Multispectral Image Processing System for Precision Detection of Reheated Coconut Oil

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Abstract: - In the pursuit of enhancing food safety protocols, this article explores a cutting-edge approach to quality control in the coconut oil industry. We present a multispectral image processing system designed specifically for the detection of reheated coconut oil, leveraging advancements in machine learning. Machine learning algorithms, fused with image classification techniques, provide a robust framework for accurately identifying reheated coconut oil. It is proposed to develop a spectral clustering-based classifier to determine the effect of reheating and reuse of coconut oil. Post-processing methods refine classification results, while validation ensures the system's adaptability to diverse datasets.

Key-Words: - Multispectral image, Accuracy, oil reheating, food safety, Convolutional neural network, image classification.

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1 Introduction

In the ever-evolving landscape of food safety, technological advancements play a pivotal role in ensuring the quality and authenticity of consumables. One such innovation takes center stage as we explore the development of a multispectral image processing system designed specifically for the detection of reheated coconut oil. Coconut (Cocos nucifera), belonging to the palm family is a multipurpose tree with many uses. The fibrous one-seeded drupe is used for the production of coconut water, coconut milk, desiccated coconut, and coconut oil. Coconut oil has been used as a cooking or frying oil, as an ingredient in some foods, production of skin care products and pharmaceuticals among others. The use of frying oil over and over many times is common in food service establishments and at the domestic level to cut down on the cost. However, unfortunately, the chemicals and thermo physical properties are altered during reuse and these physiochemical changes compromise the safety of edible oils and thus make fried foods unsafe for consumption. The image processing technique for oil reheat detection can be further improvised for not only coconut oil but also for other types of oils like groundnut oil, palm oil, sunflower oil, etc.

This mechanism can also be used to detect the quality of fruits classifying them as raw, ripe, and rotten classes. With some improvements, this can be used in satellite imaging and military applications with the advancements in broadband devices and mobile technologies. In industries, it allows real-time monitoring of the products during the manufacturing process efficiently. The primary objective of this system is to identify reheated coconut oil accurately, leveraging multispectral data sources. The significance lies in the ability to enhance food safety measures, particularly in the context of the coconut oil industry where the quality of the product is paramount.

2 Related Works

The authors, [1], proposed Hyperspectral imaging and chemometrics for real-time monitoring to predict microbial growth on Longissimus dorsi along the meat supply chain. The differential scanning calorimetry method was to study the thermal behavior of edible oil at elevated temperatures, [2]. The authors, [3], presented the significant elements of a computer vision system and described the main aspects of image processing technique with a review of the latest improvements in the food industry. A multispectral imaging system for detecting the percentage of the common adulterant; tartrazine colored rice flour found in turmeric powder was discussed in literature, [4]. In [5], it was described that how hyperspectral imaging is suitable for determining TVC value for evaluating microbial spoilage of grass carp fillets in a rapid and non-invasive manner. The previous study, [6], proposed the approach for quantifying mold growth by providing an accurate tool for measuring different segments of mold colonies. The method was based on clustering multispectral images by k-means, an unsupervised and simple clustering algorithm. The hyperspectral imaging system was explored for early detection of bruises on 'McIntosh' apples in the literature, [7]. Standardization of near-infrared hyperspectral imaging for quantification and classification of DON-contaminated wheat samples has been investigated in [8]. The authors, [9], [10], discussed the hyperspectral imaging and its applications. A multispectral imaging system with two dichroic beamsplitters, two band-pass filters, and three prism-based 2CCD multispectral progressive area scan cameras was developed in the literature, [11]. The fourier transform infrared spectroscopy method for classification and quantification of virgin coconut oil was discussed in [12]. A hyperspectral imaging system was investigated for real-time monitoring of water holding capacity in red meat was discussed in the previous study, [13]. A multispectral imaging system in the visible and near-infrared) regions was developed to determine the aerobic plate count in cooked pork sausages, [14]. The hyperspectral imaging method was proposed, [15], to check the changes in sarcoplasmatic and myofibrillar proteins contents in boiled pork. The previous study, [16], discussed methods for the classification and analysis of multivariate observations. The authors, [17], conducted a study to evaluate the effectiveness of Fourier transform infrared spectroscopy in detecting adulteration of virgin coconut oil with palm kernel olein as a potential adulterant. The literature, [18], provided a non-linear classification technique based on Fisher's discriminant. The previous study, [19], developed a spectral clustering algorithm that uses the eigenvectors. Applications of near, mid, and Raman infrared spectroscopy combined with multivariate analysis in edible fats and oils were discussed in [20].

