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Combination of computer vision and laser-light backscattering imaging for oil palm fruit ripeness classification: A review

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ABSTRACT

Laser-light backscattering imaging (LLBI) is an optical imaging technique that records the interaction of light with plant tissue, generating light reflection data relevant for assessing product quality. This research combines LLBI and an RGB-based computer vision system to non-destructively classify the maturity level of oil palm fresh fruit bunches. This technique offers a faster, more cost-effective and more accurate solution than traditional methods. The analysis includes RGB imaging and light reflection, where parameters such as color intensity, principal axis length, and area are analyzed using image processing algorithms. Results showed that the combination of LLBI and a computer vision system significantly improved the accuracy of ripeness classification, with a strong correlation between imaging parameters and quality attributes such as oil content and color. This approach provides an important step in improving harvesting efficiency and the production of high-quality palm oil.

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1. INTRODUCTION

Oil palm is a crop that produces edible oil and is very desirable to grow in Indonesia since it has the ability to boost the country's economy and the welfare of its citizens [1, 2]. The primary products, palm oil and its derivatives, are significant export goods that play a significant role in the national economy [3]. Indonesia surpassed all other countries as the world's top exporter of palm oil in 2018. As a result, oil palm farms are growing an dispersing throughout Indonesia's provinces [4].

A more effective and precise method of determining the maturity of fresh fruit bunches (FFBs) is required due to the rising demand for palm oil worldwide [5]. To guarantee palm oil quality and production, FFB maturity must be determined; however, traditional techniques like visual inspection and laboratory analysis are frequently laborious and unreliable. Carotenoids and chlorophyll have an impact on fruit colour changes and oil content, which are linked to FFB maturity. Maximising the production of palm oil requires accurate maturity determination [6].

In this study, we suggest using a computer vision system in conjunction with laser-light backscattering imaging to non-destructively evaluate the maturity level of TBS. Compared to conventional techniques, this optical imaging technology provides a quicker, less expensive, and more precise solution. It is anticipated that this method, which combines visual metrics taken from RGB and laser backscattered pictures, would offer a more accurate and consistent maturity classification, which will enhance oil palm harvest management effectiveness and optimise oil yield [6].

2. THEORITICAL REVIEW

2.1. Palm Oil

One plant that originated in Africa is the oil palm (*Elaeis guineensis Jacq*). Nowadays, palm oil trees may be found in many nations, including Indonesia. Oil palm is a key product in the plantation industry and contributes significantly to the Indonesian economy. Compared to other plantation commodities, its primary product, crude palm oil (CPO), has a very high economic value and is one of the biggest sources of foreign cash. Plantations and processing facilities are now used to manage palm oil in order to create palm oil and its derivative goods [7, 8].

Indonesia's oil palm farms have been expanding quickly, which suggests that the industry has seen substantial changes. Currently, 22 of Indonesia's 33 provinces are home to oil palm plantations. About 90% of oil palm farms are found on the islands of Sumatra and Kalimantan, making these two areas the primary centres for oil palm crops. Additionally, around 95% of Indonesia's total production of CPO comes from both. The sector had a significant shift between 1990 and 2015, which was marked by a sharp rise in smallholder plantations, which expanded by an average of 24% year. According to the Ministry of Agriculture (2015), Indonesia's oil palm plantations covered 11.3 million hectares in 2015; by 2017, that number had grown to 16 million hectares. At the moment, state-owned plantations only provide 5%, while smallholder plantations account for 53% of the total, followed by private plantations at 42% [9].

2.2. Classification of Oil Palm Fresh Fruit Bunch Maturity

One of the primary elements influencing the quality of oil palm FFB is maturity level. High oil content and low free fatty acid (ALB) concentration are characteristics of the highest quality FFBs. The high ALB concentration of CPO, which should, by standard, be less than 5%, is one of the causes of its poor quality. Overripe oil palm FFB entering the processing process is typically the cause of high ALB levels [5]. Therefore, in order to generate high-quality palm oil, equipment that can determine the ripeness of oil palm fruits is required.

3. RESEARCH METHODS

3.1. Imaging by Laser-Light Backscattering (LLBI)

The use of LLBI techniques is one of the most popular optical imaging-based approaches for food safety and management. The idea behind LLBI is to record scattered light that arises from the interaction of light and plant tissue. Because of this interaction, backscattered photons can be utilised to test the quality of a product by providing valuable information on tissue morphology. Since the scattered light and the assessed plant image are captured on the same camera and system, eliminating the need for spectral analysis as is the case with near infrared radiation (NIR) imaging techniques, this approach is particularly cost-effective. In comparison to other optical techniques, LLBI technology is quicker and less expensive, and it shows promise and feasibility [10].

