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A fast and non-invasive imaging procedure to fight red tuna fraud

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ABSTRACT

Recently, a food fraud regarding tuna samples has been detected in Europe. Some batches of tuna treated with illegal adulterants like vegetable extracts, including beetroot, were detected after several cases of food poisoning. This paper proposes a new fast and non-destructive technique based on smartphone imaging which contributes to the fight against tuna fraud. The color of different samples of three species of tuna (*Thunnus thynnus*, *Thunnus albacares* and *Thunnus obesus*) has been analyzed by a colorimetrically characterized smartphone. Descriptive analysis of the samples shows that different species of tuna can be grouped by their color in CIELAB space, and that samples adulterated with beetroot extracts can be detected by the proposed image processing procedure. A logistic regression model was implemented to distinguish between real and fraudulent samples, and its suitability checked by k-folding cross validation ($n = 189$), achieving a 0.59% false positive rate with a 10% false negative rate.

1. Introduction

According to the "Key figures on the European food chain" published in 2022, bluefin tuna represents 1.9% of the total catch by the European fleet and represents up to a 6.6% share of the total aquaculture production in terms of economic production (Eurostat, 2022). Looking at data from the EU fish market in its 2022 edition (Directorate-General for Maritime Affairs and Fisheries (European Commission), 2022), the mean apparent consumption of fishery products in the European Union was 23.28 kg of live weight equivalent per person per year, 3.06 kg corresponding to tuna. For the particular case of Spain, data shows that fish consumption, including bonito and tuna, is also a big part of the national dietary patterns (Ministerio de Agricultura, Pesca y Alimentación, 2022). Hence, food fraud in this field can result in major health concerns among the general population.

Studies have proven that consumers are willing to pay more for certain products like bluefin tuna (red tuna) for a variety of reasons, including organoleptic properties, or culinary quality, but, interestingly, "color" was the reason why 17.7% of the population preferred red tuna over other kinds of fish (Caniglia & Zarbà, 2008). In this same study it is reported that 37.1% of the public's perception is shaped by the "freshness" aspect of red tuna.

In this context, tuna adulteration through different methodologies has been detected in the European Union, including the addition of nitrite, carbon monoxide and/or vegetable extracts (Directorate-General for Health and Food Safety, 2018). In 2017, an audit was carried out in Spain (Directorate-General for Health and Food Safety, 2017), following several food poisoning cases derived from the consumption of spoiled fish, which, according to the food safety inspectors (Nuño Domínguez, 2017), had been adulterated with beetroot extracts.

The application of vegetable extracts is strictly forbidden in the European Union following the Regulation No 1333/2008 (Regulation (EC) No 1333/2008 of the European Parliament and of the Council of December 16, 2008 on Food Additives, 2008, p. 16) even though some retailers try to add them as flavors. These extracts contain nitrates and natural pigments, and are therefore considered as additives, subjected to the aforementioned Regulation.

The application of these adulterating methods on tuna pursues two different aims. First, to improve the appearance of spoiled flesh, making it redder and more appealing to the public. As a consequence, high quantities of histamine could potentially be ingested (Colombo et al., 2018; DeBeeR et al., 2021; Demoncheaux et al., 2012). Second, to modify the color of cheaper tuna species (Agencia Española de Seguridad Alimentaria y Nutrición, 2019; 2021), increasing their appeal for the consumer. The altered samples may be sold at higher prices than the original species but are still more affordable than legitimate red tuna. In this sense, prior research has demonstrated that beetroot was one of the

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Abbreviations

AUC	Area Under the Curve
CIE	Comission Internationale de l'Éclariage (International Commission on Illumination)
LR	Logistic Regression
PC	Principal Component
PCA	Principal Component Analysis
PCR	Polymerase Chain Reaction
ROC:	Receiver Operating Characteristic

most efficient treatments to modify tuna flesh appearance (Sáez-Hernández et al., 2022).

To tackle this problem, many analytical approaches to the identification of adulterated tuna samples have been published, involving gas chromatography (Niederer et al., 2019), spectroscopy (Smulevich et al., 2007), proteomics (Hu et al., 2022) or infrared spectroscopy (Boughattas et al., 2020). Genetic approaches like Polymerase Chain Reaction (PCR) have also proven to be effective in detecting food fraud (Druml et al., 2015; Kaltenbrunner et al., 2018; Wu et al., 2021) and methods specifically developed for tuna can be found (Chuang et al., 2012; Hwang et al., 2010; Lin & Hwang, 2008).

