Agr. Nat. Resour. 57 (2023) 859–868

AGRICULTURE AND NATURAL RESOURCES

Journal homepage: http://anres.kasetsart.org

Research article

Real-time oil palm ripeness classification of fresh fruit bunches using fluorescence technology

Phaireepinas Phimpisan[a,*], Chatchapol Chungchoo[b,†]

[a] *Department of Maritime Engineering, Faculty of International Maritime Studies, Kasetsart University Sriracha Campus, Chonburi 20230, Thailand*

[b] *Department of Mechanical Engineering, Faculty of Engineering, Kasetsart University, Bangkok 10900, Thailand*

Article Info

Article history:
Received 7 June 2023
Revised 11 October 2023
Accepted 13 October 2023
Available online 31 October 2023

Keywords:
Fluorescence technique,
Fluorescence spectroscopy,
Non-destructive method,
Oil palm grading,
Oil palm ripeness classification

Abstract

Importance of the work: The precise and non-destructive grading of oil palm fresh fruit bunches (OPFFBs) is crucial in determining the profit for farmers selling the product to factories.

Objectives: To investigate the accuracy of fluorescence technology combined with image analysis technology in categorizing OPFFB ripeness.

Materials & Methods: A combination of eight ultraviolet light-emitting diodes (UV LEDs) were used in the wavelength range 395–400 nm along with image processing techniques to classify oil palm ripening in the Tenera variety (80 ripe and 20 under-ripe bunches). Afterward, the UV LEDs stimulated the OPFFBs in darkness, as indicated by fluorescence in the image processing. To validate the results, the fluorescence visibility results were compared with the results manually provided by five experts and with crude palm oil percentages obtained from 600 fruits samples extracted using an organic solvent (six fruits were sampled from each bunch).

Results: The equipment yielded results that were deemed 100% accurate, as confirmed by experts and the crude palm oil percentages obtained from laboratory analysis.

Main finding: The research equipment demonstrated enhanced fluorescence visibility for assessing the maturity of Tenera variety oil palm fresh fruit bunches. This technique may have potential applications in assessing the maturity of other oil palm varieties, as well as different types of fruit.

† Equal contribution.
* Corresponding author.
E-mail address: phaireepinas.ph@ku.th (P. Phimpisan)

https://doi.org/10.34044/j.anres.2023.57.5.12

Introduction

Oil palm is one of the top commercial agricultural crops in Thailand and Southeast Asia with the main by-product after oil extraction being oil palm fresh fruit bunches (OPFFBs) that can be utilized in many products used daily, including as an alternative fuel for firing a steam turbine in a ship or in any other vehicle as a biodiesel (Olisa and Kotingo, 2014; Suwajittanont et al.,). There are more than 200,000 oil palm farmers across Thailand, with most of their oil palm plantation areas along the southern coast in many provinces, including Krabi, Surat Thani, Nakhon Si Thammarat and Chumphon that account for 85% of oil palm plantation and the crude palm oil industry (Vanichseni et al., 2002; Sowcharoensuk, 2020). The major oil palm varieties found in Thailand are Dura, Pisifera and Tenera. The current research investigated the Tenera variety in Nakhon Si Thammarat province, which has the largest oil palm plantation area in Thailand (Regional Information Center (Southern), 2005). In addition, based on general discussion with representatives of the Department of Agriculture and oil palm cooperatives, the major issue between plantation owners as sellers and factories as buyers was the degree of oil palm ripeness because the oil and free fatty acid contents are influenced by the ripeness (Makky and Soni, 2014).

The correct classification of oil palm fresh fruit bunches (OPFFBs) for the factory is very important and needs to be carried out as rapidly as possible because OPFFB quality and a long storage time could decrease the crude palm oil (CPO) percentage, which would greatly impact on the economics of the industry. Generally, the plantation owner thinks primarily of the income earned from selling OPFFBs by weight, whereas the CPO quality is the greatest concern for the factory. Therefore, the factory needs to categorize OPFFBs as quickly as possible to process the ripe OPFFBs and maximize the profit and CPO percentage. The normal method to determine the batch CPO percentage involves oil samples after the milling and refining processes being analyzed in a laboratory, based on solvent extraction. Manual grading of OPFFB is very difficult for a plantation owner, even an expert grader.

Some non-destructive methods of OPFFB ripeness classification are briefly reviewed below: evaluation of color models, laser-based imaging, machine vision, near infrared spectrometry (NIRS) and fluorescence techniques.

The oil palm skin color is a common characteristic indicating ripeness and oil content, with the surface color being the most common OPFFB grading system which produced 55–56% accuracy (Choong et al., 2006). The colored edge method used in determining the oil skin palm color using machine vision system has a classification accuracy of 19.89 %. (Teh and Tan, 2021). OPFFB physical growth stages were classified according to the spine fruitlet (green sharp spines or brownish blunt spines) on a weekly basis where the coefficient of determination for the developed model was 0.95 (Kassim et al., 2014). Furthermore, Hazir et al. (2012a) studied the relationship between flavonoids and anthocyanin as predictors of the oil palm ripening stage, achieving the highest overall classification accuracy of 87.7%.

