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Oil Reheating Analysis Using a Multispectral Image by Machine Learning

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ABSTRACT:

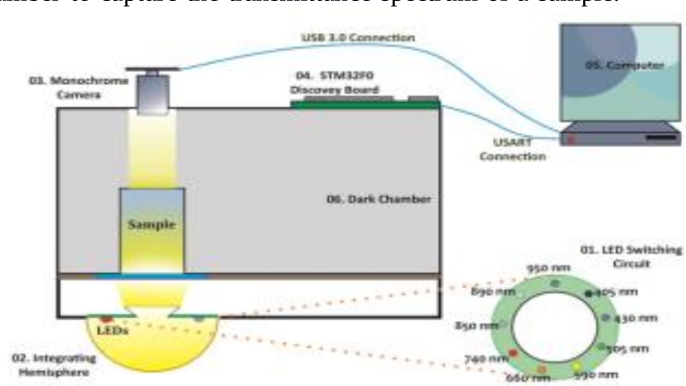
This project describes Oil reheating analysis using a multispectral image. The quality of food consumed plays a pivotal role in assuring the health of a society the reheating of oil condition is predicted using a machine learning algorithm with a multispectral image.Thereafter, another algorithm is proposed to develop a spectral-clustering-based classifier to determine the effect of reheating and reuse of coconut oil. Distinct clusters were obtained for different levels of reheated oil classes and the classification was performed with an accuracy of 0.983 on training samples. Further, the input images for the proposed algorithms were generated using in-house development.

KEYWORDS: Oil Reheat, Multispectral Image, Convolutional Neural Network, Feature Extraction

INTRODUCTION:

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 skincare products, pharmaceuticals, among others. Palm oil which shows quite similar physical properties is often used to adulterate coconut oil (Young, 1983; Pandiselvam et al., 2019) as their cost of production is significantly less than that of coconut oil. However, unfortunately, the chemical and thermo physical properties are altered during reuse and these physico-chemical changes compromise the safety of edible oils and, thus making fried foods unsafe for consumption.

A multispectral imaging system was developed utilizing nine spectral bands with peak wavelengths from 405 nm to 950 nm. An algorithm was developed based on Principal Component Analysis (PCA) and Bhattacharyya Distance. A low-cost multispectral imaging system (Goel et al., 2015; Prabhath et al., 2019) to measure the transmittance spectrum of liquids was developed. This imaging system has the capability of capturing monochrome multispectral images from ultraviolet (UV) to near-infrared (NIR), having an overall resolution of 9 spectral bands. The details of the LEDs which were used for this build. The imaging system used in this study consists of several major components. A 10-bit CMOS monochrome camera (FLIR Blackfly S Mono,1.3 MP, USB3 Vision camera, Resolution – 1280×1024) was mounted on top of the portable dark chamber to capture the transmittance spectrum of a sample.



Schematic diagram of the in house developed transmittance based multispectral imaging system

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LITERATURE SURVEY:

- W.A.R.N. Weerasinghe, S. H. P. Malkanthi, P. Sivashankar :Urban Consumers' Perception and Buying Behavior toward Virgine and Normal Coconut Oils:Around 15–20% of the annual fresh coconut produce is used for coconut oil production, a promising industry in the country due to increasingly recognized health benefits and global demand, IEEE, 2022.
- Emmanuel Ekene Okere, Ebrahiema Arendse, Helene Nieuwoudt, Olaniyi Amos Fawole, Willem Jacobus Perold and Umezuruike LinusOpara Non-Invasive Methods for Predicting the Quality of Processed Horticultural Food Products, with Emphasis on Dried Powders, Juices and Oils: A Review:spectroscopic techniques, nuclear magnetic resonance, and hyper spectral imaging techniques, is presented, IEEE, 2021.
- E.J. Rifna, R. Pandiselvam ,AnjineyuluKothakota , K.V. Subba Rao, Madhuresh Dwivedi, Manoj Kumar, Rohit Thirumdasf , S.V. Ramesh: Advanced process analytical tools for identification of adulterants in edible oils – A review: nuclear magnetic resonance (NMR), hyperspectral imaging (HSI), e-tongue and e-nose combined with chemometrics were used, IEEE, 2022.
- Amita, Rahul Jamwala, Shivani Kumaria , Simon Kelly, Andrew Cannavanc, Dileep Kumar: Rapid detection of pure coconut oil adulteration with fried coconut oil using ATR-FTIR spectroscopy coupled with multivariate regression modelling: Attenuated total reflection- Fourier transform infrared (ATR-FTIR) spectroscopy along with multivariate regression modelling, IEEE, 2020.
- WeleGedara Chaminda Bandara, GodeWithanage Kasun Prabhath, DissanayakeWalawweSahanChinthanaBandara : Validation of multispectral imaging for the detection of selected adulterants in turmeric samples: multispectral imaging system, IEEE, 2020.

