Colour Image Processing for Non-Invasive Prediction of the Quality of Edible Oils

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This research article highlights the innovations in the area of non-invasive methods for the quality prediction of Edible oils. The concept of quality is dependent on its related characteristics which are used for evaluation of the edible oils. Currently existing non-invasive methods include spectroscopy, Nuclear Magnetic Resonance (NMR), and hyper-spectral imaging methods. Prediction of the oil quality depends on the colour of the oil. A quality detection scheme with colour extraction technique from the images of various cooking oils is developed through image analysis that uses the pixel intensities in Red (R), Green (G) and Blue (B) plane. A brief outline about the commercialization for quality prediction, control and monitoring of edible or cooking oils is discussed here. The various types of oils used for quality prediction include highly virgin olive oil (HVOL), Light Olive Oil (LOL), Sunflower Oil (SO), Canola oil (CAO), Grape Seed Oil (GSO), Corn Oil (COO), Avocado Oil (AO), Peanut Oil (PO), Palm Oil (PAO) and Sesame Oil (SO). The images of these oils are subjected to preprocessing, attribute extraction and finally the prediction of the quality using Convolutional Neural Network (CNN). The conventional imaging methods require upgradation in terms of data gathering, processing time, maintenance cost reduction and enhancement in market value. On the whole, this research article enlightens that the non-invasive techniques have the scope for horticultural application and can be used to determine its quality.

Keywords: Non-Invasive, Quality Prediction, Convolutional Neural Network, Edible or Cooking oils and Image Processing

1. Introduction

Oil consumption and cholesterol moderation plays a vital part in nutrition and health of humans. Oil is a major ingredient in cooking which has some main and negligible macronutrients, omega-3 fatty acids, monounsaturated fat and polyunsaturated fats [1]. There are certain types of oils which holds up with high heat energy when used for longer cooking time. While other types of oils can handle high heat energy for a short cooking period. Those oils which are capable of withstanding high heat energy with low smoke point damages the taste of the cooked food.

Therefore, oils with high smoke point are considered to be value-added products to extend the shelf-life, reduce the food waste, and protect the dietetic nature of the cooked food. The important aim behind various types of cooking oil extraction is to make the fat break down easier and preserve their nutritional, textural and sensory properties [2]. As a result of harvesting process, storage, and transportation of oil seeds, the physiological quality of processed variety of oil seeds vary with time. As a result, it is important to monitor the quality and food safety of the processed food products which uses oil as the main ingredient to add taste without loss of nutrition value in the food chain [3].

Processing the edible oil in the food chain need to forgo many stages in which it is subjected to pathogen invasion, adulteration, and contagion with usage of many pesticides which are used with or without intensions. In due course of oil processing and all the way through the value chain, oil and its related products are at a higher risk of adulteration induced by various harmful agents. Accordingly, it is highly important and necessary that processed oil and oil related products are subjected to rigorous quality check.

The important constituents of the South Indian foods are edible oils and fats which form an essential part of our diet, every day [3]. Edible oils are obtained by mechanical ejecting or solvent removal from peanuts, sesame and sunflower seeds [2]. Some of the components like diglycerides, vitamins, phyto-sterols, tocopherols, and poly-phenols have significant health impact on the human community [5, 6], and henceforth, such important ingredients are not to be removed, while oil processing.

Globally, the oil processing industries are frequently facing new challenges in technology to provide good quality oils for cooking and meet the rising demand for oil without compromise in its quality. Therefore, in the past ten years, the edible oil processing industry has undergone a paradigm shift to enhance the quality using non-invasive methods to provide reliable edible oils within a short span. These non-invasive methods are currently available for commercial use to control the quality. A number of studies have stressed the potential importance for various non- invasive methods of quality assessment of edible oils [4-7]. The various methods used are infrared spectroscopy [8], hyper spectral and multi-spectral imaging [9, 10], Raman spectroscopy [11], NMR [12] and X-ray Computed Tomography (CT) [13]. Many of the methods are successfully deployed in categorization, accuracy, and quantification of edible oils [14].