3 Proposed Work

The primary objective of this work is to identify reheated coconut oil accurately, leveraging multispectral data sources. The significance lies in the ability to enhance food safety measures, particularly in the context of the coconut oil industry where the quality of the product is paramount. The Convolution Neural Network (CNN) algorithm is used to determine the estimation of the oil reheating count cycle. The proposed work contributes to multispectral imaging under the food image analysis research, and we are proposing two analytical methods for the detection of oil reheating. It is to determine the reheat level count class and to detect significant chemical property changes in the oil. A novel application was proposed for MISs to estimate reheat cycle count class and discrimination of appreciable alterations in the chemical and thermo physical properties under repetitive heating for frying oil, Machine learning algorithm is implemented for the classification of food quality conditions. CNN scheme-based algorithm is implemented for predicting higher accuracy.

This paper presents two multistage signal processing algorithms to estimate the level of adulteration of authentic coconut oil, adulterated with palm oil, and a mechanism to determine the number of times a coconut oil sample has been repeatedly heated. The algorithms are developed for multispectral images acquired from an in-house developed transmittance-based multispectral imaging system. The MIS is also used as a visual assistance for the reheating and to detect the significant changes to the oil quality to help them come to the conclusion the used oil is suitable for consumption or not. This can be further experimented with using palm oil etc.

To initiate the process, multispectral data is collected from the data sets. The main part of the system lies in its capability to extract relevant spectral features indicative of reheated coconut oil. Multispectral image processing systems play a crucial role in extracting valuable information from the electromagnetic spectrum, enabling a wide range of applications for scientific, industrial, and environmental purposes.Figure 1 describes the block diagram of our proposed work which includes preprocessing, image segmentation, feature extraction and processing using CNN.

The proposed algorithms were applied to independent samples with known adulteration levels, and several reheats for validation.

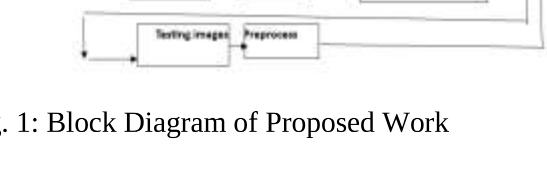

Fig. 1: Block Diagram of Proposed Work

4 Multispectral Imaging System

This multispectral imaging system was developed based on 9 wavelengths selected from ultraviolet (UV) to near-infrared (NIR) region of the electromagnetic spectrum. The system comprises five components. An LED switching circuit consisting of diodes as described in the table, an integrating hemisphere (inner diameter - 130mm and made up of Aluminum), a monochrome camera (FLIR Blackfly S Mono, 1.3 MP, USB3 Vision camera, resolution - 1280 x 1024, ADC - 10 bit), a discovery board (STM32F0). The emission intensities of all the LEDs were adjusted to approximately constant using the LED driver ICs (MAX16839ASA+). The multispectral frequency table provides the dominant wavelength and bandwidth for UV, visible, and near-infrared (NIR) regions. Table 1 provides the details.

