DEVELOPMENT OF A SYSTEM FOR IDENTIFYING THE QUALITY OF DIESEL OIL PRODUCED BY AN OIL INDUSTRY

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ABSTRACT

Diesel oil is the most widely used fuel in the Brazilian highway system. Controlling the technical specification parameters of this oil is of utmost importance for the oil industry, and the color and appearance of the product are some of the main parameters in this process. This paper presents an application of the median in digital image processing, the objective of which is to identify, among the various images of the diesel color scale, the appropriate quality or not of the oil produced. For this purpose, samples of diesel oil with their respective color gradations, ranging from 1.0 (lightest) to 8.0 (darkest), with variations in brightness, contrast, and saturation, were used. To analyze the performance of this identification, the median values of each of the following components were used: Y, YDifference, Cb, Cr, R, G, and B, as well as a comparison threshold for each of them, to classify the test sample as approved or failed oil. According to experimental results, using the YDifference, Cb, and Cr components, the accuracy, precision, and sensitivity (recall) were all equal to 100% and the false negative rate was equal to zero. Using YCbCr, a false negative rate of zero and an accuracy of 99.48% were also obtained. In the case of RGB, the false negative rate was less than 1% with precision and sensitivity equal to 99.07%.

Keywords: Digital Image Processing. Image Subtraction. Median.

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INTRODUCTION

Because the global energy matrix still depends largely on fossil fuels, oil, and its derivatives will remain essential for many years to come for the movement of various sectors of the economy and society, ranging from the food industry to the fuels used in a country's road system. Given this global scenario of dependence, oil refining is essential to guarantee Brazil's energy independence. (NATIONAL PETROLEUM AGENCY, 2005). Oil refining is focused on the production of derivatives such as gasoline, kerosene, liquefied petroleum gas (LPG), and diesel oil, among others. This activity is directed according to the derivative with the greatest existing demand; in the case of the Brazilian road matrix, this derivative is diesel oil.

According to Brasil et al. (2011), diesel oil is composed of paraffinic, naphthenic, and aromatic hydrocarbons, with a predominance of paraffinic and naphthenic hydrocarbons with chain sizes of 10 to 25 carbon atoms and a distillation range commonly between 150°C and 400°C. To obtain diesel oil, petroleum is refined by a separation process called atmospheric distillation, which consists of separating hydrocarbon fractions present in petroleum-based on the difference in their boiling temperatures.

To be used in industry, diesel oil produced by an oil refinery must follow technical specifications standardized by the Brazilian regulatory agency, in this case, the National Petroleum Agency (ANP). Among these parameters, the color and appearance of diesel oil are of fundamental importance in the final specification of this derivative, since once it is non-compliant, in most cases the other parameters such as density and distillation will also be non-compliant. In a refinery, the quality control of the color of diesel oil is done manually and subjectively, by visually checking a sample of the oil during the routine of a technician operating the process unit and comparing it with a standard previously learned by him. This method causes many errors of interpretation and losses in the millions of dollars to the sector that stores the derivatives, due to the failure to immediately identify a color standard that is inadequate for storage.

Having a quality control system for the color of the diesel oil produced and making this information available to the controlling agents of the supervisory system is of fundamental importance for the operational continuity of a refinery and reducing the probability of financial losses due to the storage of diesel oil that does not meet technical specifications. Given this, this work demonstrates the development of a diesel oil quality identification system, using concepts and applications of digital image processing through the MATrix LABoratory (MATLAB) tool (BACKES, Junior, 2016) whose objective is to signal to a process control and supervision system that the diesel oil produced at the time exceeded the maximum permitted color limit.

THEORETICAL FRAMEWORK

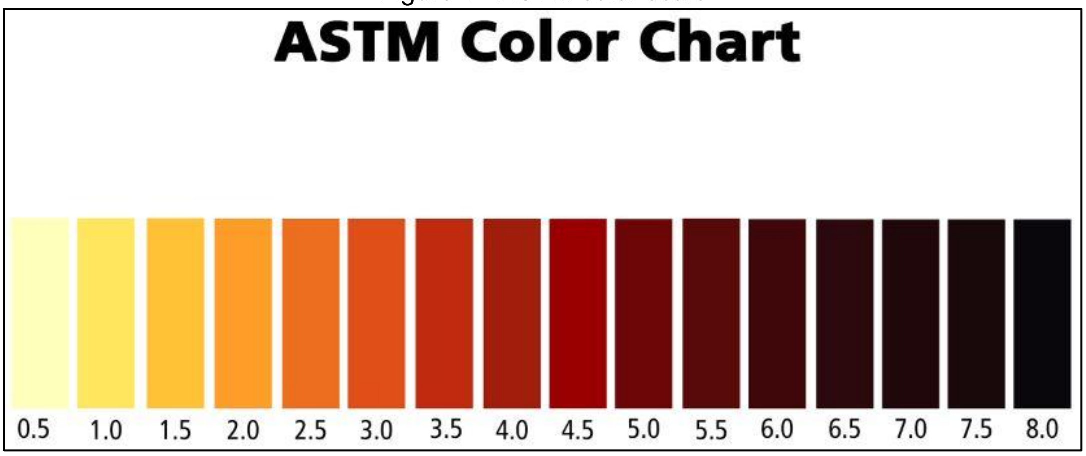
This section presents the bibliographic survey of works related to the diesel oil color scale, digital image processing, image subtraction, and application of the median in digital image processing. For this, searches were made in the IEEE Xplore, Engineering Village, and Research Gate literary databases.

