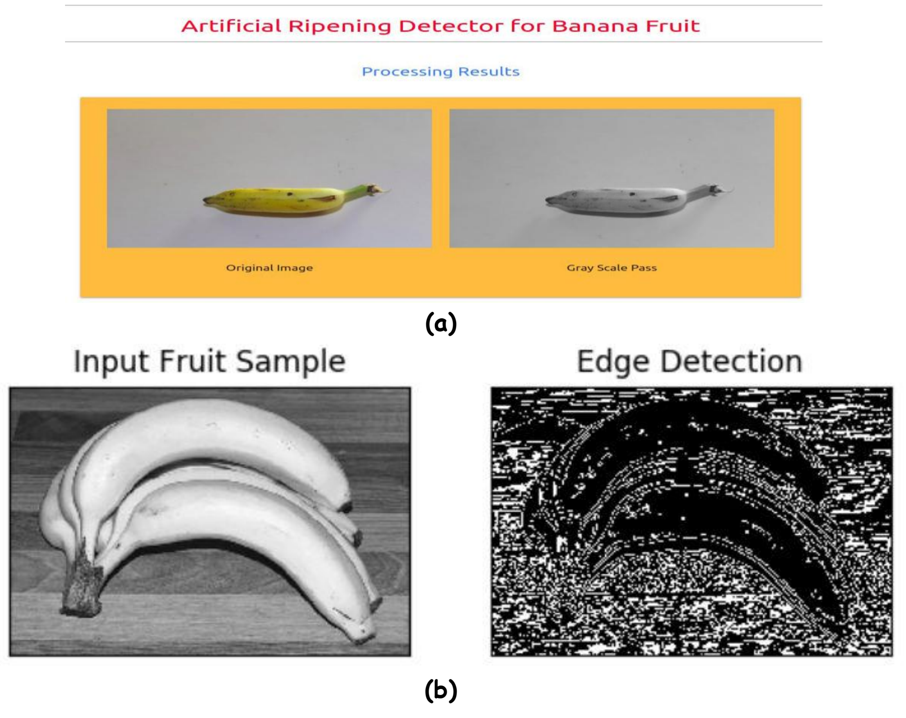


Fig. 10. (**a**) Gray scale conversion, (**b**) edge and shape detection of the input fruit image.

data size of more than 600 banana images, determines the ripening category of the sample input image. The confidence level measurements are evaluated for both the naturally ripened as well as chemically ripened categories, in order to predict exactly, whether the sample fruit is artificially ripened or not.

7.2. Chemical ripening detection results

Fig. 12a shows the snapshot of output prediction results in terms of confidence levels of 83.16% for artificially ripened banana fruit whereas Fig. 12b indicates the snapshot of output results in terms of confidence levels of 81.14% for naturally ripened banana fruit. After the completion of detection results, the back end results can be transferred to the application front end, and also to the web portal, so that the end user can view the results. Further, the mobile application interface version of the proposed CRCD framework is shown in Fig. 13, which demonstrates the performance of the proposed system in terms of displaying the results on the mobile application.

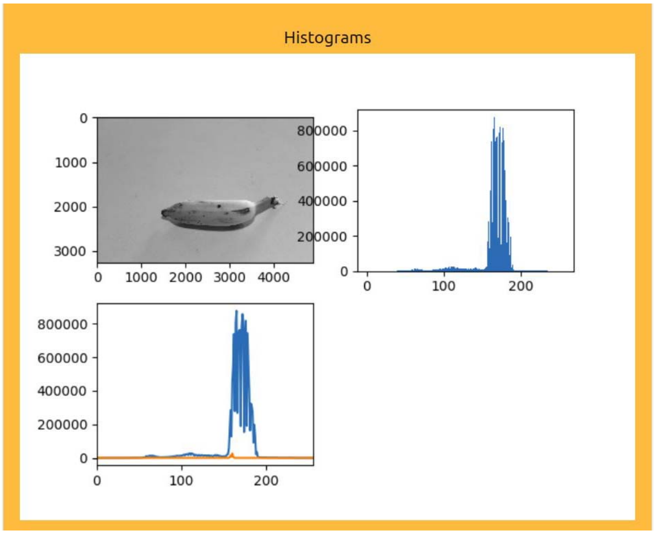


Fig. 11. Histogram graphs of the sample input fruit image.

7.3. Spectral analysis and chemical contamination computation

In the second module of the proposed CRCD framework, the NIR spectra of sample fruit image is computed and prediction results are calculated by comparing against the pre-processed spectra signatures. Specifically, for the purpose of NIR data analysis, a total of 12 readings are considered for both naturally as well as artificially ripened mango fruit samples. Further, as a preliminary classification step, principal component analysis (PCA) is performed on the selected spectra and different principal components are plotted in order to indicate the groups of samples based on their varieties. Specifically, the signature spectrum of database fruits is computed using PCA approach, before the analysis of samples, in order to reduce the noise effects as well as to obtain the better representation of the data. Fig. 14 represents the pre-processed spectra considered in the proposed framework in terms of the NIR analysis of sample mango fruits. Fig. 15 presents the signature spectra of naturally ripened mango fruit in which huge variations can be observed in the range of 600-640 nm as well as 700-800 nm wavelength measurements. In Fig. 16 the spectral signature of artificially ripened mango fruit is indicated, in which more variations are visible in the range of 700-750 nm wavelengths and thereby clear classification of ripening type of fruits can be achieved. The spectral results are further analysed with PCA, which clearly indicates that the naturally and artificially ripened mango samples spectra are falling in different wavelength segments. Further,