A laser-based imaging system (called hyperspectral imaging) with two diode lasers was used to examine the reflectance due to interaction with an OPFFB pigment of anthocyanin and chlorophyll contents (Shiddiq et al., 2017). Techniques using color-based machine vision linked to computer applications used the color intensity to differentiate OPFFB ripeness categories (Abdullah et al., 2002), with further application to classify the ripeness based on the color and texture successfully achieving an accuracy of 98.3% (Septiarini et al., 2021). This technique could use any visible color light source (Zheng et al., 2006). Makky (2016) applied imaging software to calculate and classify an OPFFB ripeness image in RGB color. Another machine vision technology developed an automated photogrammetric grading system (Jaffar et al., 2009). The first automatic grading machine in Indonesia also used image processing with an average classification success rate of 88.7% (Makky and Soni, 2013), while another approach applied the Kullback-Leinler distance method based on the same technology to achieve 96% accuracy (Taparugssanagorn et al., 2015) and Alfatni et al. (2014, 2020) applied image processing with expert rules on color histograms and statistical color features that resulted in an overall correct ripeness classification accuracy of 94%. A portable, multi-band system with active optical sensors was developed to detect OPFFB ripeness with four spectral bands (Saeed et al., 2012). The OPFFB spectral reflectance was investigated using two statistical analyses based on a forward-stepwise method and a combination of principal component analysis and a multilayer perceptron neural network, producing a classification accuracy of greater than 80% (Makky and Soni, 2014), while Hong et al. (2021) also included Raman spectral features and achieved 95.48% accuracy. An artificial neural network based on principal component analysis was combined with color vision to improve the classification accuracy by 1.66% (Fadilah et al., 2012), while Suharjito et al. (2021) included this approach in an Android application on a mobile device with 81–89% accuracy.

Near infrared spectrometry (NIRS) is one of the non-destructive methods (Ismail, 2010), consisting of light detection and ranging (LiDAR) scanning systems that have been studied to classify oil palm ripeness in the Malaysian oil palm industry, where the proposed approach was based on calculating the reflectance percentage using the concept of linearity (Zulkifli et al., 2018). Another application classified oil palm ripening into under-ripe, ripe and over-ripe categories using hand-held, multi-parameter fluorescence sensors and blue-green (447 nm) and far-red (685 nm) wavelengths. The excitation light source was an ultraviolet light-emitting diode with overall testing classification of 90% (Hazir et al., 2012b). With a different technology, oil palm ripeness was tested using a proposed air coil sensor based on an inductive sensor with a frequency range from 20 Hz to 20 MHz (Misron et al., 2014).

Most research into oil palm classification methods has been based on classifying OPFFB ripeness using the spectral color stage and equipment on a laboratory scale. The aim of the current research was to apply fluorescence techniques as a nondestructive way to classify OPFFBs by the color change in the skin pigment ripening stages based on machine vision. Developing a fluorescence grading machine instead of relying on a human expert grader could speed up the process and reduce human errors.

Classification of oil palm ripening stage

Most plants and fruit have almost the same compounds but might have different pigment types determining their skin color during the ripening stage, with harvesting and transporting potentially damaging some OPFFB characteristics and releasing lipolytic compounds and enzymes that affect the color properties (Hazir et al., 2012a). The relationship of the OPFFB skin color to the oil contents can be used to determine ripeness stages (Balasundram et al., 2006; Choong et al., 2006). There are three major pigments found in plants (chlorophylls, carotenoids and flavonoids) that absorb and reflect different wavelengths of light (Daniele, 2022) as shown in Fig. 1.

Fluorescence spectroscopy was used to differentiate closely related citrus genotypes (Santana-Vieira et al., 2014). Oil palm ripeness is also related to these methods.

Use of fluorescence for OPFFB grading

In general, fruit and plants contain pigments that can absorb and reflect energy from light. Chlorophyll fluorescence and the application of the technique were studied in samples at ripening, storage and postharvest. During fruit ripening, the physiological pattern of pigment composition changed markedly, accompanied by the progressive disappearance of chlorophyll. The main features of the spectral fluorescence belong to anthocyanins, flavonoids, carotenoids and chlorophyll A after excitation of the fruit skin (Hazir et al., 2012a). Flavonoid and anthocyanins are particularly useful for differentiating plant quality, such as pigments in different tomato skin ripening stages that were obtained at excitation wavelengths to absorb and reflect the spectral fluorescence of chlorophyll/flavonoids and carotenoids/chlorophyll (Lai et al., 2007).

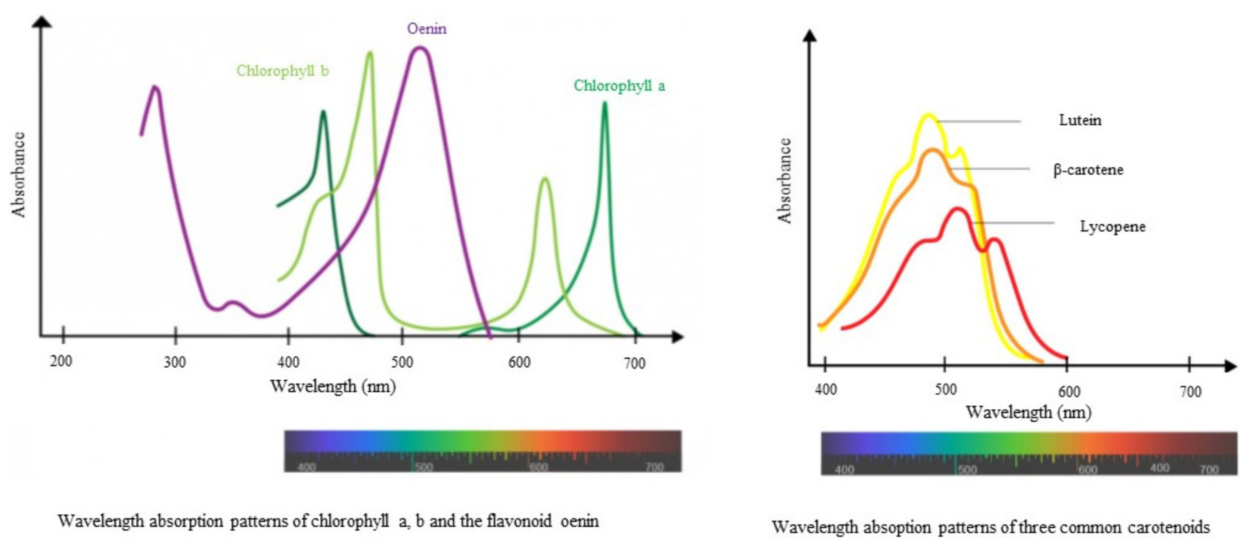

Fig. 1 Plant wavelength absorption patterns (Daniele, 2022)