Presently, the literature review states that there are many methods using non-destructive and non-invasive methods for quality assessment of edible oils extracted from vegetables, seeds, fruits and flowers [1, 15, 16]. Additionally, the review with information on some methods for edible oil extraction primarily focuses on examining the edible oils using non-destructive method and does not combine the examination procedures related to other edible products. The lack of scientific methods on non-invasive quality assessment of edible oils has made this domain more popular in research field. This preamble is the aspiration for the recent innovative developments in non-invasive technology for the quality estimation of various types of edible oils.

2. Literature Survey

Quality is a word used to express the inherent nature of the body [17]. Many researchers have described the meaning of the word quality to be ‘fit for usage’ [18], “conform with needs” [19], “loss prevention” (Taguchi, cited in [20]), “extent of fineness” [21], with a notion to optimize and comprehend the entire scheme, so that its value increases on exchange [22]. Many definitions are proposed by experts depending on the area on which the research studies are carried out. The terms used has a variety of concepts. In case of agriculture, the quality of cleanliness and freshness of agricultural produce is introduced depending on a variety of principles which determine the features of a particular agricultural product. The quality depends on cleanliness of the cooking oils extracted which is inter-dependent on some reasonable traits like outlook, feel, essence, and smell. The nutritional value of the cooking oil depends on the presence of biological and chemical substances, texture and its freshness [24]. Hence, the task becomes a challenging one from the point of view of the stakeholders in the field of horticulture [25, 26].

The estimation of quality of the cooking oil is very important to sustain the quality of the cooking oil during post-harvest handling of the vegetables, fruits and seeds. The values of the smoke point, saturated fats, monounsaturated fats and polyunsaturated fats, measured will facilitate the quality determination and comparison against the standards by ensuring that the cooking oil matches the threshold values of acceptability by the end user [17]. Product quality attributes may be evaluated using a sensory panel or instrumental analysis. The quality traits of different cooking oils are frequently supported by a blend of characteristics, like physical, chemical, and microbial characteristics [16]. The quality traits include size, shape, surface shine, colour, defect free along with the nutritive value of the dietary fiber content, vitamins, minerals, and phyto-nutrients [6, 21, 22]. Other quantifiable traits of quality are fat content, moisture, and protein content, are also analyzed [3]. Figure 1 shows a block diagram of different food quality aspects and related parameters. The upper line indicates the different food quality aspects, while the bottom line indicates the different attributes of the different aspects of quality.

Initially, the colour in various substances can be separated using a technique called chromatography and later showed way to sophisticated devices for segregating the mixtures [6]. For separation of compounds in cooking oil, a method called column chromatography was used to measure the total polar materials. Officially it is declared that the limit of the total polar compounds is nearly 24. Fatty acid composition widely determines the property of cooking oils. Hence, there is an indication about the type and level of the fatty acids that are detected during gas chromatography [7]. The main difficulty of column chromatography is in its implementation and inconsistency in outputs which varies depending on the weighing agent. Additionally, the proportion of polar and non-polar compounds present in the cooking oil may vary with respect to the quality. Oil colour plays an important role in subjective evaluation and is an easier way to identify the oil quality. Cooking oil gets darkened and the rate at which darkening takes place differ from one type of cooking oil to another type and is also dependent on the preliminary color of the oil and the type of the food that is to be fried [4, 8]. Repeated usage of the same oil for frying process makes the colour of the oil to appear dark and loses its taste and aroma [9]. In recent years, Fourier transform infrared (FTIR) spectroscopy is now used as an alternative way for measuring various properties of the cooking oil [7]. The entire infrared spectrum can be recorded using FTIR spectrometer [10].

The biologically stimulated network that mimics the neurons in the human brain is called as Artificial Neural Networks (ANN). This concept is very much used in pattern recognition, classification and object recognition. [11]. Ishak et al. have identified a method for classification of weeds using ANN [12]. Nevertheless, there are many devices for measurement of the quality of cooking oil. Consequently, a smart recognition scheme for quality evaluation of the cooking oil is required.