DIESEL OIL COLOR SCALE

Among the various technical specifications of diesel oil, the ASTM (American Society for Testing and Materials) color comes from the American standard D 1500 and D 6045 for identifying appearance. The unit is dimensionless and divided into levels of 0.5. The Brazilian standard ABNT NBR 14483 grades these levels from L0.5 to L8.0. According to the TELUB website, “The ASTM color scale, also called "mineral oil color value", is primarily used for the classification of petroleum products such as lubricating oils, heating oils, and diesel fuel oils. The color of mineral oils is constantly checked during the process to determine when they have been refined to the required level. Color is also used to confirm that the correct oil or fuel is used for its intended use and that no contamination or deterioration in quality has occurred.

The determination of the color of petroleum products is primarily used for manufacturing control purposes and is an important quality characteristic since the color is easily observed by the user of the product.” (2022). Figure 1 shows the ASTM color standard adopted by the D 1500 and D 6045 methods described above.

Figure 1 - ASTM color scale



TELUB

NBR 14483 also describes in its appendix A the characteristics of the Colorimeter instrument and complementary devices used to compare the color of the oil sample with the pre-existing standard seen in figure 1. Among the recommendations are the need for adequate lighting and colored glass standards (figure 2) which describe, for each color level, the RGB chromaticity coordinate and the luminous transmittance suitable for comparison..

Figure 2 - Table of colored glass patterns

Cor ASTM	1) Chromaticity coordinates (USC System)			Light transmittance 2) (CIE standard source C)
	r	g	b	Tw
0.5	0.462	0.473	0.065	0.86 ± 0.06
1.0	0.489	0.475	0.036	0.77 ± 0.06
1.5	0.521	0.464	0.015	0.67 ± 0.06
2.0	0.552	0.442	0.006	0.55 ± 0.06
2.5	0.582	0.416	0.002	0.44 ± 0.04
3.0	0.611	0.388	0.001	0.31 ± 0.04
3.5	0.640	0.359	0.001	0.22 ± 0.04
4.0	0.671	0.328	0.001	0.152 ± 0.022
4.5	0.703	0.296	0.001	0.109 ± 0.016
5.0	0.736	0.264	0,000	0.081 ± 0.012
5.5	0.770	0.230	0,000	0.058 ± 0.010
6.0	0.805	0.195	0,000	0.040 ± 0.008
6.5	0.841	0.159	0,000	0.026 ± 0.006
7.0	0.877	0.123	0,000	0.016 ± 0.004
7.5	0.915	0.085	0,000	0.0081 ± 0.0016
8.0	0.956	0.044	0,000	0.0025 ± 0.0006

1) The tolerance for chromaticity coordinates is ± 0.006.

2) Commission Internationale de l'Eclairage (International Commission on Illumination).

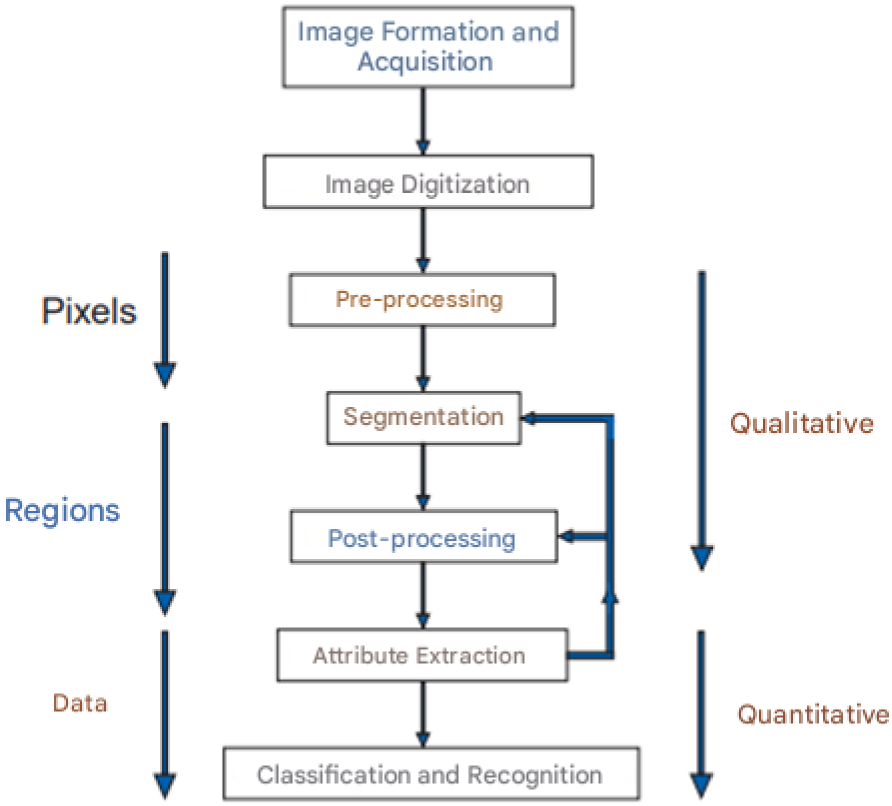
NBR 14483

DIGITAL IMAGE PROCESSING

Digital Image Processing is a set of procedures related to the manipulation and analysis of images through the computer (QUINTANILHA, 1990). These procedures include the input of digital data, enhancement, statistical analysis, and generation of outputs, which can be images in grayscale or color.