Image processing-based analysis has been extensively applied in the field of food science and analysis. Different characteristics of interest, such as texture and color, can be extracted from images using adequate software. For instance, fruit damage can be studied though X-ray, thermal or hyperspectral imaging (Mahanti et al., 2022), and works reporting methods to measure the color of foodstuff surfaces in the CIELAB color space have been reported (Yam & Papadakis, 2004). Adulteration of food matrices has been assessed by smartphone-based technology, as, for example, in diluted milk samples, with results comparable to the reference method (Silva & Rocha, 2020), in meat (Seddaoui & Amine, 2021; Song et al., 2020, 2021) and oil (Hakonen & Beves, 2018).

Based on the reported cases of beetroot adulterations, and the demonstrated adulterant potential of this extract, a smartphone-based procedure is proposed to distinguish adulterated tuna samples (mainly *Thunnus albacares* and *Thunnus obesus*) from non-adulterated samples. To this end, color calibration of the smartphone camera is carried out and color data of tuna samples used to build a chemometric approach that allows to distinguish between beetroot adulterated and non-adulterated samples. With this approach, a portable, convenient, available and low cost procedure is proposed to fight food fraud (Lu et al., 2019).

2. Materials and methods

2.1. Instruments

A Samsung Galaxy Edge 7 smartphone (model SM-G935F with a 12.2 MP camera) was used to capture the images and a spectroradiometer (SpectraScan PR 665, Jadak, USA) was the reference device.

2.2. Samples' description

Certified samples and samples from representative retailers were included in the study (see Table 1). Certified red tuna samples (*T. thynnus*) were supplied by Balfegó, a specialized company that grows and sells exclusively this species. The biological identity of these samples is guaranteed by the company, and hence these samples –extracted from the back part of the spine– were used as a reference set. A representative cross-section of the retailer market, including both fresh and frozen samples, was obtained from sellers at different locations.

Table 1
Dataset description.

Source	Adulteration	Species	Number of samples
Supermarket	None	*T. albacares*	6
		T. obesus	1
	Beetroot	*T. albacares*	6
		T. obesus	1
Local market	None	*T. albacares*	16
		T. obesus	10
		E. alletteratus	1
		T. thynnus	2
		Unknown[a]	5
	Beetroot	*T. albacares*	7
		T. obesus	2
		E. alletteratus	1
		Unknown[a]	2
Red tuna retailer	None	*T. thynnus*	129
Total			189

[a] Samples labelled as "Unknown" were acquired at a local market and lacked the legal tracing sheet.

T. thynnus and *T. albacares* were the main species under investigation, since they were the most readily found, although several samples of *T. obesus* (bigeye tuna) and one of *Euthynnus alletteratus* were also found and studied. These species are less commonly found in the market, given that *T. albacares* and T *thynnus* cover most of the demand from consumers. Additionally, some unidentified samples bought locally from a retailer who refused to show the identification label of the tuna piece, were also included.

All samples, except for the reference *T. thynnus* samples from the specialized company, were adulterated with beetroot extract, and their color was subsequently measured and analyzed, as described in the sections below. Adulteration was only carried out on cheaper samples because these are the ones that fraudsters would use to fake *T. thynnus*. No economic benefit would arise from the adulteration of already valuable *T. thynnus*. Hence, the interest resides in discriminating potentially adulterated samples from non-adulterated *T. thynnus*, since having an adulterated sample could potentially mean that illegal treatments have been used.

To adulterate the samples, boiled beetroot was submerged into hot water to obtain a concentrated extract. Tuna samples were put in vacuum plastic bags and 20 mL of beetroot solution were added. Vacuum was made in the bag, and samples were left for 48 h at 4 °C. After this period, the bags were opened and measured.