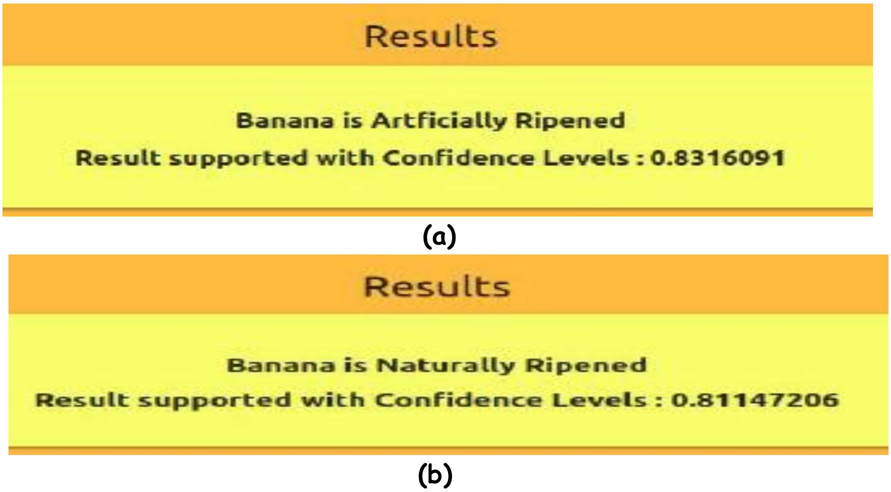


Fig. 12. (**a**) Final detection results for artificially ripened banana fruit. (**b**) Detection results for naturally ripened banana fruit.

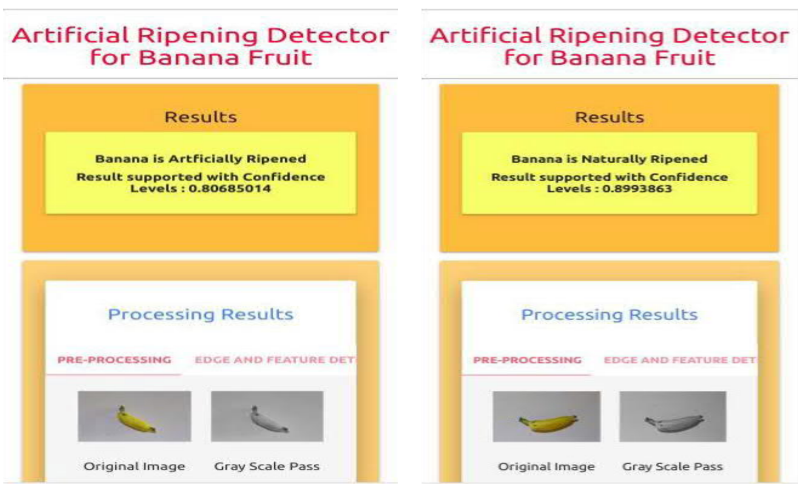


Fig. 13. Snapshots of artificial vs. natural ripening detection results displayed on mobile application interface.

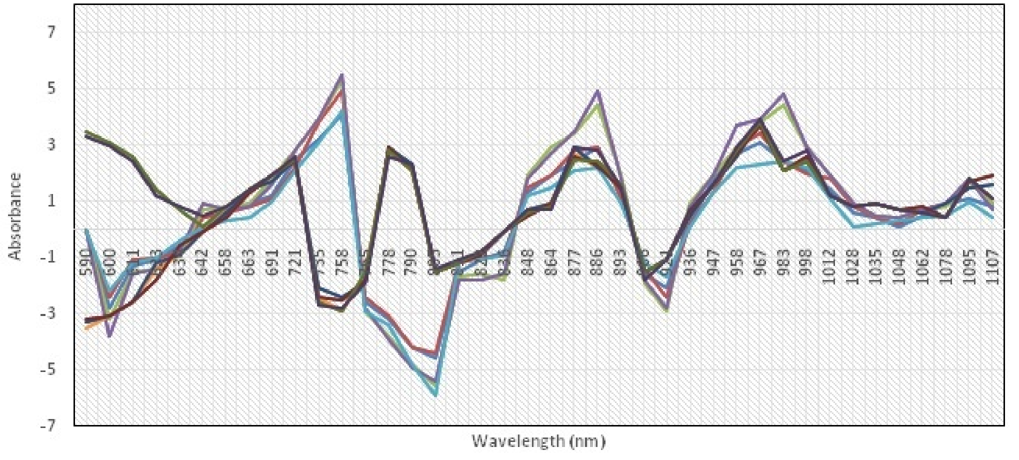


Fig. 14. Pre-processed spectral signature computed for a sample mango fruit.

