Journal of Oil Palm Research
DOI: https://doi.org/10.21894/jopr.2022.0029

COUNTING OF OIL PALM FRESH FRUIT BUNCHES USING COMPUTER VISION

MINARNI SHIDDIQ[1]*; DODI SOFYAN ARIEF[2]; DEFRIANTO[1]; VICKY VERNANDO DASTA[1]; DEBORAH MARGARETHA PANJAITAN[1] and DONI SAPUTRA[2]

ABSTRACT

Oil palm fresh fruit bunches (FFB) are the sources of crude palm oil (CPO). CPO is one of the largest export commodities for Indonesia and Malaysia. Automation or mechanisation in CPO processes is crucial to saving time, labour, and cost. This study used the computer vision method to count moving oil palm FFB using video frames. It is possible to implement this counting method in the oil palm FFB sorting and grading stage to estimate the CPO mill capacity. Video recordings used an RGB camera with a frame rate of 20 FPS for 117 oil palm FFB of Tenera *varieties. The counting program consisted of two parts, a detector and a tracker. The detector algorithm was self-developed by adding a colour feature, converting the RGB images of oil palm FFB to HSV colour space. The counting results were validated using the confusion matrix method. The results showed that the counting accuracy could reach 100.00%. However, the counting accuracy depends on the colour of the FFB and room light intensity. The confusion matrix validation resulted in average counting accuracy of 79.35% for 10 videos. The results showed the potential use of computer vision in counting moving oil palm FFB.*

Keywords: computer vision, confusion matrix, fruit counting, oil palm FFB, video frame.

Received: 27 November 2021; **Accepted:** 29 March 2022; **Published online:** 27 May 2022.

INTRODUCTION

Nowadays, counting fruits on trees or in a postharvest sorting and grading stage is very important to save time and labour costs. Recently, fruit counting using imaging methods has been developed due to innovations in counting algorithms, computer, and camera technology (Syal *et al.*, 2013). Information on the number of fruits on trees is needed to estimate the total harvesting yield. Likewise, the total fruits sorted in a postharvest sorting process can be applied to calculate the sortation capacity in tonnes per hour (TPH) or the storage capacity. Fruit counting is usually carried out manually by human intervention or traditional mechatronic machines. Both methods possess some disadvantages. Fruit counting by human vision creates errors due to psychological states. Mechatronic counting using electronic sensors does not have spatial resolutions which contain the information on fruit shape, size, and texture. The information is crucial for further evaluation (Bhargava and Bansal, 2018). Computer vision is the potential method to be implemented for a quick, non-destructive, reliable, in-line counting process because it offers speed and spatial resolution.

Crude palm oil (CPO) is one of the largest export commodities for Indonesia and Malaysia. Oil palm industries need remarkable breakthroughs for their sustainability. Maintaining CPO quality and increasing efficiency in time and labour costs need automation in some stages of the CPO processing. Labour shortage is another reason for automation in oil palm industries (Murphy, 2014). Oil palm fresh

[1] Department of Physics,
Faculty of Mathematics and Natural Sciences,
Universitas Riau Kampus Bina Widya,
Jalan HR. Soebrantas KM 12,5, Pekanbaru, 28293, Indonesia.

[2] Department of Mechanical Engineering,
Faculty of Engineering,
Universitas Riau Kampus Bina Widya,
Jalan HR. Soebrantas KM 12,5, Pekanbaru, 28293, Indonesia.

* *Corresponding author e-mail: minarni.shiddiq@lecturer.unri.ac.id*

fruit bunch (FFB) is the source of CPO. However, oil palm FFB harvesting, sorting, and grading are still being carried out manually and traditionally using trained or experienced personnel (Utom *et al.*, 2018).

Oil palm FFB have to pass through sorting and grading before entering the CPO processing steps. The activities of sorting and grading at a palm oil mill start with a loaded FFB transporting truck entering the sorting site. After unloading the oil palm FFB, two experienced graders, equipped with axes and crowbars, begin sorting unwanted FFB such as empty, defective, long stalks, and rotten bunches. Next, the graders pick randomly 100 FFB as grading samples and use ripeness levels and the variety of either *Tenera* or *Dura* as the grading criteria. The site location is usually next to a loading ramp. After the grading process, all the sorted FFBs that meet the grading requirements are pushed toward the loading ramp by a tractor. The ramp will load FFB into lorries which then bring the FFB to the steriliser to begin the process of CPO extraction (Akhbari *et al.*, 2020). At a later stage, CPO samples are collected to determine the CPO qualities such as moisture content and free fatty acid (FFA) level. The oil palm mills use the sorting and grading information results to calculate the grade and end prices of the sorted FFB.