An image processing system consists of several stages, such as: image formation and acquisition, digitization, pre-processing, segmentation, post-processing, feature extraction, classification and recognition (ESQUEF et al, 2003), as illustrated in the figure.3.

Figure 3 – Stages of a PDI system



Source: (ESQUEF et al, 2003)

Given that the present work deals with the manipulation of image-type signals, digital image processing fits as the main basis for this research. The main steps used in this work are the following: acquisition of static (in file) and dynamic test images, using a video camera; pre-processing to obtain the color components Y, YDifference, Cb, Cr, R, G, B; obtaining the median of each color component and using a comparison threshold to classify the images of diesel oil tests as approved or failed.

IMAGE SUBTRACTION

Image subtraction is a process by which the digital numerical value of a pixel or entire image is subtracted from another image. This can be used to detect changes between two images to detect moving objects in a video scene (SINGLA, 2014; ZHAO, 2022). Furthermore, temporal image subtraction can be used to emphasize the change interval of patient tomography images to aid in the investigation and diagnosis of lung cancer, that is, to perform the segmentation of candidate nodules (TANAKA et al, 2017).

Another application of image subtraction is in image segmentation using the technique called background image subtraction (BENRAYA; BENBLIDIA, 2018; PANDEY, 2022). In this case, a reference image of the scenario is stored in the system containing, for example, the average values of the image elements. This reference image is used to classify each image element as belonging to the background image or the object (foreground image). For this comparison, the current image is subtracted from the average reference image. Then, the resulting difference image is compared with a predefined threshold. Image elements whose differences are above the threshold are classified as belonging to the object, otherwise as belonging to the background or reference image.

In this work, image subtraction is used to detect differences in brightness information between the images of the test samples and the image of the reference sample.

APPLICATION OF THE MEDIAN IN DIGITAL IMAGE PROCESSING

The median m of a set of n elements is the value such that half of the n elements of the set are below m and the other half are above m. When n is odd, the median is the central element of the ordered set. In cases where n is even, the median is calculated by the arithmetic mean of the two elements closest to the center. (FILHO; NETO, 1999)

One of the applications of the median in digital image processing is in the implementation of spatial filters of statistical ordering whose response is based on the ordering of the pixels contained in the area of the image encompassed by the filter. In this case, the value of the central pixel is replaced by the value determined by the ordering result, that is, by the median of the gray levels in the neighborhood of that pixel (the original pixel value is included in the median calculation). Median filters are popular because, for certain types of random noise, they provide excellent noise reduction capabilities, with less blur than linear smoothing filters of similar size. Median filters are particularly effective in the presence of impulse noise, also called salt and pepper noise because of their appearance of overlapping black and white dots in an image (GONZALEZ; WOODS, 2002). An example of the application of the median filter in the image preprocessing stage is presented by Silva et al. (2019) in which the authors address the processing and analysis of medical images. In the thesis work presented by D'AVILA (2019), the median filter was used in the analysis of chromatographic profiles. An algorithm was developed as an alternative to the manual process, which is imprecise, for analyzing the presence of substances in plants. In this way, it was possible to reduce the time spent on analysis, find the centers of the stains according to their distribution, and compare the colors according to their exact values, in contrast to the visual method that uses the subjectivity of the analyzer.

In this work, the median is used as a measure of the brightness intensity of the color components in the YCbCr and RGB planes of the reference and test images of the diesel oil samples.

METHODOLOGY

The methodological aspects of the research carried out are discussed below, describing the procedures necessary to evaluate the application of image subtraction and the median in identifying the quality of diesel oil. The purpose of this study was to conduct applied research. To achieve the proposed objectives and better appreciate this work, a qualitative and quantitative approach was used. To understand the problems in the study area, exploratory and bibliographical research was carried out (GIL, 2019). The following are the materials used throughout the research, as well as the methodological procedures, are written.

MATERIALS

This section presents the environment in which this work was developed and the data set used in the validation and testing of this system.