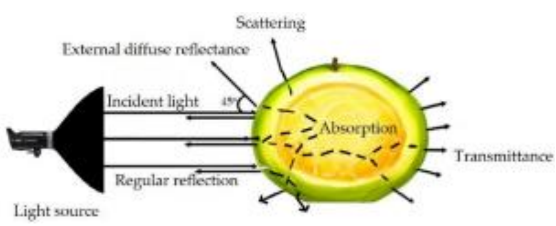

Figure 1. Reflection and light distribution in fruit [8].

One of the low-cost, cutting-edge methods that has drawn a lot of interest as a non-destructive method for a variety of food and agricultural items is LLBI. The technique makes use of the dispersed light that is caught when light interacts with plant tissue and the light source. About 4% – 5% of the interaction light is reflected back, with the remainder being absorbed or permeated into the epidermal tissue and dispersed throughout the fruit or vegetable's porous internal components. The backscattered photons that have been penetrated include pertinent information about the plant's morphological characteristics that can be used to measure the quality of the final product. Since photon scattering is dependent on the physicochemical parameters of the sample under analysis, scattering characteristics can be used to characterise the quality of a product [10].

3.2. Computer Vision Systems

Red-green-blue (RGB) imaging, often known as computer vision, is a quick and non-destructive technique that is frequently used in agricultural product classification and food quality detection. Flaw identification, variety classification, maturity level, classification, and measurement of quality attributes of different agricultural crop varieties are just a few of the jobs and inspections that have made use of computer vision. The quick picture acquisition technique and inexpensive instrumentation setup are the primary benefits of computer vision. For instance, researching the application of RGB imaging to assess how the colour of apples changes under various storage conditions [3]. In a similar vein, using RGB imaging to identify cold damage in bananas revealed a strong relationship between fruit ripeness stage and colour space. These results demonstrate that computer vision presents opportunities for the future to overcome issues with traditional approaches, especially in the areas of palm fruit ripeness detection and quality attribute monitoring [6].

3.3. Combining LLBI with Computer Vision

Two fluorescent lamps (HFB RB 218, Natural Daylight, TC-L18W, Germany), a charge-coupled device (CCD) camera (QICAM Colour Fast 1394, QImaging, Surrey, BC, Canada) with a 5.6-mm zoom lens and an 18-mm focal length, a laser diode that emits light at a wavelength of 658 nm with a maximum power of 30 mW, and a computer with imaging software (Image-Pro Insight 9, Media Cybernetics Inc., USA) for RGB and backscattering images make up this optical imaging [7].

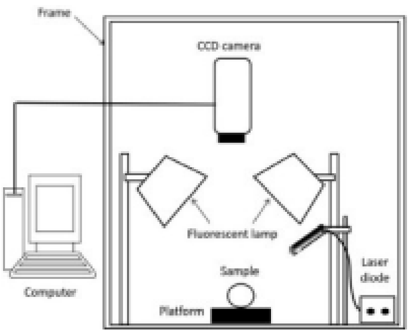

Figure 3. Schematic diagram of a combined computer vision system and LLBI [6].

The fluorescent lamp is turned on prior to the picture acquisition procedure for RGB images. In order to capture RGB photos with a resolution of 24 bit colour (1392 × 1040 pixels), the oil palm FFB sample was placed 24 cm from the reference surface onto a CCD camera in a light-tight frame with a black fabric to prevent light interference. In contrast, backscattering images were obtained using a laser diode with a wavelength of 658 nm. To ensure that the light beam was perpendicular to the sample surface, the angle of incidence between the laser diode and the TBS sample was fixed at 22°. To provide comparable dimensions during the image acquisition process, RGB and backscattering photos were both taken at the same 24-cm distance. For every TBS sample, three photos were obtained, yielding 270 RGB and backscattering images in total. The following are the items that the system examined using this combination of laser light backscatter imaging and computer vision:

3.4. Backscattering Image Analysis

The back-reflected picture of a light is analysed to classify the maturity degree of oil palm fruits. Image processing techniques created in MATLAB software (Version R2016a, The Mathworks Inc., Natick, MA, USA) are used to preprocess these backscatter images. A Gaussian filter was used to create a smoother image once the backscatter image was converted to greyscale. According to [6], a backscatter algorithm was created to calculate backscatter parameters based on picture areas.