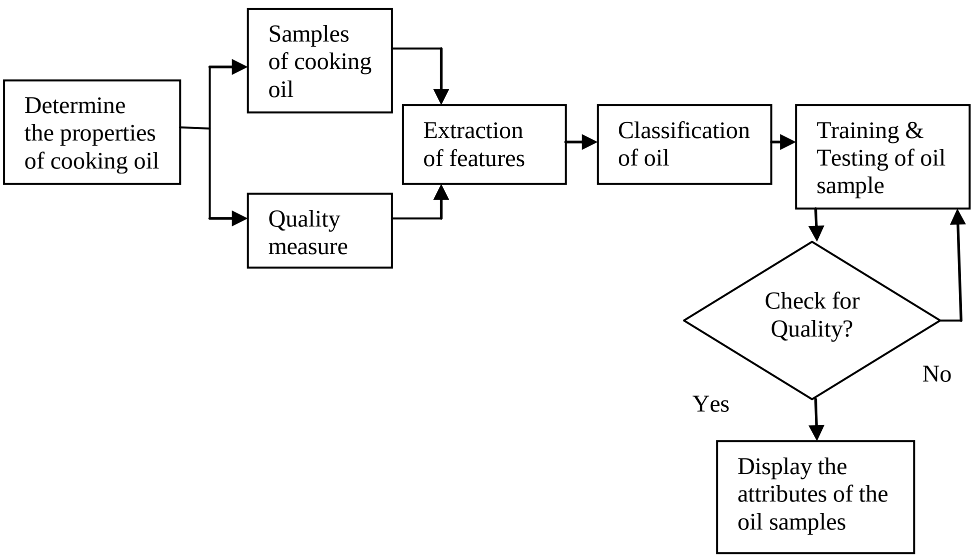

Figure 1. Prediction of Cooking Oil Quality

3. Objective and Novelty of this work

The major objective of this work is to predict the quality of various cooking oils like Highly virgin olive oil (HVOL), Light Olive Oil (LOL), Sunflower Oil (SO), Canola oil (CAO), Grape Seed Oil (GSO), Corn Oil (COO), Avocado Oil (AO), Peanut Oil (PO), Palm Oil (PAO) and Sesame Oil (SO) from the images of these oils. The quality of the cooking oil is determined by the presence of saturated fats, monounsaturated fats and polyunsaturated fats along with its smoke point. The novelty lies in developing an expert system with high accuracy using AI and image processing techniques.

4. Collection of Cooking oil Samples

The images of nearly ten (10) cooking oil samples were collected arbitrarily from https://blog.mountainroseherbs.com/how-to-choose-the-best-culinary-oil-with-oil-smoke-point-chart. The samples of the cooking oil along with their attributes are displayed in Table 1. The variation in colour is considered to be the major attribute which facilitates the classification of the images using CNN, thereby establishing an expert system using colour image processing for prediction of quality of the edible oils using non-Invasive Prediction.

Table 1. Attributes of Cooking Oil

S. No	Name of the Oil	Images of Oil varieties	Smoke Point	Saturated fat (gm)	Monounsaturated fat (gm)	Polyunsaturated fat (gm)
1.	Highly virgin olive oil (HVOL)		175°C - 210°C	1.9	10	1.5
2.	Light Olive Oil (LOL)		218°C - 241°C	2	10	2
3.	Grape Seed Oil (GSO)		190°C - 195°C	1	2	9
4.	Sunflower Oil (SO)		230°C - 232°C	1	11	0.8
5.	Canola oil (CAO)		204°C - 230°C	1	9	4
6.	Corn Oil (COO)		210°C - 230°C	1	8	5
7.	Sesame Oil (SO)		163°C - 210°C	1.9	5.3	5.6
8.	Peanut Oil (PO)		227°C - 230°C	2.5	6	5
9.	Avocado Oil (AO)		271°C - 299°C	2	10	2
10.	Palm Oil (PAO)		227°C - 230°C	7	5	1

5. Methodology for quality determination of cooking oils using color image processing

5.1. Algorithms for Oil quality prediction

Contrast image classification can be done with an input image which contains many objects. It is possible to recognize these objects inside the sample of oil image with appropriate identification of every entity along with the exact position in that image by using CNN models. One type among CNN is the mask R-CNN which is used for prediction of oil quality.