Under ultraviolet excitation, green plants emit red, far-red and blue-green fluorescence, mainly coming from hydroxycinnamic acids (Buschmann et al., 2000), where the range of colors depends on the amount of carotenoids contents in the oil palm skin ripeness stages (Hadi et al., 2009). The advantages of rapid and nondestructive OPFFB classification are reduced time and human errors regarding the CPO extraction percentage. OPFFB ripening quality, specifically the skin anthocyanin and flavonoid contents, has been detected using fluorescence sensors (Hazir et al., 2012a).

Other studies have found that OPFFB classification requires using the right light source with the right wavelength range (to be able to see the fluorescence of the various OPFFB ripening stages) combined with machine vision technology. The core technology of the current research was applied based on the advantages of those technologies.

The current study was conducted to investigate the accuracy of fluorescence technology combined with image analysis technology in categorizing OPFFB ripeness.

Materials and Methods

Sample collection and preparation

The random samples consisted of the three Tenera oil palm varieties (Surat Thani one, Surat Thani two and Univanich) grown in Nakhon Si Thammarat province, Thailand whose OPFFBs had the same characteristics of skin color shades of ripening stages (yellow, orange, reddish-orange, reddish-brown, dark reddish), as shown in Fig. 2.

The first sample set was 100 OPFFBs that were classified using the real-time fluorescence grader, where the palm fruit sample had previously been classified by five expert graders at the factory who based their decisions on OPFFB ripeness skin color, total number of empty sockets, mesocarp color and detached fruitlets (Hazir et al., 2012a). The sample was split into two sub-groups with 20 under-ripe OPFFBs and 80 ripe OPFFBs.

Based on the natural oil palm ripeness stage, oil palm fruit can be separated into three major categories: under-ripe, ripe and over-ripe. It was hypothesized that these stages could be differentiated using plant pigments. For grading into these categories, other research and a common grading technique found that mostly OPFFBs depends on the skin pigment colors, the number of empty sockets and detached fruitlets, representing classification accuracy (Hazir et al., 2012a). In general, most farmers working in oil palm plants use the same concept as Choong et al. (2006) and Hazir et al. (2012a), as described in Tables 1 and 2 (Hazir et al., 2012a).

Categorization of OPFFB ripeness was based on fruit skin colors, as shown in Fig. 2. For Tenera, the young OPFFB was black or dark purple, with an interim change to orange and when fully ripe final turning red, reddish-brown or even dark reddish-purple.

The second sample set was oil palm fruit that was used to confirm the results of the rapid fluorescence grader equipment, with oil palm fruits from each bunch being tested using solvent extraction in the laboratory. As shown in Fig. 3,

Table 1 Oil palm fresh fruit bunch ripeness categories based on total number of empty sockets and mesocarp color (Hazir et al., 2012a)

Total number of empty sockets	Mesocarp color		
	Yellow	Yellowish/Orange	Orange
0	Under-ripe	Unripe	Ripe
1–10	Under-ripe	Under-ripe	Ripe
>10	Under-ripe	Ripe	Ripe

Source: (Hazir et al., 2012a)

Table 2 Detached fruitlets of oil palm fresh fruit bunch

Category	Description
Ripe	10–50% of fruits detached from bunch
Over-ripe	51–90% of fruits detached from bunch
Under-ripe	1–9 fruits detached from bunch

Source: Hazir et al. (2012a)

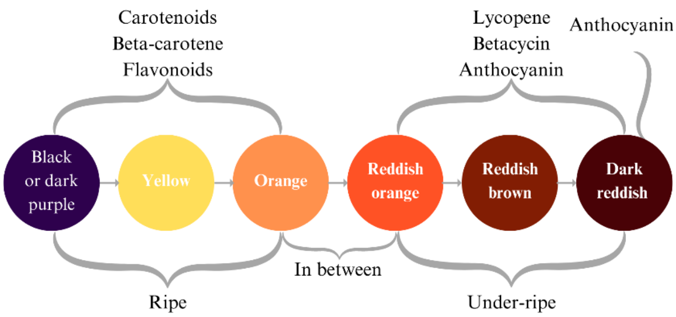

Fig. 2 Oil palm ripening stage colors

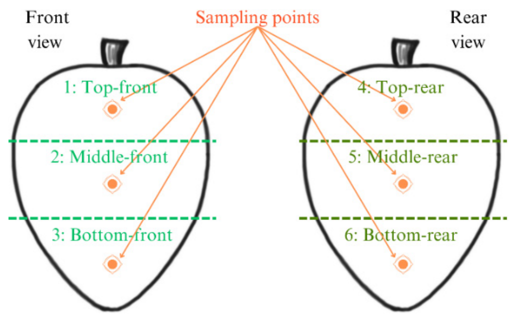

Fig. 3 Sample selection method

the bunch was separated into two halves and divided into six sections (top-front, top-rear, middle-front, middle rear, bottom-front and bottom-rear), with both the front and rear sides flipped 180° and then one fruit per section was collected as a sample. After the solvent extraction process, the average crude oil palm percentage yield was calculated for each bunch.

The organic solvent extraction process was used to confirm the results of the real-time visible fluorescence grading equipment. Generally, solvent extraction is used to extract the residual oil from oil palm fruit, with many possible solvents, including hexane, acetone, chloroform, methanol and ethanol (Sivarao et al., 2012) Therefore, in the current research, the CPO was extracted to confirm the equipment results.