Table 1. Multispectral Frequency Table

LED No.	Region (UV, Visible and NIR)	Manufacturer Part Number *(Manufacture)*	Dominant Wavelength (nm)	Bandwidth (nm)
1	UV	VLMU3100 *(Vishay)*	405	10
2	Visible	SM0603BWC *(Bivar)*	430	50
3		SM1204PGC*(Bivar)*	505	20
4		5973209202F-ND *(Dialight)*	590	10
5		5975112402F *(Dialight)*	660	20
6	NIR	QBHP684-IR4BU *(QTBrightek (QTB))*	740	20
7		VSMY2850G *(Vishay)*	850	10
8		VSMF4710-GS08 *(Vishay)*	890	10
9		VSMS3700-GS08 *(Vishay)*	950	20

5 Results and Discussions

The data collection part is first described in this section. A 30x30 window was cropped from the multispectral image obtained from the imaging system. The cropped image was reshaped into a 900 x 10 dimensional matrix. Each row of the matrix corresponds to a pixel in the cropped image. The first nine columns of the matrix represent the nine spectral bands of the imaging system. The 10th column represents the label of the included class. Each value of entry can range from 0 to 255. The dataset corresponds to images obtained of the coconut oil adulterated by palm oil. The dataset consists of 9 adulteration levels. Class 1 corresponds to the 0% adulteration level. Each class steps by a 5% adulteration level up to 40% indicated by class9. Each class consists of 15 replicates. Therefore, the dataset includes 15 x 9 x 900 =121500 rows. Another dataset corresponds to images obtained of the coconut oil after reheating and reused for several iterations (days). The dataset consists of 6 classes corresponding to the number of days reheated from 0 to 5. Each class consists of 9 replicates. Therefore, the dataset includes 9 x 6 x 900= 48600 rows. Figure 2 shows the sample input image. In Figure 3, the convolutional layer image is given. Figure 4 gives the corresponding output image.

Fig. 2: Input Image

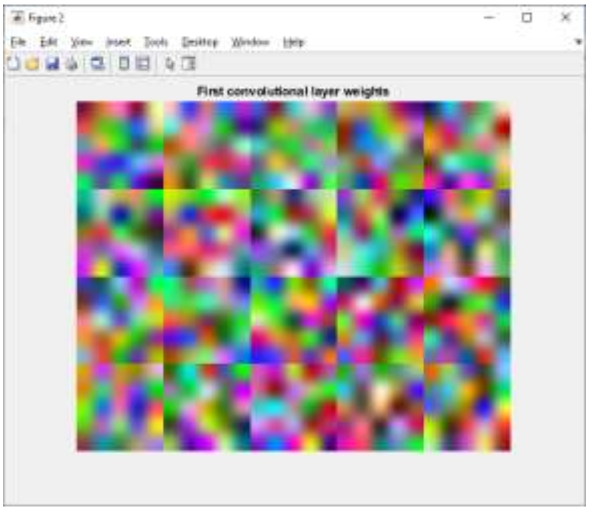

Fig. 3: Convolutional Layer image

Fig. 4: Output Image

6 Conclusion

Coconut Oil has many uses in our domestic daily life as well as industrial applications. In this paper, an algorithm was proposed for MISs to estimate reheat cycle count class by using the physical characteristics of the Coconut oil. The proposed work introduced the transmittance configuration of the MIS to acquire images of translucent liquid specimens. This system gives a positive result to both the market demand and the industrial use to detect the reheat cycles of the oil we use. This can be used by the food service providers and food authorities for the adherence to health and safety protocols regarding the safe reheating of coconut oil. This could be used by the food authorities to check the use of reheated oil which is under use in the food establishments. The vendors also use the MIS as a visual assistance for the reheating and to detect the significant changes to the oil quality to help them conclude that the used oil is suitable for further use or is deemed unfit for consumption. The datasets and the case study used in this system are only based on coconut oil. Hence, we can also expand the proposed system for other oils like palm oil, groundnut oil, sunflower oil, and much more.

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Conflict of Interest

The authors have no conflicts of interest to declare.