5.2. Mask R-CNN

This concept of mask R-CNN [12] is an extension of the Faster R-CNN for identifying the location of the pixels exactly. On the other hand Faster R-CNN simply identifies the bounding boxes of every object present in the scene. This CNN algorithm uses a RoI Align layer as an alternative of RoI pooling layer in same structure of the Faster R-CNN. The function of RoI Align layer is to orient and locate the extracted attributes in the scene. As a result three outputs will be generated from mask R-CNN to yield three outputs which includes the predicted class, the location of the object and the binary object mask. The architecture of Mask R-CNN is shown in Figure 2.

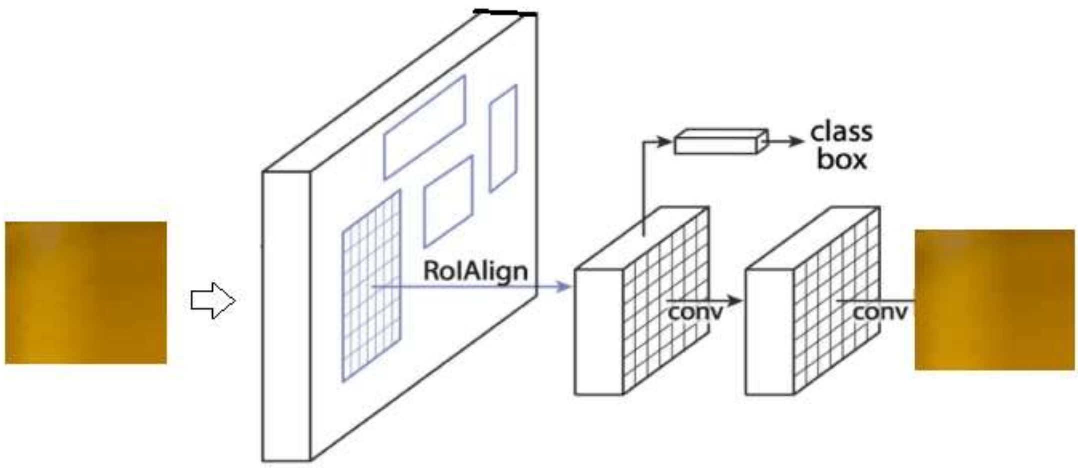

Figure 2. Architecture of Mask R-CNN

The colour detection was carried out to detect the intensities pertaining to RGB colours of the oil sample. The snapshots of the different oil samples were taken by a high resolution RGB camera which is processed using MATLAB simulation package for extracting the RGB colours and classifying them using CNN to identify the quality based on the presence of saturated fats, monounsaturated fats, polyunsaturated fats and smoke point. The first step is pre-processing, where the images of the various cooking oils are resized for square image extraction. From this square image the RGB values are extracted from the respective three planes. Pre-processing is done to ensure uniformity in dimension and traceability of boundaries before extraction of RGB intensities. These intensities are mathematically modified using the formula R+B-G followed by the extraction of the centroids. These attributes are then used to train and test the CNN for predicting the cooking oil quality whose schematic is depicted in Figure 3.