Classification accuracy as a percentage (Taparugssanagorn et al., 2015) for OPFFBs based on samples correctly classified by experts from the factory, was calculated using Equation 1:

$$\text{Classification accuracy} = \frac{\text{Number of correct samples}}{\text{Number of total samples}} \times 100 \qquad (1)$$

Equipment overview

The OPFFB classification equipment used ultraviolet (UV) light-emitting diode (LED) light sources to stimulate the OPFFB that was combined with image processing that captured the OPFFB fluorescence reaction, as shown in the concept design in Fig. 4A.

In this experiment, the light source was changed from a RGB light to a UV LED because plants can easily detect and reflect energy and grow well under UV LEDs, as evidenced by the many plants grown indoors. Another benefit of UV LEDs is that they are cheaper and easier to obtain.

The real-time OPFFB classification equipment was created using computer-aided design software, as shown in Fig. 4B and could be applied to a conveyor or chamber OPFFB ripeness sorting system. The classification equipment consisted of the mechanism, image processing and a fluorescence ripeness classification program. The structure was designed to be manufactured using mainly stainless-steel for the frame and most other parts, to avoid corrosion and to reduce the weight. The dimensions (width, length, height) of the equipment were 510 mm × (760–1,040) mm × 240 mm. The attached machine vision system consisted of an adjustable camera (±40 mm to ±100 mm focal length) and controller circuit systems.

Equipment description

The equipment developed used an ESCAM C0004426 high-definition autofocus camera (ESCAM Technology Company Limited, ShenZhen, China) with a resolution of 1920 pixels × 1080 pixels, an OEM High Power integrated chip on board (UMAKED, ShenZhen Yike Technology Company Limited, Guangdong, China) supplying 10 W to eight 8 UV LEDs, producing a wavelength range of 395–400 nm for stimulating OPFFBs. The working distance between the light sources and the peak of the OPFFB was not less than 30 cm. To classify the OPFFBs in real-time takes 2–5 s to capture the fluorescence images using the PALM_CAMERA software (Microsoft Visual Studio 2019, Microsoft Company

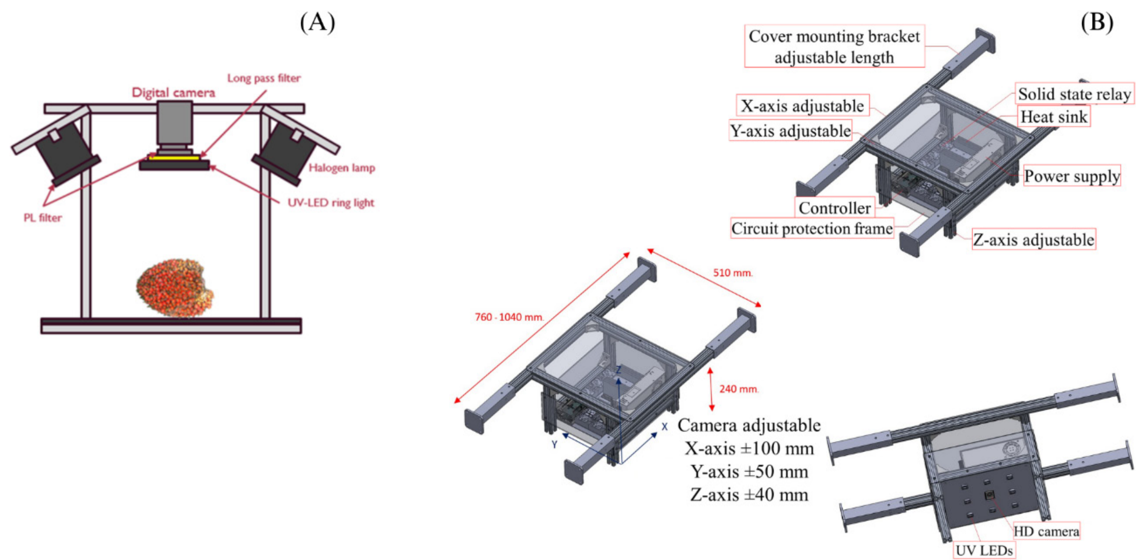

Fig. 4 Equipment design: (A) concept design; (B) hardware design using computer-aided design software

Limited. Redmond, WA, USA), using the C language program and statistical analysis from luminous pixels as shown in Fig. 5A.

Several systems needed to be interconnected before operating the program. The software needed to interact with the camera that was plugged into the computer by clicking and holding the connect button until it turned green and showed “Connected”, followed by the operational process shown in Fig. 5C, which produced the software onscreen window, similar to Fig. 5B at which stage, the equipment was ready to classify OPFFB ripeness. The verification process differed for the different samples.

Experimental setup and design

The objective of this research was to verify the relationship between OPFFB fluorescence and the ripening stage and to investigate the accuracy of fluorescence technology in categorizing OPFFB ripeness. Based on the literature review, fruit and plants have different pigments depending on their type and ripening stage, with additional complexity due to the same type of fruit presenting different colors on the skin during the ripening stage. Fruit skin color change can result from changes in the amounts of various plant pigments, such as chlorophyll, anthocyanin, carotenoid and beta-carotene. Since color is an important indicator used by agriculturists to determine the ripeness of OPFFB, it is critical to determine the right ripeness color. Oil palm fruit contains beta-carotene (Hong et al., 2021), which can become fluorescent when stimulated by the appropriate UV LED spectrum. The RGB color system is based on the combination of red, green and blue light with additive combinations. The HSV (hue saturation value) color system determines which color to use for the hue saturation and value, with the hue primary color values of red, green and blue (Sabri et al., 2018). Hyperspectral imaging has been reported to produce the best visible wavelengths for OPFFB ripeness category in the range 600–1000 nm (Hazir et al., 2012b).