Counting of oil palm FFB has two purposes, to estimate harvest yield and to count oil palm FFB leaving the plantations and arriving at the site of the oil palm mill. The benefits of oil palm FFB counting are to avoid embezzlement (Aripriharta *et al.*, 2020) and to estimate the daily palm oil process capacity. Oil palm mill capacity is the size of an oil palm mill that is usually in TPH. Throughput is the capacity target measured every day and collected yearly for oil palm plant capacity estimation. This capacity target is often obtained by estimating the number of FFB entering the loading ramp or before entering the transporting lorries to the FFB sterilisation stage in an hour (Raharja *et al.*, 2020).

The computer vision system embedded in a sorting machine with moving conveyors could be used to determine the total capacity where the weight and the number of the oil palm FFB are the parameters for the capacity estimation. Here, oil palm mills can introduce an automatic counting system using computer vision to count the number of FFB unloaded from a transporting truck or to count the number of FFB entering lorries after the sorting process. The counting system can also be designed to measure the mass of each FFB by adding a load cell-based scale below the conveyor floor.

Counting fruit on trees using computer vision has been adopted widely for many conditions and types of fruits. The innovations in machine vision technology such as higher frame rates, image processing algorithms, cloud computing, and camera resolution make the implementations easier. The computer vision method and digital image analysis with RGB and YCbCr colour space are being employed to count the yield of fruits and flowers. The image processing used were noise removal, segmentation, size thresholding, and shape analysis (Nisar *et al.*, 2015). The technique was also applied to locate and count green and red pepper fruits involving a tremendous amount of datasets in a greenhouse with controlled lighting (Song *et al.*, 2014). Estimating the individual size and mass and counting olive fruits have also used computer vision (Ponce *et al.*, 2019). The yield of agricultural products such as apples can be estimated automatically using two cameras carried on a vehicle that scans each tree from two sides and produce image sequences (Wang *et al.*, 2012).

Postharvest sorting and grading process can also implement fruit counting. This measurement is essential for agriculture industries in planning market needs and estimating necessary resources. Fruit counting can estimate harvested yield, the amount of materials for fruit storage, and then the capacity of a storage facility. Estimating harvest yields usually use manual fruit counting which needs labour. The manual counting has some issues such as insurance, salary, and housing. In addition, the time used to count fruits is 10% of the whole sorting process time. The miscalculation of fruit quantity is also about 10% for the large agriculture industry (Syal *et al.*, 2013). Therefore, automatic, non-destructive counting methods for fruits and vegetables are needed.

Computer vision methods have been proposed and used in automatic sorting systems to count the number of agriculture products. Computer vision has a broader term than machine vision, including three-dimensional imaging and spectral imaging. Machine vision often refers to computer vision used along with a conveyor-based machine. Counting objects using image processing and machine vision becomes a trendsetter because it offers automatic, low cost, non-destructive measurement (Baygin *et al.*, 2018). However, counting fruit on a moving conveyor has not been explored intensively. Counting fruits on moving conveyors can be related to counting the number of objects from video frames, such as counting the number of people passing a gate or entrance in a train station (Velastin *et al.*, 2020) or the number of vehicles on a particular street in a busy highway (Song *et al.*, 2014).

Nowadays, artificial intelligence (AI) and machine learning (ML) have been used in the field of smart or precision agriculture, such as for counting harvest yield (Osman *et al.*, 2021) and for sorting and grading machine vision (Jacques *et al.*, 2021). The applications have many advantages, such as real-time monitoring, measurement, and efficient quality management and assessment. AI is the simulated intelligence used by a machine to do some tasks. It intends to imitate the work of the human brain in making a decision. ML is a tool that can be used to develop AI. ML gives the ability for a machine to do a task automatically. The other definition of ML is developing a computer program to do a task. Counting fruit using AI and ML is the latest research interest motivated for low cost, non-destructive, intelligent methods for precision agriculture. You only look once (YOLO) model and deep learning have been used in fruit counting (Yi *et al.*, 2021).