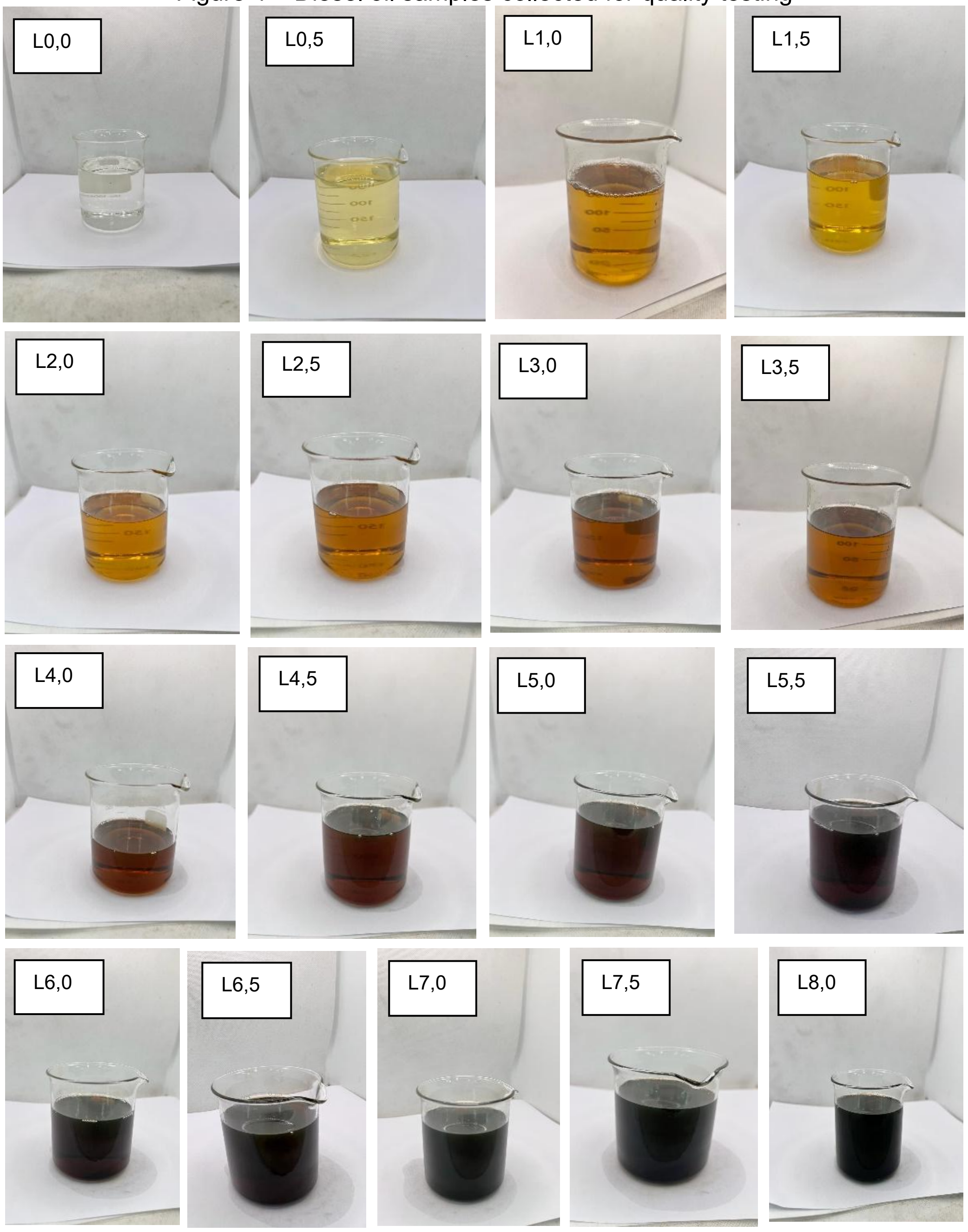
Development environment

The hardware used in this research has the following configuration: 11th Gen Intel(R) Core (TM) i5-11400H Processor @ 2.70GHz 2.69 GHz; RAM 16.0 GB (usable: 15.7 GB); 64-bit operating system, x64-based processor; Matlab® software version 2022b; 1 TB SSD HD.

Dataset

The data set of this study is formed by images with samples of diesel oil with varied aspects, that is, different color gradations as illustrated in Figure 04. Samples with aspects L0.0 to L3.5 (lighter) are considered as oil of acceptable or approved quality and those with aspects of L4.0 to L8.0 (darker) are considered as oil of disapproved quality..

Figure 4 – Diesel oil samples collected for quality testing

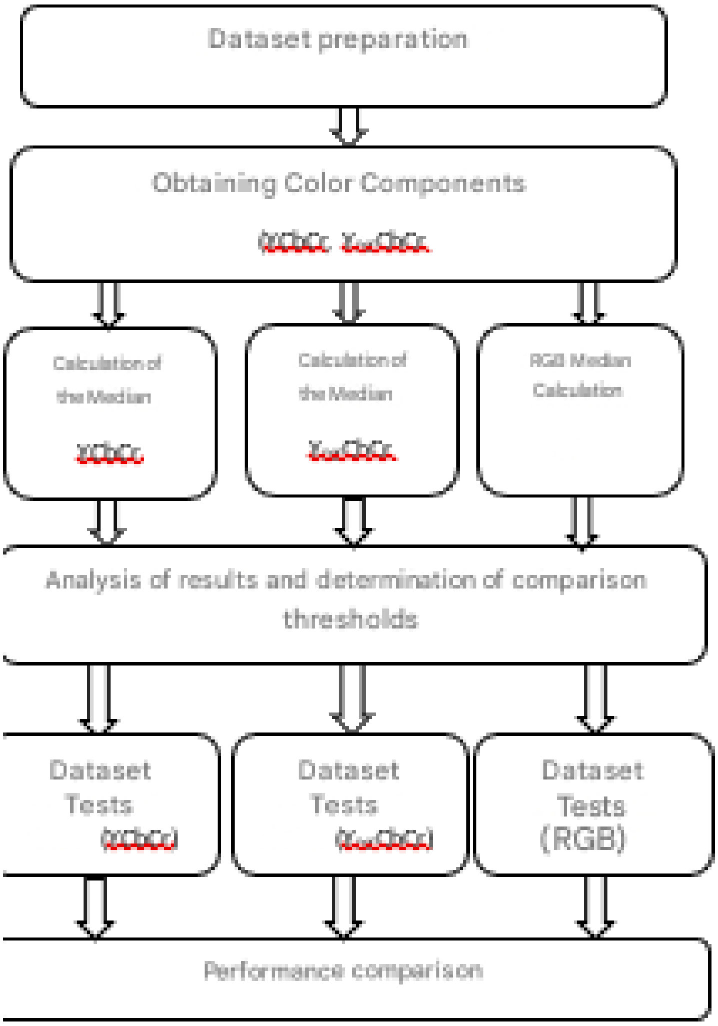


Source Authors

METHODS

The block diagram in Figure 05 presents the steps of the methodology used in the development of this work, namely: preparation of the data set, obtaining the color components, calculating the median, analyzing the results and determining the comparison thresholds, testing the data set in the color planes, and comparing performance. Each of these steps is described below.