For most of the common fluorescence techniques, the chamber or working area must have less light or be in relative darkness to see fruit luminescence clearly. Thus, the current research equipment consisted of a dark chamber as the working space to stimulate the OPFFB and capture obvious fluorescence based on image processing technology

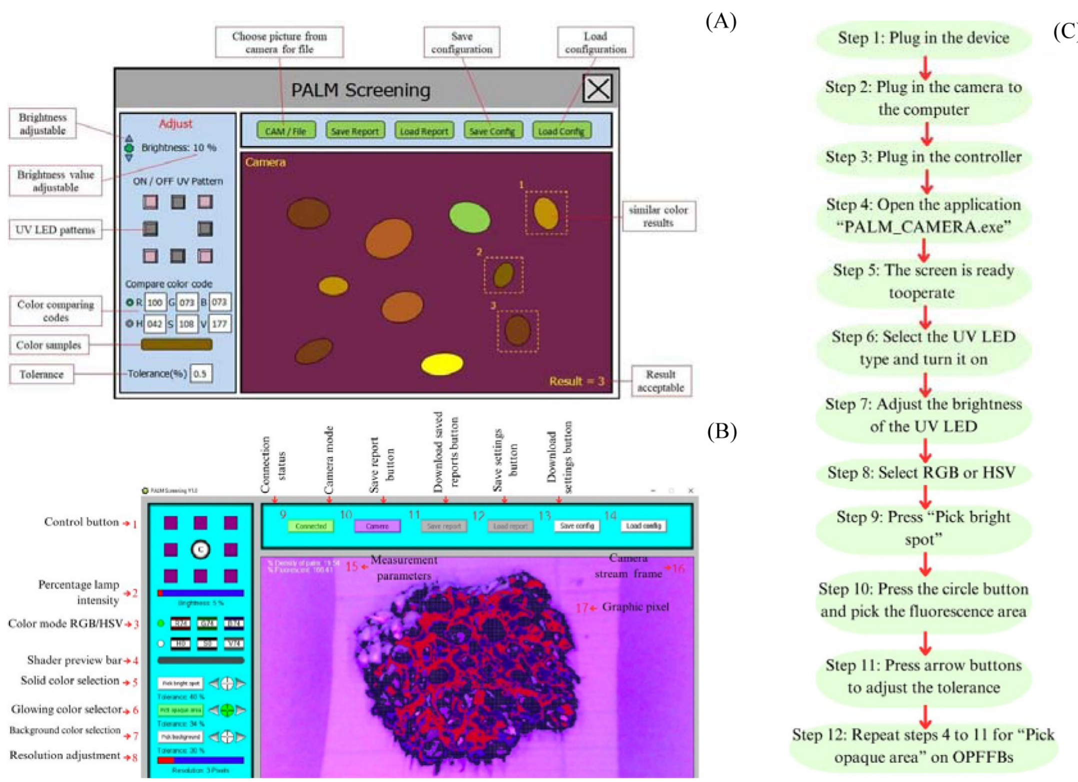

Fig. 5 A) PALM_CAMERA software window; (B) program window details for equipment operation; (C) operational flow chart for equipment

Ethics statements

This research did not contain any studies with human or animal subjects.

Results and Discussion

Oil palm fresh fruit bunch ripeness using visible fluorescence

Examples of ripeness prediction of oil palm fruit based on the visible fluorescence of RGB light source detectors are shown in Fig. 6.

Comparing the green-light and red-light sources indicated that it was difficult to see the oil palm fruit based on the green-light source detector, especially for under-ripe fruit (Fig. 6A). The red-light source for the same bunch is shown in Fig. 6B. Based on green-light and red-light sources, the visible fluorescence of the ripe oil palm fruit was more readily detected than for the under-ripe bunches. Thus, while it was confirmed that the fluorescence reflection from an RGB light source was visible, it was not that accurate, as shown in Figs. 6A and 6B where the luminosity is not clearly evident. Sabri et al. (2018) assumed the fluorescence spectral method model could determine the OPFFB ripeness more clearly and tested eight color models using 500 images of OPFFBs, with their results indicating that two color models which are YCbCr (operation in digital video and image compression) and YUV (defines a color space) produced higher luminosity levels than other models. Thus, the next step was to classify OPFFB ripeness from the fluorescence technique combined with the programmable machine vision technology.

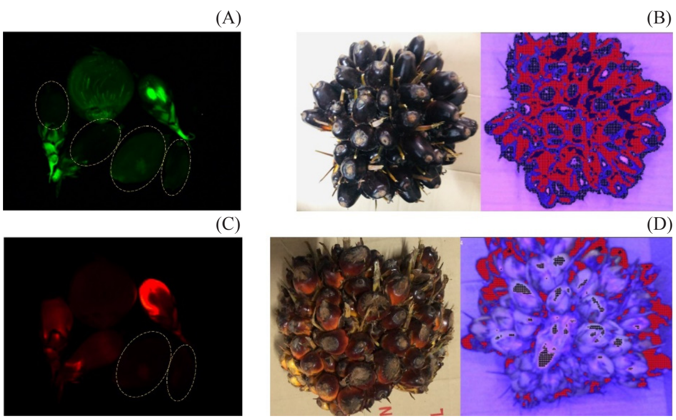

Fig. 6 Oil palm fruit visible fluorescence, where yellow dashed-line ellipses represent under-ripe oil palm fruit using: (A) green light; (B) red light. Fluorescence luminosity (C) invisible (under-ripe); (D); visible (ripe)

Oil palm fresh fruit bunch ripeness using fluorescence technique combined with machine vision system

The programmable machine vision equipment used the UV LED light source with wavelengths in the range 395–400 nm to stimulate the first sample set of OPFFBs, using 100 OPFFBs (both ripe and under-ripe) to test the equipment.