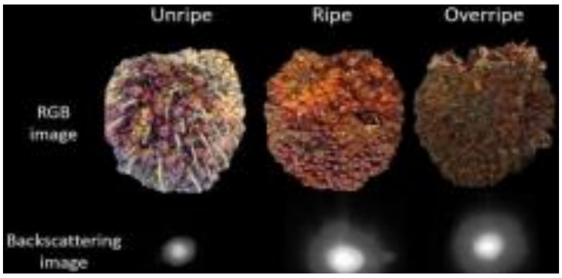

Figure 4. Images of oil palm FFBs at various stages of maturity using RGB and back-reflection techniques [6].

3.5. Analysis of RGB Images

Image processing techniques created in MATLAB software (Version R2016a, The Mathworks Inc., Natick, MA, USA) were used to segment the RGB images. To enhance image quality and distinguish the region of interest from the background, pre-processing and image segmentation are crucial. Using a thresholding technique, the RGB images of oil palm FFB samples are segmented. The ideal threshold value is found to eliminate the image's background and produce the region of interest. To eliminate background noise, a filtering procedure is used. The segmented image's original colour is recovered using a mask operation, and it is subsequently transformed into a binary image for feature extraction using RGB parameters. Red, green, and blue colour spaces are among the RGB parameters that were taken from the picture.

4. RESULTS AND DISCUSSIONS

4.1. Variations in FFB Quality at Different Maturity Levels

Every FFB maturity level has a unique characteristic. Unripe and not overripe oil palm fruits yield the highest grade. The oil content and colour quality (L*, a*, and b*) of oil palm FFB at three distinct maturity levels are shown in Table 1. The colour values of oil palm FFB varied significantly ($p < 0.05$) across the maturity phases. From the unripe to the ripe stage, the L* value increased; however, in the overripe group, it then dropped to 40.20. Additionally, the raw group's a* value rose from 16.76 to 32.37, while the overripe group's a* value slightly declined to 32.10. The b* value followed a same pattern, rising from the unripe to the ripe stage before falling to 31.06 in the overripe group. The presence of carotenoid pigments, which are known to be the source of red colour, is responsible for the red hue observed on the surface of oil palm FFBs.

Table 1. lists the quality metrics for oil palm FFB at various stages of maturation.

Level of Maturity	L*	a*	b*	The percentage of oil content %
Raw	34.62 ± 1.66	16.76 ± 1.96	15.35 ± 3.15	15.21 ± 1.01
Unripe	44.41 ± 1.39	32.27 ± 1.20	33.10 ± 2.80	38.98 ± 1.08
Overripe	40.20 ± 1.51	32.10 ± 1.54	31.06 ± 2.51	41.22 ± 2.55

As shown in Table 2, the average values of the RGB and backscatter characteristics of oil palm FFB—red, green, blue, major axis length, minor axis length, average intensity, and area—at three distinct maturity levels—unripe, ripe, and overripe—are displayed by the ANOVA (Analysis of Variance) results.

The maturity level had a significant impact on all parameters at $P < 0.05$. The overripe group had the highest mean values for red and green, at 0.70 and 0.59, respectively. The mature group was shown to have an impact on the measure blue (0.45). Likewise, the major axis length (156.99) and minor axis length (141.47) were the most impacted characteristics in the ripe group. On the other hand, the mature group had an impact on the parameters (481.68), but the raw group had an impact on the average intensity (106.23). Overall, it was found that the various maturity levels of the oil palm FFBs had a substantial impact on the RGB and back-reflection parameters (red, green, blue, main axis length, minor axis length, average intensity, and area).

Table 2. Results of an ANOVA comparing the average RGB parameter and reflectance values at various stages of development (raw, ripe, and overripe).

Parameter	Raw	Ripe	Overripe	Probability
Red	0.21	0.33	0.70	0.0026
Green	0.36	0.53	0.59	< 0.0001
Blue	0.35	0.45	0.38	0.0012
Principal axis length	92.35	156.99	154.42	< 0.0001
Length of the minor axis	80.90	141.47	138.41	< 0.0001
Average intensity	106.23	97.00	94.96	< 0.0001
The perimeter	275.52	481.68	476.78	< 0.0001