2.3. Color capture procedure

Measurements were made in a darkened room. A lighting box was constructed using a white foam semi-sphere with LED lights around the edge to supply homogeneous lighting conditions (Fig. 1). This setup was used to measure both the reference color chips (with the smartphone, obtaining raw RGB, and the spectroradiometer, obtaining CIE XYZ) and the tuna samples. The smartphone was placed on a methacrylate support parallel to the ground, at 25 cm from the sample (see Supplementary Fig. 1). The pro mode was selected in the built-in camera application, and white balance (5000 K), aperture (1/350) and ISO (80) were defined. Images (in.*jpg* format) were transferred to Matlab® for image analysis. Both sides of the tuna samples were photographed to obtain representative information. Every 10 photographs, a reference blank was measured to check for potential lighting variations. Such blank consisted of a white plain and highly reflecting Teflon surface, which was used as reference white in the CIELAB formulae. This allowed for the control of small lighting conditions change.

Images were analyzed by the means of the ColorLab library (Malo & Luque, 2002). A lab-made routine was created to automatically extract color parameters from the surface of the samples. Details about the image segmentation routines can be found in the Supplementary

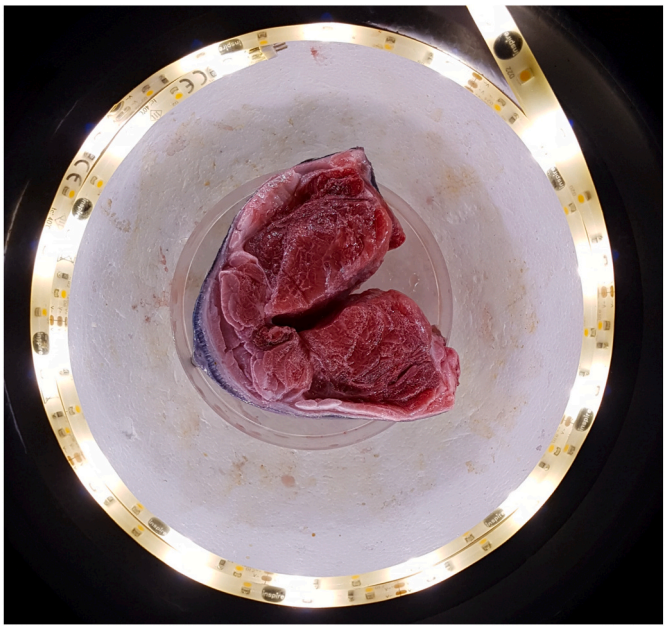


Fig. 1. Example of *T. thynnus* sample under investigation in the proposed set-up: samples were introduced in a white semi sphere and illuminated by a white LED strip.

Information. An average value was obtained as representative of the whole piece.

2.4. Smartphone sensor colorimetric characterization

Image raw RGB values depend on the illumination and capture conditions, on sample reflectance and on the image processing algorithms implemented in the smartphone software to improve automatically image quality, to adapt to average luminance and to increase color contrast. To extract device independent color descriptors from these RGB values, the camera must be colorimetrically characterized.

For this process, a set of 60 color chips, covering the region of color space containing the tuna samples and a reference white sample (a plain, homogeneous, and highly reflective Teflon surface), were selected from a color chart. Reference chips were chosen to cover the region of color space containing the tuna samples. The chips' CIEXYZ tristimulus values were measured with the spectroradiometer and their RGB values were obtained from the images captured by the smartphone camera, under the same illumination conditions that would be subsequently used for the tuna samples. A fourth-degree polynomial model was fitted to the RGB and XYZ experimental values. To reduce the influence of the illuminant, L*a*b* values were computed from the tristimulus values, using the tristimulus values of the white sample as reference white and the Matlab function *xyz2lab* included in ColorLab toolbox (Malo & Luque, 2002).

In Scheme 1 there is a summary of the whole image analysis process to obtain colorimetric data from the smartphone. Data from the reference instrument is provided in CIEXYZ color space, while smartphones usually provide RGB values. The relationship between XYZ and RGB is modelled by a 4th order polynomial as described above. Using this model, new RGB inputs (tuna samples) can be converted to corrected CIEXYZ values. This information can be transformed into CIELAB or other colors spaces like CIELCh by using values of an achromatic reference sample.

Unlike RGB, the obtained XYZ descriptors are device independent, although the coefficients of the polynomial model are only valid for the camera and capture settings used in the experiment. This means that, as long as the polynomial is correcting for both lighting conditions and smartphone characteristics, each setup will generate a polynomial with different values, but which all work in the same direction: modelling the instrumental variables while allowing to isolate the analytical variable of interest -the color of the sample. Information is shown and analyzed in the CIELAB color space since it has been widely used in the field of analytical chemistry.