PROPOSED APPROACH:

Next we describe our proposal with more details. We also compare it to the other solutions already presented in literature. We select from literature the works that have addressed the topic of edible oil quality and multispectral imaging system.

The proposed work contributes to multispectral imaging under the food image analysis research, and we are proposing two analytical methods for oil reheating. It's to determine the reheat level and condition reheat system. It's to determine the reheat level count class and secondly to detect significant chemical property changes of 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 classification of food quality condition. Convolution neural network scheme based algorithm is implemented for predicting high accuracy.

Algorithm we used is CNN(Convolutional Neural Network), CNN is of the well-regarded machine learning method sin the literature. One of the reasons of its popularity is due to the automatic hierarchical feature representation in recognizing objects and patters in images CNNs reduce the parameters of a given problem using spatial relationships between them. This makes them a more practical classifier specially in image processing where we deal with a large number of parameters (pixels), rotation, translation, and scale of images. In fact, CNNs alleviate the drawbacks of Feel Forward Neural networks and Multi-Layer Perceptons by using an alternative to matrix multiplication. We use this powerful method in this study due to the nature of OCT Image Classification via Deep Learning

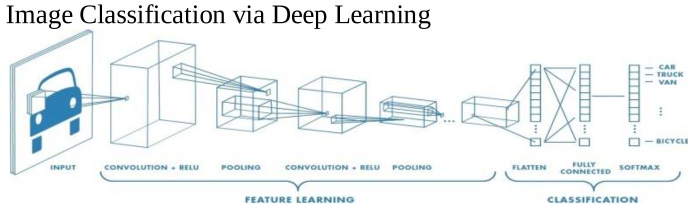

Figure: classification using CNN

A convolutional neural network can have tens or hundreds of layers that each learn to detect different features of an image. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer. The filters can start as very simple features, such as brightness and edges, and increase in complexity to features that uniquely define the object. Like other neural networks, a CNN is composed of an input layer, an output layer, and many hidden layers in between. These layers perform operations that alter the data with the intent of learning features specific to the data. Three of the most common layers are: convolution, activation or ReLU, and pooling. A pooling layer provides a typical down sampling operation which reduces the in-plane dimensionality of the feature maps in order to introduce a

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translation invariance to small shifts and distortions, and decrease the number of subsequent learnable parameters. It is of note that there is no learnable parameter in any of the pooling layers, whereas filter size, stride, and padding are hyperparameters in pooling operations, similar to convolution operations.**Convolution** puts the input images through a set of convolutional filters, each of which activates certain features from the images.

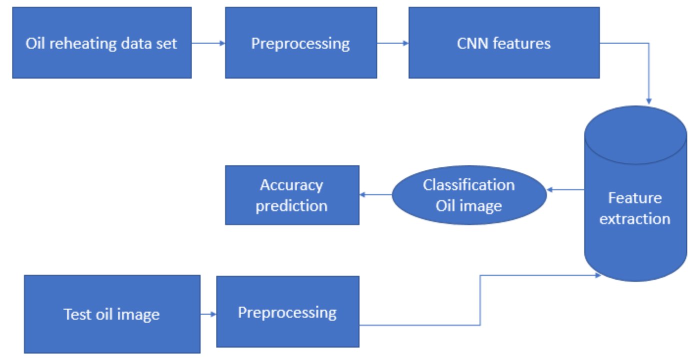
Rectified linear unit (ReLU) allows for faster and more effective training by mapping negative values to zero and maintaining positive values. This is sometimes referred to as activation, because only the activated features are carried forward into the next layer.

Pooling simplifies the output by performing nonlinear down sampling, reducing the number of parameters that the network needs to learn.

CNN Architectures:

Before exploring AlexNet it is essential to understand what a convolutional neural network is. Convolutional neural networks are one of the variants of neural networks where hidden layers consist of convolutional layers, pooling layers, fully connected layers, and normalization layers. Convolution is the process of applying a filter over an image or signal to modify it. Now what is pooling? It is a sample-based discretization process. The main reason is to reduce the dimensionality of the input. Thus, allowing assumptions to be made about the features contained in the sub-regions binned. A detailed explanation of this can be found at Understanding Neural Networks. A stack of distinct layers that transform input volume into output volume with the help of a differentiable function is known as **CNN Architecture.** (e.g. holding the class scores) In other words, one can understand a CNN architecture to be a specific arrangement of the above-mentioned layers.