Figure 5 – Methodology used in system development



Source: Authors.

Dataset Preparation

The dataset preparation consisted of obtaining reference and test images from the images with the diesel oil samples illustrated in the previous section. They were edited using the Windows 11 photo editing program, where the images were cropped in the oil region of each sample (L0.0 to L8.0). From these images, others were obtained with variations in brightness, contrast, and saturation. In total, the dataset was prepared with 192 images. Figure 6 illustrates some images obtained after cropping and variation in brightness, contrast, and saturation.

Figure 6 – Images used for validation and testing

Source: Authors.

Obtaining the Color Components

For each standard image (L0.0 to L8.0), the color components were obtained in the YCbCr and RGB planes. In addition, the difference images between the Y component of the standard image L0.0 and all the other Y components of the other images (L0.5 to L8.0) were obtained. At the end of this step, the images of the following components were obtained: Y, YDifference, Cb, Cr, R, G, B.

Calculating the Median

From the images of the color components obtained in the previous step, the median values for each of these images were calculated. At the end of this step, 17 median values corresponding to the 17 standard images (L0.0 to L8.0) were obtained for each of the components (Y, YDifference, Cb, Cr, R, G, B).

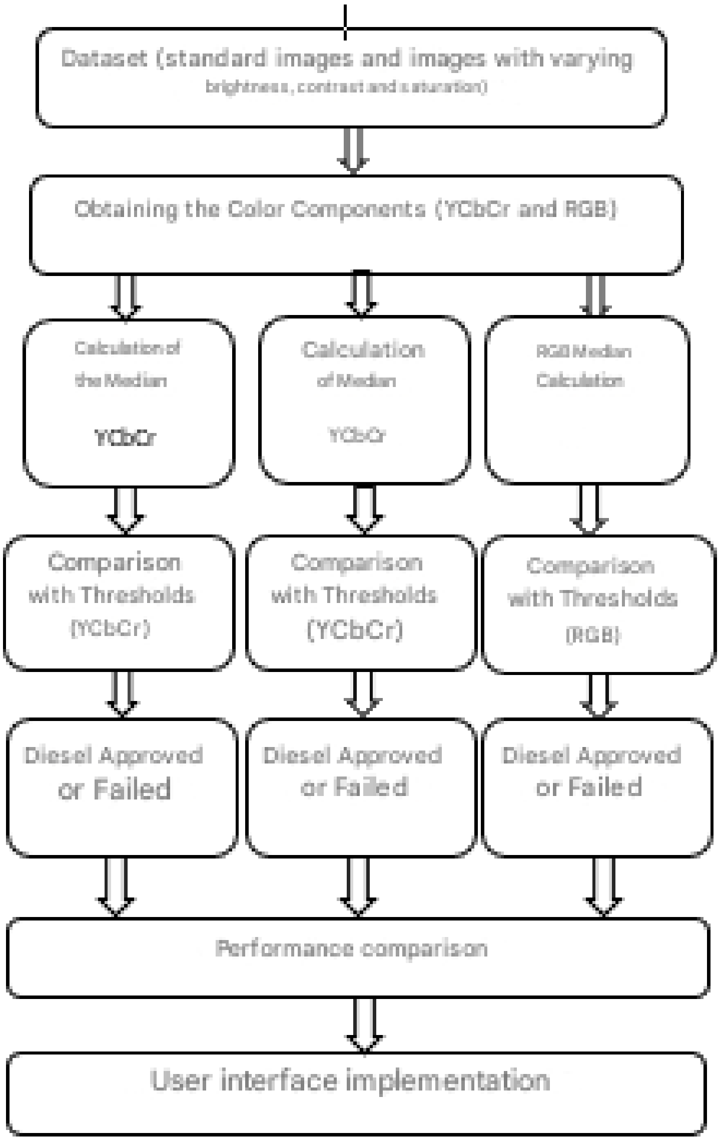
Analysis of results and determination of comparison thresholds

Based on the median values obtained in the previous step, the results were analyzed. The objective of this step was to evaluate the behavior of the diesel oil samples in each of the components (Y, YDifference, Cb, Cr, R, G, B) to verify the variation of the median values according to the colors of the diesel oil samples. From this analysis, it was possible to establish comparison thresholds for each of the components (Y, YDifference, Cb, Cr, R, G, B) with the cutoff point being the L4.0 sample, from which the oil is considered to have failed.

Data set testing

In the testing step, the previously prepared data set was used to evaluate the performance of the algorithm implemented in identifying samples with approved or failed diesel oil. Figure 7 illustrates the flowchart of the algorithm developed to automatically perform the tests on the diesel oil samples. Each of these steps is described below..

Figure 7 – Flowchart of the algorithm developed for the .... tests.