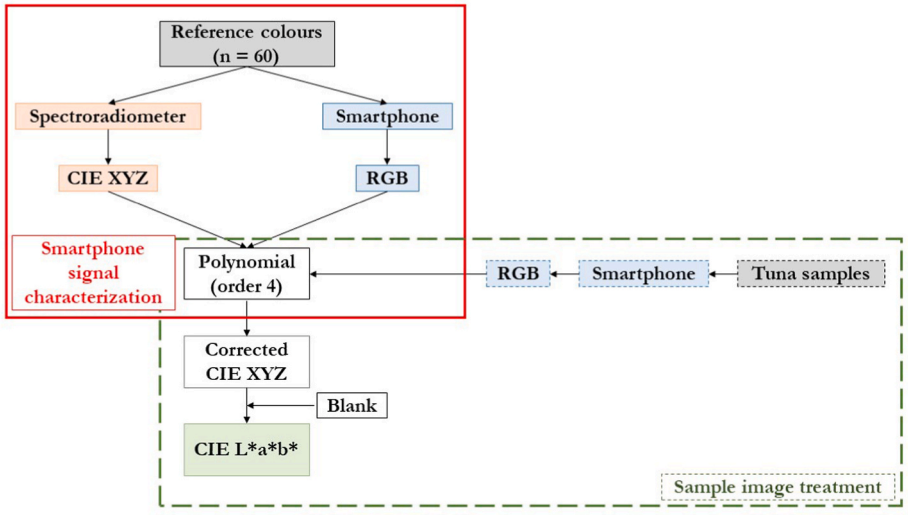
2.5. Statistical treatment

Statistical analysis was performed in (R Core Team, 2022), using *e1071* (Meyer et al., 2021) and *mdatools* (Kucheryavskiy, 2020). Descriptive analysis was done using Principal Component Analysis (PCA), and the classification of the samples was accomplished through a Linear Regression (LR) model.

3. Results and discussion

3.1. Color measurement errors

The validity of analytical procedures based on smartphones depend on the image capturing, processing and analyzing steps (Brosnan & Sun, 2004) and on different distortion factors in each of these stages. For instance, the built-in camera apps in a smartphone usually treat the



Scheme 1. Smartphone colorimetric characterization and image treatment process.

images to modify and enhance the color in a specific way. A recent review (Nelis et al., 2020) pointed out that one of the main drawbacks for the application of smartphones to food safety problems is the fact that the signal obtained depended upon the device, and as a consequence there exists an *interphone* variability. That is, responses to the same object from different devices may differ. Hence, it becomes necessary to characterize the response of the sensor to accurately represent the real color of the samples.

To assess the accuracy of the smartphone's colorimetric characterization model, the CIEXYZ tristimulus values measured by the spectroradiometer and by the camera for 60 reference colors were compared using the CIE DE2000 color difference formula (Luo et al., 2001). To this end, reference CIEXYZ values were converted to CIELAB, and then compared to the corrected CIELAB values obtained by smartphone imaging. The results (Supplementary Fig. 2) are acceptable when compared with the tolerance value of 3.5 units proposed by Liu and co-workers for printed samples (Liu et al., 2013). Mean differences are around 1.5 units, with a standard deviation of 1.1 units. The confidence interval of the mean (calculated at 95% probability) for CIE DE2000 is (1.25, 1.71). Only one sample (Supplementary Fig. 2) gives a value above the stablished threshold value in CIE DE2000. Supplementary Fig. 3 shows the paired plot comparing the real value versus the value obtained by the characterization of the smartphone. No clear pattern arises, and distances are randomly distributed around the scatter plot, so no bias in the colorimetric characterization is observed. Under these conditions, the model derived is within acceptable tolerance limits.

It is important to consider that samples were captured under the same conditions as the reference chips, to ensure that the correction model was suitable for the RGB values of the samples. Additionally, two considerations should be taken into account regarding the influence of the illuminant: first, that the same LED strips were used for every analysis, to minimize the potential variation caused by them. The coefficient of variation related to the CIE XYZ values of the reference white ($n = 3$) during a measuring session was below 2.3% for all three parameters, showing the stability of the lighting system. And second, that even if small changes happened, they were corrected during the color analysis step, as it includes a step in which color values are corrected based on the white reference used (see Scheme 1).

3.2. Exploratory analysis of the samples

All the samples under investigation were measured following the procedure described in 2.3. and 2.4.