The fluorescence reaction for the under-ripe sample tested is shown in Fig. 6C. After stimulating the bunch with the UV LEDs, there was not much fluorescence reaction on the screen of the under-ripe sample. It showed most of the thick red shading on the OPFFB shape. On the other hand, with testing of the ripe sample (Fig. 6D), there was more obvious fluorescence than just the thick red shading on the screen. Clearly, ripe OPFFBs had substantially greater luminosity than under-ripe ones, with all 100 bunches sampled producing the same result. The equipment worked well and could distinguish the ripeness of the OPFFBs.

The second sample set of average CPO yields of each bunch was used to confirm the ripeness classification from real-time fluorescence equipment detection based on solvent extraction; the results are shown in Table 3.

Comparing the use of the UV LEDs to stimulate OPFFBs with the results from other research, the equipment in the current tests combined with the software also created for the current study (as shown in Fig. 5) was better at showing visible fluorescence in the image, regardless of whether under-ripe or ripe stages were tested. For example, the result of Choong et al. (2006) showed 55–56% accuracy. Specifically, with the RGB light source, it was difficult to see the visible fluorescence in the under-ripe oil palm fruit and was not satisfactory for the ripe one shown in Fig. 6.

The second sample set was extracted using an organic solvent (hexane) to determine the crude palm oil percentage and the average yield of each bunch was calculated. The average potential oil yield, based on the percentage of OPFFBs, for the ripe bunches was in the range 13.309–15.673% and for the under-ripe bunches was in the range 20.625–22.795% (Ruswanto et al., 2020). The results of the average CPO yields (shown in Table 3) indicated that the average CPO for the under-ripe samples was less than the under-ripe potential average oil yield (the under-ripe samples were considered to have low CPO which affected the average CPO potential of the collected samples) based on the quality index of CPO references from Table 4 (Ruswanto et al., 2020). In addition, the average CPO for the ripe samples was greater than or equal to the ripe potential average oil yield. Both major categories showed that the average CPO results from the solvent extraction laboratory were related to the results of the expert graders and the visible fluorescence images from the equipment program and equipment accuracy, where the classification result accuracy was 100%.

Table 3 Results of luminous visibility and average crude palm oil (CPO) yields

No.	Expert	Visibility	Avg. CPO	No.	Expert	Visibility	Avg. CPO	No.	Expert	Visibility	Avg. CPO
UR01	UR	A	13.78	R15	R	B	31.22	R49	R	B	29.46
UR02	UR	A	11.70	R16	R	B	29.71	R50	R	B	31.52
UR03	UR	A	8.49	R17	R	B	25.60	R51	R	B	32.18
UR04	UR	A	8.53	R18	R	B	20.58	R52	R	B	29.95
UR05	UR	A	6.52	R19	R	B	30.06	R53	R	B	25.84
UR06	UR	A	7.24	R20	R	B	32.65	R54	R	B	30.63
UR07	UR	A	15.16	R21	R	B	27.96	R55	R	B	29.42
UR08	UR	A	11.75	R22	R	B	23.95	R56	R	B	31.23
UR09	UR	A	17.32	R23	R	B	22.17	R57	R	B	26.53
UR10	UR	A	4.05	R24	R	B	27.93	R58	R	B	32.15
UR11	UR	A	13.70	R25	R	B	23.96	R59	R	B	29.78
UR12	UR	A	5.63	R26	R	B	23.49	R60	R	B	31.86
UR13	UR	A	7.44	R27	R	B	22.90	R61	R	B	32.04
UR14	UR	A	7.56	R28	R	B	36.90	R62	R	B	24.57
UR15	UR	A	12.56	R29	R	B	24.40	R63	R	B	23.65
UR16	UR	A	17.33	R30	R	B	32.85	R64	R	B	30.49
UR17	UR	A	2.44	R31	R	B	28.05	R65	R	B	21.94
UR18	UR	A	16.74	R32	R	B	31.29	R66	R	B	25.38
UR19	UR	A	14.93	R33	R	B	25.93	R67	R	B	30.62
UR20	UR	A	9.69	R34	R	B	24.96	R68	R	B	28.74
R01	R	B	30.85	R35	R	B	30.52	R69	R	B	24.08
R02	R	B	32.91	R36	R	B	27.49	R70	R	B	29.34
R03	R	B	33.34	R37	R	B	28.59	R71	R	B	27.84
R04	R	B	30.90	R38	R	B	31.56	R72	R	B	30.12
R05	R	B	30.53	R39	R	B	23.65	R73	R	B	29.35
R06	R	B	35.22	R40	R	B	26.57	R74	R	B	21.64
R07	R	B	30.97	R41	R	B	29.58	R75	R	B	29.72
R08	R	B	33.79	R42	R	B	32.39	R76	R	B	30.12
R09	R	B	25.86	R43	R	B	30.15	R77	R	B	25.68
R10	R	B	31.78	R44	R	B	30.48	R78	R	B	27.61
R11	R	B	29.85	R45	R	B	28.14	R79	R	B	31.08
R12	R	B	29.36	R46	R	B	26.87	R80	R	B	28.97
R13	R	B	30.38	R47	R	B	30.24				
R14	R	B	30.15	R48	R	B	23.79				

No. = bunch number; UR = under-ripe; R = ripe; A = invisible; B = visible; Avg. = average

Table 4 Potential oil yields based on oil palm fresh fruit bunch (OPFFB) percentage

Level of ripening of OPFFB	Storage time (hr)	Potential oil yield/ OPFFB (mean±SD)
Under-ripe	12	15.673±0.315
	36	14.610±0.446
	60	13.309±0.239
Ripe	12	23.618±0.354
	36	22.544±0.410
	60	20.625±0.323

Source: Ruswanto et al. (2020)

Conclusion

The fluorescence equipment built and tested could categorize OPFFBs with 100% agreement with the manual expert approach and confirmed the efficacy of using the solvent extraction process. The advantages of the developed real-time OPFFB ripeness classification technique were that it reduced the time, labor requirement and human errors, while also being more accurate than the human eye at systematic categorization. Future work could adjust the equipment to carry out automated categorization for the oil palm industry or even grading other kinds of fruit.