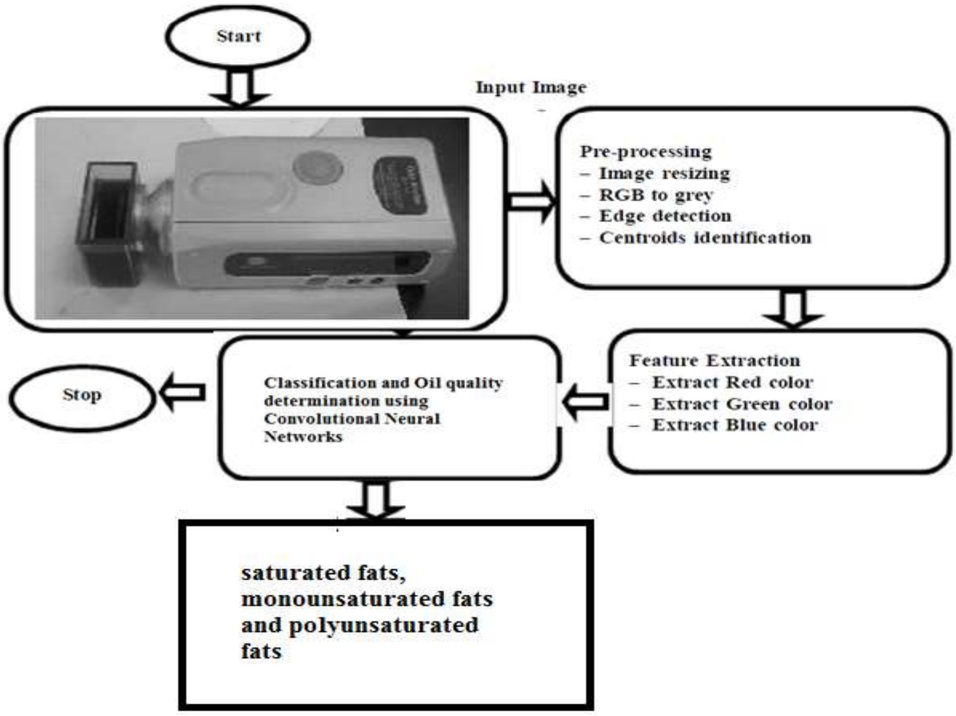

Figure 3. Methodology for Prediction of Cooking Oil Quality

6. Results and Discussion

CNN is a subset of Artificial Neural Network (ANN) which is a resemblance of human nervous system. This system has the capacity to process the input data and yield an equivalent output response as illustrated in Figure 4. CNN is a technique that is used for quality classification of cooking oils because the determination of the real quality of the oil samples was found out using titration method. The cooking oil quality classification system is trained using a set of input features and target data extracted from the images of the oil samples. CNN with weight adaptation techniques is used to predict the oil quality using minimum error criterion as the objective function.

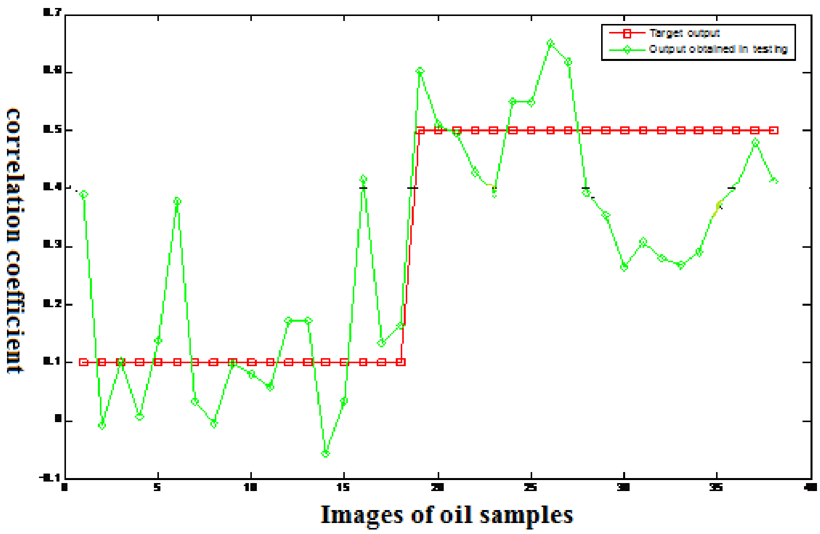

Figure 4. Output of CNN in quality prediction of cooking oils

In table 1, the RGB images of various cooking oils are separated into Red, Green, and Blue color planes. Color space conversion is done using the formula R+B-G followed by the extraction of centroids. The dimension of each image is 495 x 365, say 22.3K. The role of ConvNet is to decrease the size of the image to a structure that is simple for processing, without loss of information so as to obtain a precise prediction. This structure will enable the design of architecture to learn the patterns in massive datasets with scalability.

The results obtained, depict that a 5x5x1 input oil image, 'I' is convolved with a 3x3x1 kernel to get an output of size 3x3x1, which denotes the convolved feature. A kernel or filter of size 3x3x1 is used to perform convolution operation.

A filter is shifted nearly nine times about the stride length whose value is one, computing the Hadamard product which is an element wise multiplication between the kernel and the portion of the image. For RBG images with R, G, B channels the filter is of same size. Matrix multiplication is performed and all the results are added with bias to obtain the convoluted feature output. Convolution operation extracts the higher order attributes like boundaries from the input cooking oil image.