Fig. 2 shows the unadulterated samples' chromaticity and lightness in CIELAB space, computed from the smartphone images. Sample color belongs to the red-yellow quadrant of the a*b* plane, with dark to moderately dark lightness (L*) values. The plot hints to possible color differences between species, with more reddish and darker colors for *T. thynnus* and lighter and more yellowish colors for *T. albacares*, although the dispersion in b* values is large in this last case.

Tuna samples fall in the same quadrant occupied by the calibration set (Supplementary Fig. 3), proving that the 60 reference chips are adequate to cover the color gamut of the samples under research.

From a qualitative point of view, given the small representation of frozen samples, it is observed that frozen samples seem more achromatic than those sold as fresh yellowfin tuna (refrigerated at 4 °C, packed or unpacked) but both were different from red tuna samples. More specifically, samples that were sold as frozen presented lower a* values, meaning that less red component is present. As happened with a*, b* shows greater dispersion for *T. albacares* and lower values for frozen samples.

Thunnus obesus samples have a* and b* values similar to those of *T. thynnus*, but, generally, with higher L* values. The color of the only sample of *E. alletteratus* is much darker and achromatic. Finally, the samples labelled as "Unknown" were similar in color to *T. obesus* and *T. albacares*. As in the case of frozen samples, it must be considered that

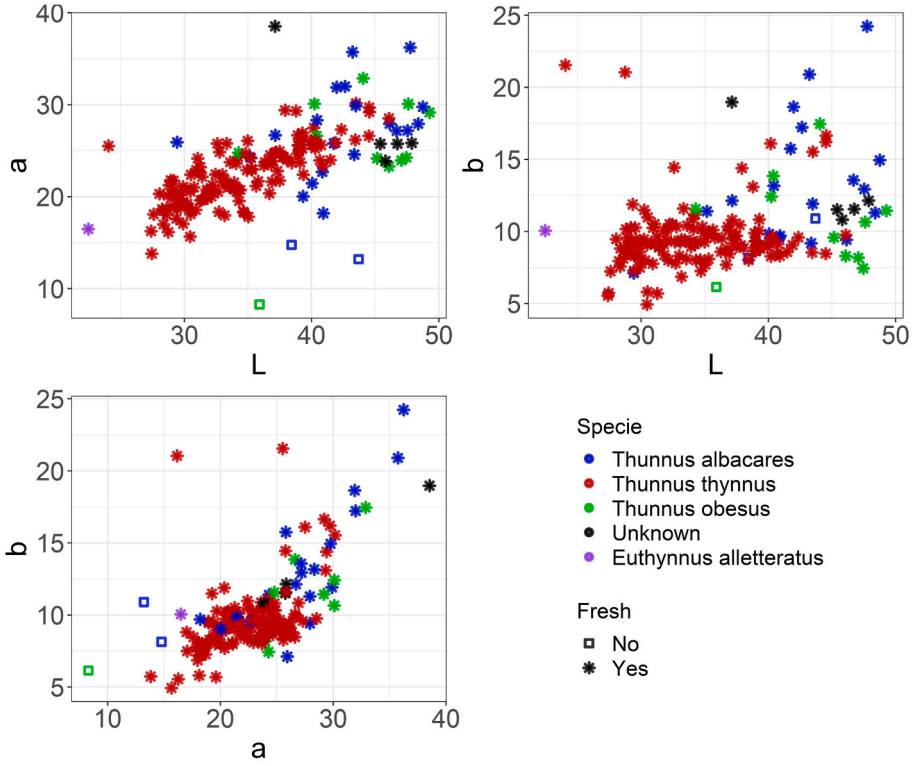


Fig. 2. CIELAB color coordinates obtained through the proposed procedure for the non-adulterated samples. Species are represented by different colors, including samples whose tracing was not obtained ("unknown"). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

these descriptions are circumscribed to these specific samples, as *E. alletteratus* was only found once, but intend to transmit a qualitative perspective of the dataset.

The results show differences in color between adulterated samples and unadulterated *T. thynnus*, as can be seen in Fig. 3. Samples treated with beetroot extract have generally lower L* (darker), and b* (more bluish). Overall, these treated samples appear to be more purplish regardless of the specie.