BLOCK DIAGRAM:



MODULE LIST:

1. Dataset collection
2. Preprocessing
3. CNN layers feature extraction
4. Training of feature
5. Classification

MODULES DESCRIPTION:

1.DATASET COLLECTION:

- The data set is collected from the Kaggle website , Data set divided into three category A training set, A validation set, testing set
- This will split our dataset into training, validation, and testing sets in the ratio mentioned above- 80% for training (of that, 10% for validation) and 20% for testing. The original dataset consisted of 162 slide images scanned at 40x. an imbalance in the class data with *over 2x* the number of negative data points than positive data points

2. PREPROCESSING:

- Preprocessing is the procedure of transforming raw data into a format that is more suitable for further analysis and interpretable for the user.
- EEG data, preprocessing usually refers to removing noise from the data to get closer to the true neural signals.

3. CNN FEATURE EXTRACTION :

- The network we'll build will be a CNN (Convolutional Neural Network) and call it Cancer Net. This network performs the following operations
- Use 3×3 CONV filters Stack these filters on top of each other Perform max-pooling Use depth wise separable convolution (more efficient, takes up less memory)
- Its consists of input layers, convolution layers, ReLu layer, maxpooling layers for extract the features of images of build model.
- Feature extraction train the model the build the model

4. CLASIFICATION:

- Segmentations CNNs that identify regions in a signal from one or more classes of semantically interpretable objects, and classification
- CNNs that classify each pixel into one or more classes given a set of real-world object categories.

5. TESTING PROCESS:

- The testing process is implemented this function we can split the model with a test set of 30% of the original data set.
- The input jusy specify the size of the input and is called D (see the code above X_ train shape).
- The dense layer is instead where the real work happens: it takes the input and does a linear transformation to get an output of size 1. The linear transformation we want to apply is the sigmoid activation function so that in output we are in a range of 0 and 1.
- loss per iteration, training loss, validating loss is implemented in module
- Accuracy and sensitivity of the analyzed in this system.

Dataset Description:

A $30x30$ window was cropped from the multispectral image obtained from the imaging system. The cropped image was reshaped into a 900×10 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 10^{th} column represents the label of the included class. Each value of entry can range from 0 to 255.

Figure:**Input Image**

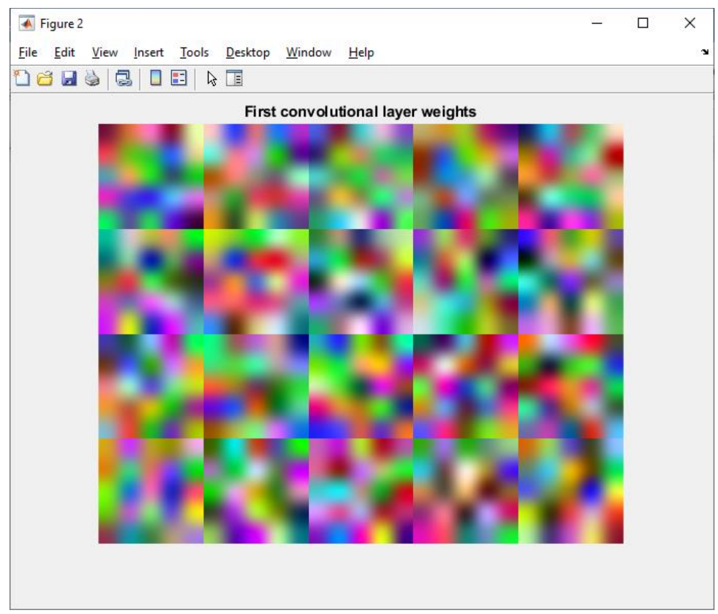


Figure:**Convolutional Layers**

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Figure: **Five time Reheated (Result)**

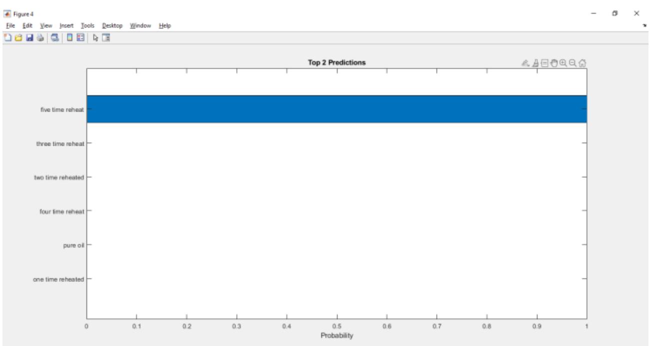

Figure:**Prediction Result**

CONCLUSION:

This study presents two novel multi-stage 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. A high curve fitting (R2 = 0.9876) was achieved for the adulteration level estimating algorithm whereas, high accuracies (mode accuracy ≥ 0.90) were recorded for the classifying algorithm. Moreover, the proposed algorithms were applied on independent samples with known adulteration levels, and number of reheats, for validation. The low mean square error of 0.0029 for adulteration level identification coupled with 0.7616 error metric for six class classification and 0.983 error metric for qualitative classification of repeatedly used oil, demonstrates a remarkable level of accuracy the proposed solution can be easily modified or extended to handle a new class of adulterants and a higher number of heating cycles.