Typically, the first convolution layer facilitates the extraction of low level attributes like, colour, pitch, direction, etc. By adding layers, the architecture is capable of adapting to the high level attributes. A valid padding technique is used to preserve the quality of the images. The next layer is the pooling layer and is accountable for spatial reduction of the convolved attributes. This method reduces the computational complexity and provides direction for extraction of dominant features using the Max pooling which returns the maximum intensity values in the convolved RGB images. Then the final layer is the Fully Connected (FC) layer which is responsible for handling high level features.

A scatter plot is used for visual comparison between varies varieties of cooking oil and its quality predicted using correlation strength as accuracy. The strength of the correlation is depicted in Figure 5. The closer the red dots towards the green line the higher the correlation between the variables which determine the quality of the oil. The correlation coefficient of *r* = 0.987 was achieved for determining the quality of the cooking oil. A Mean Square Error (MSE) of 0.0025, 0.0029 and 0.0027 was obtained during the training of CNN. The result obtained indicates that, higher the correlation coefficient, the lower is the MSE. The statistical analysis is used to substantiate the effectiveness of the CNN training.

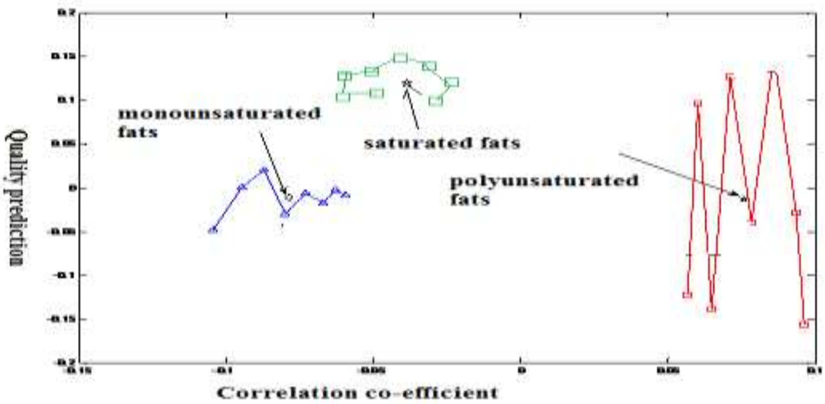

Figure 5. Determination of correlation coefficient after quality prediction in cooking oils

While the network is capable of determining three parameters of cooking oil corresponding to red, green and blue colours, with hidden nodes and three output nodes. The learning rate of both the classification system was fixed at one and there is no momentum and bias applied for training the systems. The output of the trained ANN is very much closed to the target value for both system because of minimum MSE of 0.00011 and higher regression coefficient of about 0.998 can be seen in Figure 5. The data used for validating the classification system were selected randomly for the trained data as tabulated in Table 1 below. The system successfully classified the samples according to target, though, the test data was obtained from the train data an accuracy of 98.71% was obtained with the system.

Table 1. CNN Learning Model Vs Laboratory Approach

S. No	Algorithm/ Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F_1 Score
	FORMULAE	$A=1/N\sum(T_p+T_N)/(T_p+T_N+F_p+F_N)$	$SEN=1/N\sum T_p/(T_p+F_N)$	$SP=1/N\sum T_N/(T_p+F_N)$	$P=1/N\sum T_p/(T_p+F_P)$	F1 = 2X(P X SEN)/ (P + SEN)
1.	CNN	98.71	97.24	99.34	98.42	0.97
2.	BPA	95.21	96.22	96.37	95.24	0.89
3.	Laboratory scale analysis	95.85	96.46	96.61	95.41	0.92

7. Conclusion

The concept of cooking oil quality classification system is proposed, because of its simplicity in implementation. With this system, user does not need any knowledge about the chemistry in order to carry out quality inspection of cooking oils. The trained CNN was considered to be successful because of the high regression value of up to 0.998. Finally, the ANN classification system was validated using ten randomly selected samples from the input sample and it shows a correct classification for all the tested data inputs. CNN has become state of the art algorithm for computer vision, natural language processing, and pattern recognition problems. This CNN has been using to build many use cases models from simply digit recognition to complex medical image analysis.

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