The color change caused by beetroot extract can be further checked numerically in Table 2. A set of *T. albacares* samples were measured fresh and after treatment and compared to other that had been also kept under vacuum for the same time without the addition of beetroot. Results indicated that L* was significantly decreased, turning the flesh darker, as well as b*, gaining a less yellowish color. The change in a* was not different from the observed in the (untreated) controls. These results, combined with the ones presented in Fig. 2, demonstrate the rationale behind the application of this specific adulterant: the flesh of cheaper *T. albacares* is made darker and less yellow, reaching regions in CIELAB space closer to legit *T. thynnus* (see Fig. 2). That is, looking at the b* *vs.* L* plot in Fig. 2, samples are moved left and down, closer to *T. thynnus*.

Visually, this effect can be seen in Supplementary Fig. 4, where different samples are compared. These differences can be observed when the different samples are visualized simultaneously but are not evident when judging one sample at a time, in isolation. Therefore, numerical evidence is required to support that a sample can be considered as adulterated.

The effect of the adulteration process was further assessed with Principal Component Analysis (PCA). A PCA model was built using the CIELAB values of non-adulterated *T. thynnus* and adulterated cheaper species (*T. albacares*, *T. obesus* and *E. alletteratus*). The result can be seen in Fig. 4.

Samples treated with beetroot appear lower on PC1, since they showed lower L* (darker) and b* (more blueish) and lower on PC2, given their increased redness (a*).

Table 2
Color evolution of *T. albacares* treated with beetroot extract, and *T. albacares* stored under the same conditions without the addition of beetroot extract (Control). Color difference is expressed as the difference between the final state minus the initial value.

	ΔL*	Δa*	Δb*
T. albacares (n = 11)	−15 ± 6	4 ± 5	−16 ± 11
T. albacares Control (n = 3)	0.8 ± 0.8	3 ± 6	−1 ± 3

It is interesting to see now that PC1 is mainly formed on the basis of L* and b*, which are the values altered by the adulterant solution, while PC2 keeps the information regarding redness and is mainly formed by a* itself. This means that the adulteration with beetroot extract has its main influence on L* and b*, confirming the results observed visually in Fig. 3.

3.3. Adulterated samples identification

A chemometric approach was carried out to objectively distinguish between samples that present natural colors (belonging to *T. albacares* and *T. thynnus*, as well as *T. obesus* and E. *alletteratus*) from samples belonging to *T. albacares*, *T. obesus* and *E. alletteratus* adulterated with beetroot extract.

CIELAB data was used to generate a Linear Regression (LR) model. Logistic regression was first introduced by D. R. Cox (Cox, 1958), and works as a classifier for two or more classes (Puthongkham et al., 2021) which computes the probability of one sample belonging to a certain class depending on a set of predictors (Ellison & Fearn, 2005).

The model was built to differentiate between beetroot-adulterated samples and non-adulterated ones. A dataset consisting of 189 observations was used, containing samples belonging to all the species under investigation, as well as adulterated ones. Some samples were used to calibrate the model, and some others were used to check the degree of