4.2. Light Back Reflection Laser and RGB Imaging Optical Properties

The link between the oil content, colour value, and surface area of oil palm FFBs is ascertained by applying a logarithmic equation to the dataset. Based on each RGB parameter, the surface area is computed to forecast the oil content and colour value of oil palm FFB. In an RGB image, where RGB parameters are represented by greyscale pixel components, the lighted region is chosen to evaluate the surface area determination. Table 3 displays the regression model of oil content and colour value of oil palm FFB based on RGB parameters. The a* value and Green parameter yielded the highest R^2 value related to surface area ($R^2 = 0.90$). At the same time, the Blue parameter had the strongest link with the L* value ($R^2 = 0.78$), b* value ($R^2 = 0.89$), and oil content ($R^2 = 0.61$). This is explained by the chlorophyll content's significant absorption band in the 500 – 700 nm wavelength range [1]. Because the standard errors for all quality variables were below 6.0, regression analysis also demonstrated that oil palm FFB's colour value and oil content could be accurately predicted using RGB parameters. The evolution of apple colour was also studied by [2], who found similar results, with R^2 values of 0.59 and 0.63 for the Red and Green parameters, respectively. However, the Red parameter is less effective at forecasting colour changes in apples, as evidenced by the greater standard error of 13.0. To find the right surface area for palm oil FFB samples, more investigation would be helpful.

Table 3. Oil palm FFB's colour value and oil content regression model based on RGB parameters.

Quality	RGB parameter	Model	R^2	Standard error
Oil Contents	Red	$OC = 16.35 \times \log(Ar) - 12.53$	0.56	5.64
	Green	$OC = 18.36 \times \log(Ar) - 14.65$	0.57	3.89
	Blue	$OC = 14.46 \times \log(Ar) - 18.57$	0.61	4.77
L^*	Red	$L^* = 34.65 \times \log(Ar) - 11.16$	0.71	3.56
	Green	$L^* = 42.74 \times \log(Ar) - 13.65$	2.89	2.89
	Blue	$L^* = 40.74 \times \log(Ar) - 11.82$	0.78	4.75
a^*	Red	$a^* = 36.26 \times \log(Ar) - 21.64$	0.82	1.56
	Green	$a^* = 32.72 \times \log(Ar) - 18.46$	0.90	3.67
	Blue	$a^* = 36.25 \times \log(Ar) - 23.63$	0.88	2.78
b^*	Red	$b^* = 31.63 \times \log(Ar) - 11.74$	0.85	0.89
	Green	$b^* = 25.74 \times \log(Ar) - 18.48$	0.78	3.46
	Blue	$b^* = 28.26 \times \log(Ar) - 12.54$	0.89	2.75

4.3. Optical Properties and Palm Oil FFB Quality Correlation.

Table 4 shows the relationships between the quality features of oil palm FFB and the combined imaging parameters. Based on RGB and backscatter photos, characteristics can be identified thanks to the results, which demonstrate a strong association between oil content and colour values of oil palm FFB. All of the backscatter parameters—major axis length, minor axis length, average intensity, and area—had a high association ($r > 0.50$) with the colour value and oil content of the palm oil FFB. Nevertheless, for all RGB parameters—that is, red, green, and blue—L* values were not significant. Average intensity and oil content of oil palm FFB had a positive correlation ($r = 0.822$). Between RGB parameters and oil content. Likewise, there is a positive correlation ($r = 0.798$) between the L* value and the average intensity. The only colour and oil content value that exhibited a substantial connection with the RGB parameter Green (r = 0.776) was the a* value. In contrast, the b* value showed the strongest connection (r = 0.953) with the Blue parameter. This finding implies that the development of pigments throughout the ripening process of oil palm FFBs may account for the disparity between the RGB and back-reflection parameters. In this instance, the qualitative features of oil palm FFB can be ascertained using the combined imaging parameters.

Table 4. Pearson correlation coefficients between the quality features of oil palm FFBs and the integrated imaging parameters.

Parameter	Oil contents	L*	a*	b*
Red	0.720	0.414^{ns}	0.597	0.825
Green	0.419	0.584^{ns}	0.776	0.883
Blue	0.771	0.410^{ns}	0.523^{ns}	0.953
Principal axis length	0.587	0.625	0.649	0.585
Length of the minor axis	0.582	0.606	0.634	0.567
Average intensity	0.822	0.798	0.514	0.776
The perimeter	0.606	0.613	0.647	0.578

5. CONCLUSION

In spite of various contextual factors, including variations in background lighting conditions, contrast between the fruit and its surroundings, and vibrations brought on by various harvesting angles, the deep learning model created in this study shows the ability to identify coffee fruits and categorise their ripening stages. With 86.0% accuracy for immature fruits, 85.2% accuracy for ripe fruits, and 80.0% accuracy for overripe fruits, the model demonstrated remarkable average precision rates. These outcomes demonstrate how well the model can identify and categorise coffee fruit maturation stages.

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