First, the images of each of the diesel oil samples were read, both the standard ones (L0.0 to L8.0) and those with variations in brightness, contrast and saturation. Then, the components Y, YDifference, Cb, Cr, R, G, B were obtained and the median for each of them was calculated. In the next step, the median values were compared with established thresholds to determine whether the sample under analysis would be approved or rejected, as illustrated in equations 1, 2 and 3.

$$\text{Sample} = \begin{cases} \text{Diesel Failed, if} \\ \text{(Ymediana < Limian, E} \\ \text{Cbmedian > Threshold E} \\ \text{Crmedian < Threshold)} \\ \text{Approved Diesel,} \quad \text{Otherwise} \end{cases} \tag{1}$$

$$\text{Sample} = \begin{cases} \text{Diesel Failed, if} \\ \text{(Ydifmediana > Threshold E} \\ \text{Comedian > Threshold E} \\ \text{Crmedian < Threshold)} \\ \text{Approved Diesel,} \quad \text{Otherwise} \end{cases} \tag{2}$$

$$\text{Sample} = \begin{cases} \text{Reapproved Diesel,} \\ \text{if (Rmedian < Threshold, AND} \\ \text{Gmedian < Threshold, AND} \\ \text{Bmedian > Thresholds)} \\ \text{Approved Diesel,} \quad \text{Otherwise} \end{cases} \tag{3}$$

Performance comparison

In the performance analysis stage, the results obtained from the tests of images with diesel oil samples with variations in brightness, contrast and saturation were analyzed. The metrics used in the validation and testing were the following: Accuracy, Precision and Sensitivity. To present these metrics, the following terms are previously defined:

a) True Positives (VP): failed diesel oil correctly identified as failed;

b) True Negatives (TN): approved diesel oil correctly identified as approved;

c) False Positives (FP): approved diesel oil wrongly identified as failed;

d) False Negatives (FN): failed diesel oil wrongly identified as approved;

Accuracy (FERRARI; SILVA, 2017) is defined in equation 4 and, in this context, it evaluates the percentage of correct answers in identifying diesel oil with failed quality.

$$ACC = \frac{VP + VN}{VP + VN + FP + FN} \tag{4}$$

Precision (SOKOLOVA; LAPALME, 2009), shown in equation (5), expresses in this context the ratio between the number of diesel oil samples that were correctly identified over the sum of all samples identified as having approved quality. Thus, it expresses the model's ability to avoid false positives..

$$Precisão = \frac{VP}{VP + FP} \quad (5)$$

Recall or sensitivity (SOKOLOVA; LAPALME, 2009), shown in equation (6), is a metric that determines, in this context, the rate of diesel oil samples correctly identified as diesel of failed quality.

$$Sensibilidade = \frac{VP}{VP + FN} \quad (6)$$

Furthermore, in the oil industry, a false negative indication, i.e., diesel oil of disapproved quality mistakenly identified as approved, generates enormous losses for the company. Therefore, in this work, the false negative rate (FNR) score is a measure that in this context expresses the rate of bad diesel oil mistakenly identified as approved. The FNR is defined according to the equation (7).

$$\mathrm{FNR} = \frac{FN}{FN + VP} \quad (7)$$

All stages of validation and testing were carried out automatically, including the generation of performance evaluation metrics.

In this work, the null hypothesis was also evaluated, stating that the results between the YCbCr and RGB color spaces for identifying rejected diesel oil samples are similar (KING; ECKERSLEY, 2019). To assess this null hypothesis ($H0$), the Chi-square test (χ^2) (HOWELL, 2011) was used, calculated from 2 × 2 contingency tables. A significance level of 0.05 was adopted for this inference. The null hypothesis ($H0$) indicates that there is no difference between the analyzed color spaces regarding the identification of rejected diesel oil samples.

User Interface Implementation

After the validation and analysis of the results in the previous stages, a user interface was created that uses a video camera to capture the test sample image. The video camera used was the Logitech webcam Pro9000 with a resolution of 640 x 480.

RESULTS

This chapter presents and discusses the following results: comparison threshold values, diesel oil quality identification, and user interface.

COMPARISON THRESHOLD VALUES

Table 01 presents the median values for each component (Y, YDifference, Cb, Cr, R, G, B) obtained for images L0,0 to L8,0.

Table 01: Median values for each color component

L	Y	YDif	Cb	Cr	R	G	B
0,0	177	0	126	129	188	188	186
0,5	166	9	99	139	192	177	117
1,0	117	62	71	164	174	111	1
1,5	134	45	61	159	186	138	1
2,0	114	64	72	165	172	106	0
2,5	95	82	82	164	149	81	1
3,0	71	106	96	160	115	50	0
3,5	82	95	90	161	131	64	0
4,0	53	124	112	152	82	30	10
4,5	50	126	119	146	69	28	21
5,0	47	130	124	141	55	28	27
5,5	37	139	128	130	29	22	26
6,0	41	138	127	132	36	26	27
6,5	35	144	128	130	25	20	22
7,0	44	135	128	127	31	33	33
7,5	35	143	130	127	21	22	27
8,0	24	154	129	126	5	10	11

As per the obtained results, for component Y, starting from sample L3,5, the brightness intensity values decrease to below 83. For component Ydif, intensity increases to values above 95 from sample L3,5. For component Cb, intensity increases to values above 90 from sample L3,5. For component Cr, intensity decreases to below 161 from sample L3,5. For components R and G, there is a reduction in intensities below 131 and 64, respectively, starting from sample L3,5. For component B, values above zero are observed for this same sample. Thus, comparison thresholds for each color component were derived, as illustrated in Table 02.

Table 02: Threshold values for each color component

Component	Thresholds
Y	80
Ydif	110
Cb	100
Cr	155
R	120
G	55
B	5

RESULTS OF DIESEL QUALITY IDENTIFICATION

Table 3 presents the results obtained from testing all images in the dataset, i.e., with variations in brightness, contrast, and saturation, totaling 192 images.