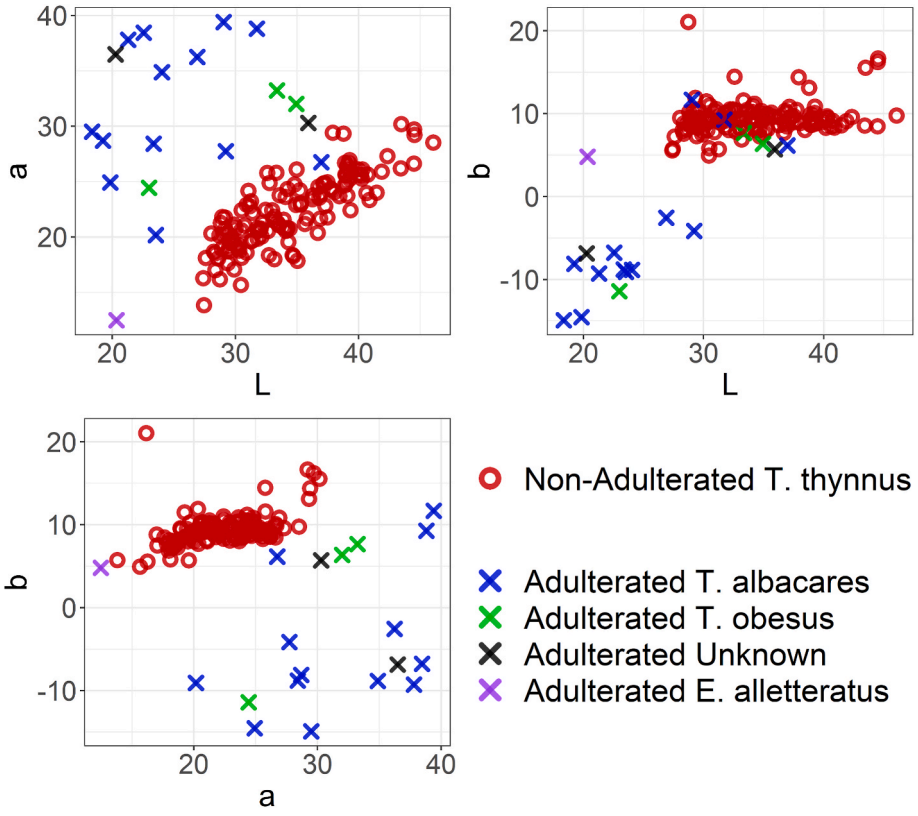


Fig. 3. CIELAB coordinates obtained through the proposed procedure for legit *T. thynnus* and adulterated cheaper species: *T.* albacares, *T. obesus* and *E. alletteratus*.

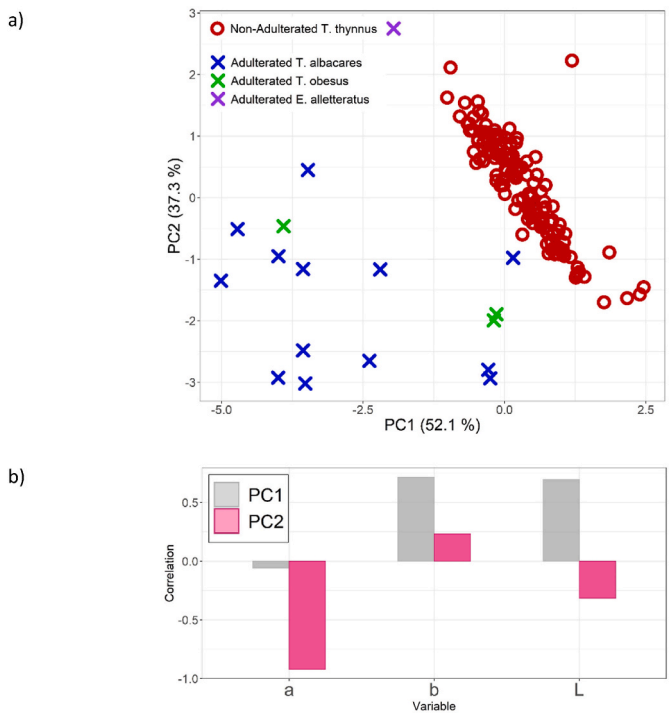


Fig. 4. Principal Component Analysis based on CIELAB descriptors of cheaper adulterated samples (*T. albacares, T. obesus and T. alletteratus*) and legit non-treated red tuna (*T. thynnus*). a) Scores plot; b) Principal component – original variable correlation plot. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

accuracy of the methodology. k-fold cross validation (k = 10, Supplementary Fig. 5) was used following the advice given by Hastie et al. (James et al., 2021). This methodology involves splitting the dataset into 10 random groups, and each time obtaining a different model which does not include one of the groups, that is subsequently used as a test set. By the means of this approximation, a more realistic error estimate is obtained than using leave-one-out cross validation (James et al., 2021). The model was trained to take the value 1 if the sample was indeed adulterated, and 0 if it was not. In this case, a threshold value of 0.70 between both classes was selected since it yielded good results.

Only 3 out of the 189 samples are wrongly classified: two adulterated samples (one from *E. alletteratus* and the other *T. albacares*) were classified as non-adulterated. The third failure was a sample classified as adulterated, despite being sold in the supermarket as fresh yellowfin tuna.

Overall, 98% of the times the classification based on the color registered by the smartphone setup is correctly discriminating between adulterated samples and non-adulterated samples. More specifically, a rate of 0.59% of false positives (samples which are not adulterated but are considered as such) and 10% of false negatives (a sample which is adulterated but is considered as not adulterated) is observed. See Supporting Information for the formulas.