Conflict of Interest

The authors declare that there are no conflicts of interest.

Acknowledgements

The Kasetsart University Research and Development Institute (KURDI), Bangkok, Thailand provided a fundamental research grant and English editing. Khuan Chalik Oil Palm Cooperative Limited, Nakhon Si Thammarat province, Thailand supplied the oil palm fresh fruit bunch samples and the experts who helped with information and sample inspection. The laboratory of Crop Production Technology, Maejo University, Chumphon, Thailand carried out the solvent extraction on samples. The Department of Maritime Engineering and the Department of Mechanical Engineering, Kasetsart University provided valuable assistance.

References

Abdullah, M.Z., Guan, L.C., Mohamed, A.M.D., Noor, M.A.M. 2002. Color vision system for ripeness inspection of oil palm *Elaeis guineensis*. J. Food Process. Preserv. 26: 213–235. doi.org/10.1111/j.1745-4549.2002.tb00481.x

Alfatni, M.S.M., Shariff, A.R.M., Abdullah, M.Z., Marhaban, M.H., Shafie, S.B., Amiruddin, M.D.B., Saeed, O.M.B. 2014. Oil palm fresh fruit bunch ripeness classification based on rule-based expert system of ROI image processing technique results. IOP Conf. Ser. Earth Environ. Sci. 20: 012018. doi: 10.1088/1755-1315/20/1/012018

Alfatni, M.S.M., Shariff, A.R.M., Saeed, O.M.B., Albhbah, A.M., Mustapha, A. 2020. Colour feature extraction techniques for real time system of oil palm fresh fruit bunch maturity grading. IOP Conf. Ser. Earth Environ. Sci. 540: 012092. doi: 10.1088/1755-1315/540/1/012092

Balasundram, S.K., Robert, P.C., Mulla, D.J. 2006. Relationship between oil content and fruit surface color in oil palm (*Elaeis guineensis* Jacq.). J. Plant Sci. 1: 217–227. doi: 10.3923/jps.2006.217.227

Buschmann, C., Langsdorf, G., Lichtenthaler, H.K. 2000. Imaging of the blue, green, and red fluorescence emission of plants: An overview. Photosynthetica 38: 483–491. doi.org/10.1023/A:1012440903014

Choong, T.S.Y., Abbas, S., Shariff, A.R., Halim, R., Ismail, M.H.S., Yunus, R., Ali, S., Ahmadun, F-R. 2006. Digital image processing of palm oil fruits. Int. J. Food Eng. 2: 1–4. doi.org/10.2202/1556-3758.1090

Daniele, P. 2022. Plant pigments. Let's Talk Science. https://letstalkscience.ca/educational-resources/backgrounders/plantpigments, 11 April 2022.

Fadilah, N., Saleh, J.M., Halim, Z.A., Ibrahim, H., Ali, S.S.S. 2012. Intelligent color vision system for ripeness classification of oil palm fresh fruit bunch. Sensors 12: 14179–14195. doi.org/10.3390/s121014179

Hadi, S., Ahmad, D., Akande, F.B. 2009. Determination of the bruise indexes of oil palm fruits. J. Food Eng. 95: 322–326. doi.org/10.1016/j.jfoodeng.2009.05.010

Hazir, M.H.M., Shariff, A.R.M., Amiruddin, M.D.B. 2012a. Determination of oil palm fresh fruit bunch ripeness—Based on flavonoids and anthocyanin content. Ind. Crop. Prod. 36: 466–475. doi.org/10.1016/j.indcrop.2011.10.020

Hazir, M.H.M., Shariff, A.R.M., Amiruddin, M.D.B., Ramli, A.R., Saripan, M.I. 2012b. Oil palm bunch ripeness classification using fluorescence technique. J. Food Eng. 113: 534–540. doi.org/10.1016/j.jfoodeng.2012.07.008

Hong, T.S., Hashim, F.H., Taj, T., Huddin, A.B. 2021. Classification of oil palm fruit ripeness using artificial neural network. IEEE International Conference on Automatic Control and Intelligent Systems. Shah Alam, Malaysia, pp. 358–363. doi: 10.1109/I2CACIS52118.2021.9495857

Ismail, N.A.B. 2010. Quick determination of actual oil content in oil palm fruit bunch using near infrared (NIR) scanning spectrometer. Thesis for Bachelor of Engineering, Faculty of Chemical and Natural Resources Engineering, University of Malaysia Pahang. Malaysia.

Jaffar, A., Jaafar, R., Jamil, N., Low, C.Y., Abdullah, B. 2009. Photogrammetric grading of oil palm fresh fruit bunches. International Journal of Mechanical and Mechatronics Engineering 9: 18–24.