Table 3 – Performance analysis metrics

Color Space	ACC (%)	Precision (%)	Recall (%)	False Negative Rate (%)
RGB	98.96	99.07	99.07	0.00925
YCbCr	99.48	99.08	100.00	0
YDif CbCr	100.00	100.00	100.00	0

The best result was obtained using the Ydif, Cb, and Cr components, with accuracy, precision, and sensitivity (recall) all equal to 100%, and the false negative rate was zero. Using YCbCr, a false negative rate of zero and an accuracy of 99.48% were also achieved. In the case of RGB, the false negative rate was below 1%, with precision and sensitivity equal to 99.07%.

In Table 4, the confusion matrix for the RGB color space is presented. According to the results, one false positive and one false negative were generated, meaning that one sample that should have been rejected was approved, and another that should have been approved was rejected. This led to an error rate different from zero. The test image that generated the false negative was L4,0, and the one that generated the false positive was L3,0, both with saturation variation.

Table 4 - RGB Confusion Matrix

	Predicted Identification
Real Identification	Approved Diesel
Approved Diesel	107
Rejected Diesel	1

In Table 5, the confusion matrix for the YCbCr color space is presented. According to the results, one false positive was generated, meaning that approved diesel oil was mistakenly identified as rejected. The test image that generated the false positive was L3,0, with saturation variation.

Table 5 - YCbCr Confusion Matrix

	Predicted Identification
Real Identification	Approved Diesel
Approved Diesel	108
Rejected Diesel	1

In Table 6, the confusion matrix for YDif CbCr is presented. According to the results, no false positives or negatives were generated. This is the ideal situation for the oil industry, as all samples were correctly identified (approved or rejected).

Table 6 - YDif CbCr Confusion Matrix

	Predicted Identification
Real Identification	Approved Diesel
Approved Diesel	108
Rejected Diesel	0

Chi-Square Test (χ^2)

Table 7 presents the results of the Chi-square tests conducted between the YCbCr and RGB color spaces. The adopted significance level was 0.05, and since the p-value obtained in all cases was higher than the significance level, the null hypothesis was accepted, indicating that no statistically significant differences were found in identifying rejected diesel oil samples between the YCbCr and RGB color spaces.

Table 7 – Chi-Square Test Results (χ^2)

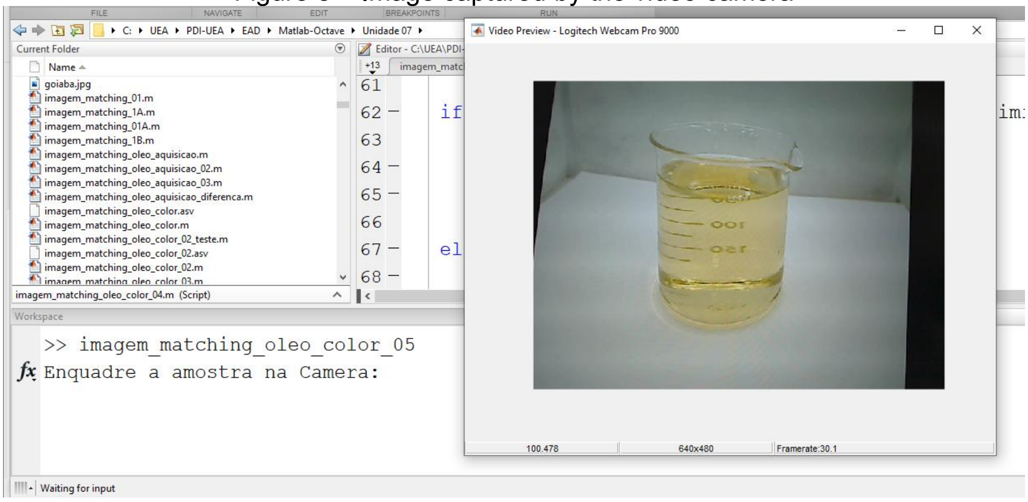
Color Spaces	(p-value)
YCbCr x RGB	0.562
YDifCbCr x RGB	0.156
YDifCbCr x YCbCr	0.316

USER INTERFACE

For the implementation of the User Interface, a video camera, the Logitech webcam Pro9000 model, was used with the following specifications and settings: resolution 640 x 480, Brightness = 128; Contrast = 32; Saturation = 28.