FUTURE WORK:

A low-cost multispectral imaging system to measure the transmittance spectrum of liquids. This imaging system has the capability of capturing monochrome multispectral images from ultraviolet (UV) to near-infrared (NIR), having an overall resolution of 9 spectral bands. The details of the LEDs which were used for this build. The imaging system consists of several major components. A 10-bit CMOS monochrome camera (FLIR Blackfly S Mono,1.3 MP, USB3 Vision camera, Resolution – 1280×1024) mounted on top of the portable dark chamber to capture the transmittance spectrum of a sample.This camera is capable of capturing images in the spectral range from 350 nm to 1080 nm. A Laptop (MSI GE626QD) required to acquire the image and to send commands to both the discovery board (STM32F0DISCOVERY) and the monochrome camera. The portable dark chamber with a LED switching circuit consisting of nine off-the-shelf LEDs. An integrating hemisphere made of Aluminum having 130mm inner diameter to provide better illumination for the sample. A locally developed AC regulated 12V DC power supply unit shall be used to provide stable power input to the LED driver ICs (MAX16839ASA

REFERENCES:

•Achata, E.M., 2020. Visible and NIR hyperspectral imaging and chemometrics for prediction of microbial quality of beef Longissimus dorsi muscle under simulated normal and abuse storage conditions. Food Sci. Technol. 14.

• Amit, Jamwal, R., Kumari, S., Kelly, S., Cannavan, A., Singh, D.K., 2020. Rapid detection of pure coconut oil adulteration with fried coconut oil using ATR-FTIR spectroscopy coupled with multivariate regression modelling. LWT 125, 109250. https://doi.org/10.1016/j.lwt.2020.109250

• Bhuiyan, M.T.H., Khan, M., Rahman, A., Chowdhury, U.K., 2016. Effect of Reheating on Thermophysical Properties of Edible Oil at High Temperature. Int. J. Adv. Res. Phys. Sci. 3, 30–34.

• Brosnan, T., Sun, D.-W., 2004. Improving quality inspection of food products by computer vision—a review. J. Food Eng. 61, 3–16. https://doi.org/10.1016/S0260-8774(03)00183-3

• Chaminda Bandara, W.G., Kasun Prabhath, G.W., SahanChinthanaBandara Dissanayake, D.W., Herath, V.R., Roshan IndikaGodaliyadda, G.M., BandaraEkanayake, M.P., Demini, D., Madhujith, T., 2020. Validation of multispectral imaging for the detection of selected adulterants in turmeric samples. J. Food Eng. 266, 109700. https://doi.org/10.1016/j.jfoodeng.2019.109700

• Cheng, J.-H., Sun, D.-W., 2015. Rapid and non-invasive detection of fish microbial spoilage by visible and near infrared hyperspectral imaging and multivariate analysis. LWT - Food Sci. Technol. 62, 1060–1068. https://doi.org/10.1016/j.lwt.2015.01.021

• De Alzaa F, Guillaume C, Ravetti L, 2018. Evaluation of Chemical and Physical Changes in Different Commercial Oils during Heating 2.

• Ebrahimi, P., van den Berg, F., Aunsbjerg, S.D., Honoré, A., Benfeldt, C., Jensen, H.M., Engelsen, S.B., 2015. Quantitative determination of mold growth and inhibition by multispectral imaging. Food Control 55, 82–89. https://doi.org/10.1016/j.foodcont.2015.01.050

• ElMasry, G., Wang, N., Vigneault, C., Qiao, J., ElSayed, A., 2008. Early detection of apple bruises on different background colors using hyperspectral imaging. LWT - Food Sci. Technol. 41, 337–345. https://doi.org/10.1016/j.lwt.2007.02.022

• Femenias, A., Gatius, F., Ramos, A.J., Sanchis, V., Marín, S., 2020. Standardisation of near infrared hyperspectral imaging for quantification and classification of DON contaminated wheat samples. Food Control 111, 107074. https://doi.org/10.1016/j.foodcont.2019.107074

• Goel, M., Patel, S.N., Whitmire, E., Mariakakis, A., Saponas, T.S., Joshi, N., Morris, D., Guenter, B., Gavriliu, M., Borriello, G., 2015. HyperCam: hyperspectral imaging for ubiquitous computing applications, in: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp '15. Presented at the the 2015 ACM International Joint Conference, ACM Press, Osaka, Japan, pp. 145–156. https://doi.org/10.1145/2750858.2804282

• Gowen, A., Odonnell, C., Cullen, P., Downey, G., Frias, J., 2007. Hyperspectral imaging – an emerging process analytical tool for food quality and safety control. Trends Food Sci. Technol. 18, 590–598. https://doi.org/10.1016/j.tifs.2007.06.001