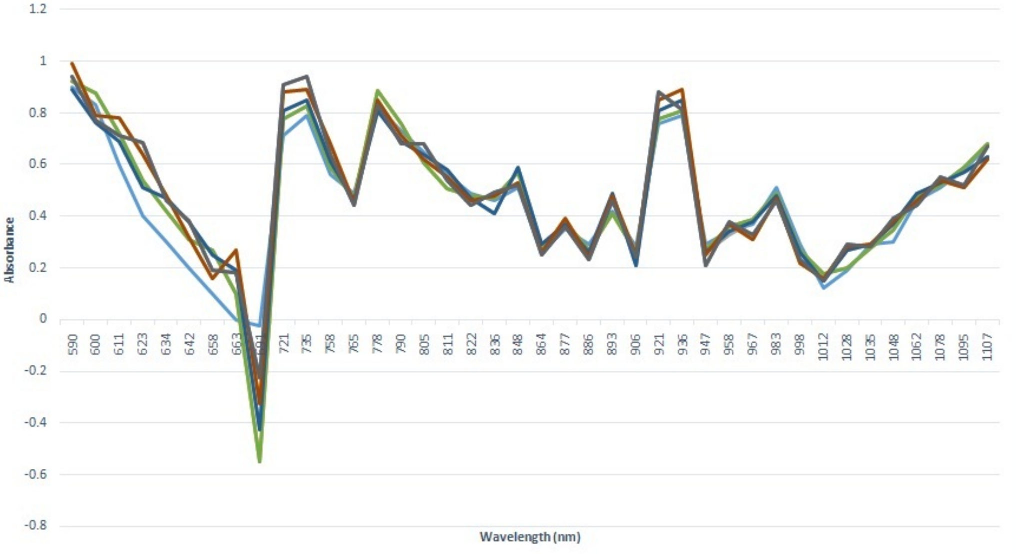


Fig. 15. Spectral signature of a naturally ripened mango fruit.

Fig. 16. Spectral signature of an artificially ripened mango fruit.

the resultant spectra graphs also indicate significant amount of variations in the spectral signatures of both fruits and thereby demonstrate the performance of the proposed CRCD framework in terms of achieving accurate prediction results for calcium carbide based artificially ripened mango fruits.

7.4. Chemical contaminations quantification and results

In the proposed CRCD framework, in order to quantify the amount of chemical contaminations in terms of arsenic contents, five different datasets consisting each of 30 fruit samples are considered as given below:

S1: Fruit samples treated with 2% calcium carbide,

S2: Fruit samples treated with 4% calcium carbide,

S3: Fruit samples stored in closed container with 1% calcium carbide,

S4: Fruit samples stored in closed container with 3% calcium carbide and

S5: Naturally ripened fruits.

Specifically, in order to confirm the presence of arsenic content in the artificially ripened fruit samples, the datasets are analysed with turbidity measurements. More specifically, Table 1 indicates the arsenic content present in chemically ripened fruits in terms of measurements in ng/g. Specifically, ng/g is equivalent to 1 ppb (parts per billion). The presence of arsenic content is ranging from 0 to 290 ng/g, in which naturally ripened fruit samples show the maximum arsenic content of 8 ng/g, whereas the largest amount of arsenic presence is observed in calcium carbide treated fruit samples, direct consumption of which is highly dangerous to humans.

Tab. 1. Presence of arsenic content in terms of levels in ng/g for different datasets: S1, S2, S3, S4 and S5, respectively.

SET	**0-30 ng/g**	**30-70 ng/g**	**70-290 ng/g**
S1	27	3	-
S2	20	10	-
S3	4	24	2
S4	-	-	30
S5	30	-	-

Fig. 17. Result display showing arsenic chemical composition.

Fig. 17 shows the output in the front panel display of the proposed CRCD framework, in which arsenic composition present in the input fruit is displayed. Specifically, arsenic composition is 78.23% for the sample input fruit, as shown in Fig. 17, which is higher than the prescribed threshold limits, hence it suggests that it is harmful to consume the given sample fruit.

The performance of the proposed CRCD framework is also evaluated in terms of sensitivity and specificity measures by means of comparisons with ground truth values.

Precisely, the 200 sample fruits consisting of both natural and artificially ripened categories are considered for evaluating the performance of the proposed framework. More precisely, sensitivity of the CRCD framework defining the probability of positive result for the given set of artificially ripened fruits is indicated as 91.25%. Further, the specificity of the proposed CRCD framework is also computed as 80.25%, which defines the probability of negative result for the given set of naturally ripened fruits. In this way, the reasonable rates of sensitivity as well as specificity rates demonstrate that the proposed CRCD framework is reliable and hence it can be employed in real-time chemical ripening detection systems.

8. Conclusion and future work

In this paper, a new chemical ripening and contamination detection framework is introduced, which utilizes both visual as well as infrared spectrometric features. The experiments conducted on both the software-based and hardware-based setups clearly demonstrate the efficiency of the proposed framework in terms of confidence levels followed by the measurement of presence of arsenic in the sample fruit.

In future, the proposed framework can be extended as real-time detection tool for analyzing other types of fruits including papaya, tomato and other species.

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