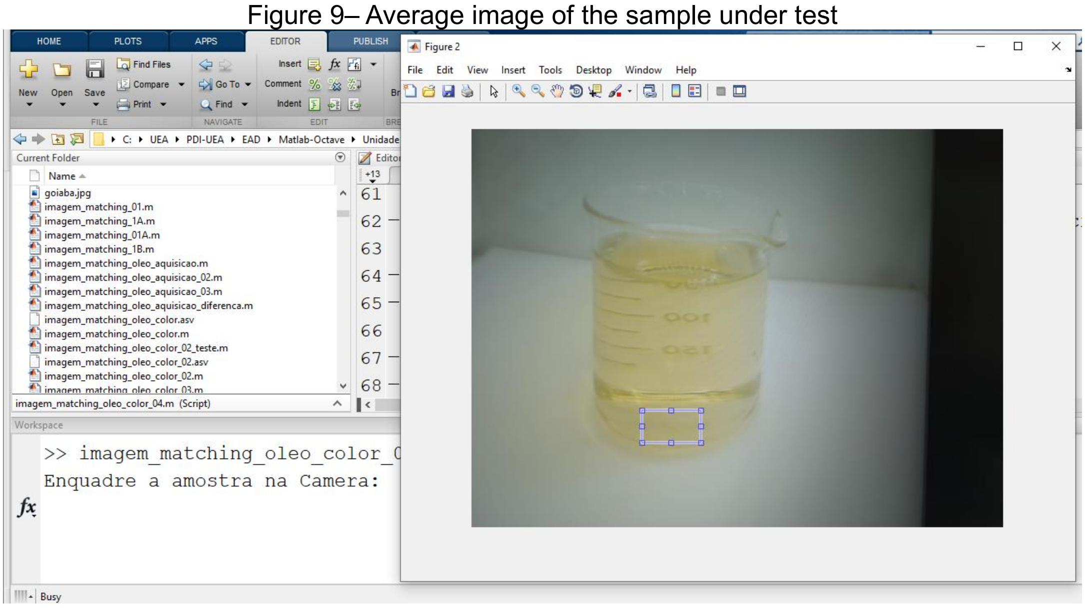
When the user runs the script in Matlab, the following message appears: “Frame the sample in the Camera,” as shown in Figure 8. The captured frame sequence is displayed so the user can position the sample image within the camera's field of view. At the bottom of the image, the resolution (640 x 480) and frame rate (30 fps) are shown.

Figure 8 – Image captured by the video camera



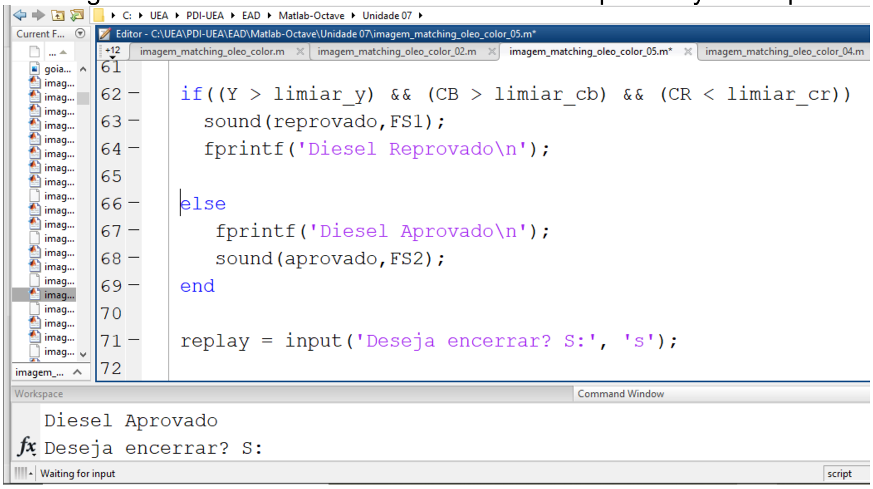
Once the sample image is positioned, the user presses the “ENTER” key and the script captures 30 frames to obtain the average image, which aims to reduce noise from the image capture process. Figure 9 illustrates the average image of the sample under test..

Figure 9– Average image of the sample under test



When the script finishes calculating the average image, it waits for the user to select a small area of diesel oil in this image, which is displayed on the screen. When doing so, the script highlights the selected area, as shown in Figure 9. When the user finishes selecting the diesel oil area, the user must double-click so that the script captures the selected area and proceeds with the analysis of the sample. At the end of the analysis, a voice message and text are emitted informing whether the sample is approved or rejected, as shown in Figure 10. The script then asks if the user wants to end or continue analyzing other samples. When typing “Y”, the script is terminated, as shown in Figure 10..

Figure 10 – Final section of the diesel oil sample analysis script



CONCLUSION

The main objective of this work was to present the application of the median in the identification of diesel oil quality. Thus, we sought to analyze three approaches using the median as a measure of the intensity of the Y, YDifference, Cb, Cr, R, G, B components. The work investigated the performance of each approach using test images on a scale of L0.5 to L8.0 with variations in brightness, contrast and saturation.

According to experimental results, using RGB, the false negative rate was less than 1% with precision and sensitivity equal to 99.07%. In this case, one false positive and one false negative were generated, that is, one of the samples that should have failed was approved and another that should have been approved was rejected. Although the false negative rate is less than 1%, this can cause disruptions in the diesel oil production process, since a false approval can cause losses to the industry, as well as a false rejection can generate unnecessary alarms.

Regarding the YCbCr color plan, a false negative rate of zero and an accuracy of 99.48% were also obtained. In this case, a false positive was generated, that is, approved diesel oil was wrongly identified as failed. The best result obtained was using the Ydif, Cb and Cr components, in which the accuracy, precision and sensitivity (recall) were all equal to 100%, and the false negative rate was equal to zero.

Analyzing the statistical inference results with the Chi-square test, no statistically significant differences were found in relation to the identification of failed diesel oil samples for the YCbCr and RGB color plans. However, considering that the use of the Ydif, Cb and Cr components did not generate false positives or negatives for the tested data set, this approach is suggested in future work that intends to implement a system for identifying the quality of diesel oil in the production process integrated with a supervisory system to assist in decision making. Regarding the video camera used to acquire images of the test samples, a resolution of 640 x 480 was used, which can be easily found on the market. If the hardware used to process the images is capable of processing 30 frames per second, in less than 2 seconds, the system will be able to identify the quality of the oil produced, which would be enough to activate the supervisory system in the refinery's production process.

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