The suitability of the model was corroborated by the area under the curve (AUC) of the ROC (Receiver Operating Characteristic) curve. With this approach, the true positive rate (rate of correctly classified adulterated samples) versus the false positive rate (rate of legitimate samples classified as adulterated) is plotted. If AUC = 0.5 the model is no better than random selection, and as AUC gets closer to 1, the predictive potential of the model increases (Hoo et al., 2017). In this case, the AUC was 0.944, proving that imaging efficiently works for this classificatory purpose.

3.4. Application range and considerations

The application of this protocol can be easily implemented for inspection and screening purposes since it requires minimal instrumentation. Additionally, the non-destructive perspective allows to analyze suspicious samples without incurring in economic losses for the retailer. The image analysis and statistical treatment can be automated to obtain a result from an inputted image in a matter of seconds. To this end, a prior colorimetric characterization of the setup is required, using reference color chips, which would mean that the utilization of more sophisticated instrumentation such as the spectroradiometer is only needed periodically, to recalibrate the device. Additionally, thanks to the image segmentation steps, sample size and heterogeneity can be tackled obtaining Regions of Interest which representatively illustrate the color of the samples.

Individual samples must be thick enough to be opaque, so that measured color depends only on its surface. If a sample is so thin that it can be considered translucid, the resulting color will be influenced by the background, and hence the results would not be valid. Also, some practical considerations need to be taken into account: for instance, fishery products often come in close contact with ice. If some ice melts in the surface of the sample and creates a little puddle, or leaves drops along the surface, that water will interact with the light and potentially modify sample color. This means that analysis should be carried out after ensuring that the surface of the flesh is clean and dry.

4. Conclusions

In this work, a non-invasive method based on digital imaging using a smartphone has been implemented to fight tuna fraud using beetroot extract. To this end, the colorimetric characterization model for the camera sensor was determined using fixed illumination and capture conditions and a training dataset covering the color gamut of the tuna samples. The procedure has proven to be effective in the color range under investigation, providing color information that correctly describes the samples without the interference of automatic and uncontrolled color transformations.

Samples from different tuna species (mainly *T. thynnus*, *T. albacares* and *T. obesus*) were investigated, and their color characteristics were described. Some differences were observed, especially in terms of their lightness: *T. thynnus* was found to have a darker aspect. However, fuzzy borders among groups were found, probably because the color of the flesh is a multifactorial variable, which depends upon the feeding, oxidation state and conservation techniques, among others.

Nonetheless, tuna samples adulterated using beetroot extracts were studied and color differences were found. The beetroot extract gave a darker aspect to the samples, and at the same time shifted the color of the samples to a redder and bluer aspect. This effect means that cheaper species (*T. albacares* and *T. obesus*) acquire a final hue that resembles that of red tuna, *T. thynnus*, explaining the reason why behind the usage of this illegal adulterant in the market. A LR model was applied to the dataset, and it allowed to discriminate between adulterated cheap species from legitimate red tuna.

This work proves the utility of smartphones as in situ tools to fight food fraud, while tackling with the often-overlooked problems that derive from the fact that they are not originally designed as analytical devices. If the proper considerations are taken into account, smartphone cameras can become a widespread instrument that may be useful as screening methods to select suspicious samples. With this device, an objective and evidence-based decision can be made, replacing the subjective criterion of the visual judgement of the personnel surveying the market.

CRediT authorship contribution statement

Roberto Sáez-Hernández: Conceptualization, Investigation,

Writing – review & editing. **Kevin U. Antela:** Conceptualization, Investigation. **Adela R. Mauri-Aucejo:** Funding acquisition, Project administration, Writing – review & editing. **Ángel Morales-Rubio:** Conceptualization, Funding acquisition, Project administration. **María Josefa Luque:** Conceptualization, Investigation, Writing – review & editing, Funding acquisition. **M. Luisa Cervera:** Conceptualization, Investigation, Writing – review & editing, Funding acquisition, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: M. Luisa Cervera reports equipment, drugs, or supplies was provided by BALFEGÓ & BALFEGÓ S.L.,. M. Luisa Cervera reports financial support was provided by Conselleria de Innovación, Universidades, Ciencia y Sociedad Digital, Generalitat Valenciana. Roberto Saez-Hernandez reports financial support was provided by Ministry of Universities, Government of Spain.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lwt.2023.115231.

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