Kassim, M.S.M., Ismail, W.I.W., Ramli, A.R., Bejo, S.K. 2014. Image clustering technique in oil palm fresh fruit bunch (FFB) growth modeling. Agric. Agric. Sci. Proc. 2: 337–344. doi: 10.1016/j.aaspro.2014.11.047

Lai, A., Santangelo, E., Soressi, G.P., Fantoni, R. 2007. Analysis of the main secondary metabolites produced in tomato (*Lycopersicon esculentum*, Mill.) epicarp tissue during fruit ripening using fluorescence techniques. Postharvest Biol. Tech. 43: 335–342. doi.org/100.1016/j.postharvbio.2006.09.016

Makky, M. 2016. A Portable low-cost non-destructive ripeness inspection for oil palm FFB. Agric. Agric. Sci. Proc. 9: 230–240. doi.org/10.1016/j.aaspro.2016.02.139

Makky, M., Soni, P. 2013. Development of an automatic grading machine for oil palm fresh fruit bunches (FFBs) based on machine vision. Comput. Electron. Agr. 93: 129–139. doi.org/10.1016/j.compag.2013.02.008

Makky, M., Soni, P. 2014. *In situ* quality assessment of intact oil palm fresh fruit bunches using rapid portable non-contact and non-destructive approach. J. Food Eng. 120: 248–259. doi.org/10.1016/j.jfoodeng.2013.08.011

Misron, N., Harun, N.H., Lee, Y.K., Sidek, R.M., Aris, I., Wakiwaka, H., Tashiro, K. 2014. Improvement in sensitivity of an inductive oil palm fruit sensor. Sensor 14: 2431–2448. doi.org/10.3390/s140202431

Olisa, Y.P., Kotingo, K.W. 2014. Utilization of palm empty fruit bunch (PEFB) as solid fuel for steam boiler. Eur. J. Eng. Tech. 2: 1–7.

Regional Information Center (Southern). 2005. Oil Palm Varieties in Thailand. Agricultural Research Development Agency (Public Organization). Bangkok, Thailand.

Ruswanto, A., Ramelan, A.H., Praseptiangga, D., Partha, I.B.B. 2020. Palm oil yield potency on different level of ripening and storage time based on fruits percentage and fresh fruit bunches. IOP Conf. Ser. Earth Environ. Sci. 443: 012005. doi: 10.1088/1755-1315/443/1/012005

Sabri, N., Ibrahim, Z., Isa, D. 2018. Evaluation of color models for palm oil fresh fruit bunch ripeness classification. Indonesian J. Elec. Eng. Comp. Sci. 11: 549–557. doi: 10.11591/ijeecs.v11.i2.pp549-557

Saeed, O.M.B., Sankaran, S., Shariff, A.R.M., Shafri, H.Z.M., Ehsani, R., Alfani, M.S., Hazir, M.H.M. 2012. Classification of oil palm fresh fruit bunches based on their maturity using portable four-band sensor system. Comput. Electron. Agr. 82: 55–56. doi.org/10.1016/j.compag.2011.12.010

Santana-Vieira, D.D.S., Milori, D.M.B.P., Boas, P.R.V., Silva, M.F., Santos, M.G., Gaiotto, F.A., Filho, W.S.S., Gesteira, A.S. 2014. Rapid differentiation of closely related citrus genotypes by fluorescence spectroscopy. Adv. Biosci. Biotechnol. 5: 903–914. doi: 10.4236/abb.2014.511105

Septiarini, A., Sunyoto, A., Hamdani, H., Kasim, A.A., Utaminingrum, F., Hatta, H.R. 2021. Machine vision for the maturity classification of oil palm fresh fruit bunches based on color and texture features. Sci. Hortic. 286: 110245. doi.org/10.1016/j.scienta.2021.110245

Shiddiq, M., Fitmawati, Anjasmara, R., Sari, N., Hefniati. 2017. Ripeness detection simulation of oil palm fruit bunches using laser-based imaging system. AIP Conf. Proc. 1801: 050003. doi.org/10.1063/1.4973101

Sivarao, S., Kumar, N., Widodo, W.S., Sihombing, H. 2012. Hexane economization in palm kernel oil plant: A study after process design improvement. Global Engineers & Technologists Review 2: 7–14.

Sowcharoensuk, C. 2020. Palm oil industry. Business/industry trends 2018–2020, Krungsri research. https://www.krungsri.com/th/research/industry/industry-outlook/agriculture/palm-oil/io/palm-oil-20, 24 January 2020. [in Thai]

Suharjito, S., Elwirehardja, G.N., Prayoga, J.S. 2021. Oil palm fresh fruit bunch ripeness classification on mobile devices using deep learning approaches. Comput. Electron. Agr. 188: 106359. doi.org/10.1016/j.compag.2021.106359

Suwajittanont, P., Thongrak, P., Srinophakun, T.R. 2022. Techno-economic analysis of commercial-scale bioethanol production from oil palm trunk and empty fruit bunch. Agr. Nat. Resour. 56: 825–836

Taparugssanagorn, A., Siwamogsatham, S., Pomalaza-Raez, C. 2015. A non-destructive oil palm ripeness recognition system using relative entropy. Comput. Electron. Agr. 118: 340–349. doi.org/10.1016/j.compag.2015.09.018

Teh, W.Y., Tan, I.K.T. 2021. Coloured Edge Maps for Oil Palm Ripeness Classification. The 32nd British Machine Vision Conference Online. UK, pp. 1–11.

Vanichseni, T., Intaravichai, S., Saitthiti, B., Kiatiwat, T. 2002. Potential biodiesel production from palm oil for Thailand. Kasetsart J. (Nat. Sci.) 36: 83–97.

Zheng, C., Sun, D.-W., Zheng, L. 2006. Recent developments and applications of image features for food quality evaluation and inspection—A review. Trends Food Sci. Techn. 17: 642–655. doi.org/10.1016/j.tifs.2006.06.005

Zulkifli, Z.M., Hashim, F.H., Raj, T., Huddin, A.B. 2018. A rapid and non-destructive technique in determining the ripeness of oil palm fresh fruit bunch (FFB). Jurnal Kejuruteraan 30: 93–101. doi.org/10.17576/jkukm-2018-30(1)