This study aimed to construct an automatic counting system that estimates the number of moving oil palm FFB on a conveyor. The computer vision method was used for the counting process by detecting and tracking FFB images in video frames. The counting algorithm was designed and written using Python language that consisted of two main components, a detector and a tracker. The detector algorithm detects the presence of oil palm FFB based on colour, while a tracker program will track the bounding box that assigned to the oil palm FFB image and count it. This study used 117 oil palm FFB. Ten videos were taken and then analysed to obtain how many FFB were counted in each video. A confusion matrix was used to measure the accuracy of the counting system.

MATERIALS AND METHODS

This study used a computer vision system that consisted of a moving conveyor, a Red-Green-Blue (RGB) camera, and a Python-based counting program with OpenCV library. Counting objects using an RGB camera in video mode and coding with the OpenCV library is more practical than using two moving cameras (Sturdevant *et al.*, 2018). The counting system is adopted from the similar counting process of vehicles or people crossing a highway or a gate (Liu and Na, 2017) and from (https://github.com) that discusses object detection intensively.

In this study, the ripeness levels of the FFB were not part of the evaluation. However, we developed the algorithm for the detection part that included the colour and fruit shape of the oil palm FFB to differentiate them from other fruits. Image processing in the counting system used Hue-Saturation-Value (HSV) colour space. An RGB camera has images in RGB colour space. Converting the images into HSV space has some advantages, such as removing the background image, saving detection time, and improving efficiency.

Figure 1 shows the counting system with one oil palm FFB. The counting system consisted of an RGB camera, a moving conveyor, a laptop connected to the camera via a USB cable, and a counting program. The camera was placed 150 cm directly above the moving conveyor (Septiarini *et al.*, 2020). We used a webcam Havit HV-V662 with a 1/3” sensor size and an unadjustable lens. One can reduce the working distance by 150 cm using a wider camera sensor and a shorter lens focal length. A stand holder for the camera was fastened to the side of a conveyor to ease the video recording process of moving oil palm FFB. The conveyor consisted of a white surface to facilitate image processing of the oil palm FFB. We used 117 oil palm FFB of *Tenera* variety. The FFB samples came with variations in size and mass.

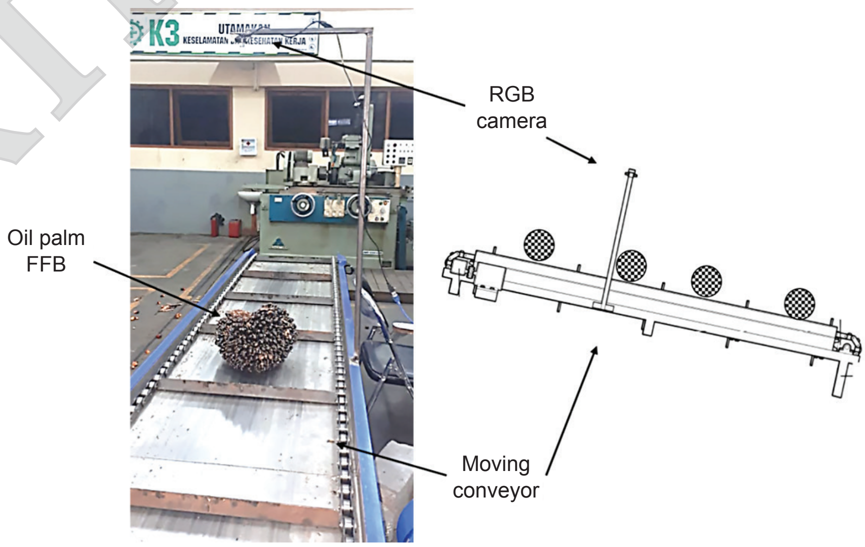


Figure 1. Counting system for oil palm fresh fruit bunches (FFB).

The conveyor unit is a vital part of this counting system. The conveyor type was a bucket conveyor as seen in *Figure 1*. The conveyor consisted of reducers as the speed controller of motor rotation, roller chains connected to a motor, and sprockets. These roller chains used sprockets that function to change the rotation motion to the translation motion of buckets. The buckets pushed the oil palm FFB moving on the floor of the conveyor. All of the components positioned on the conveyor support frame. The white conveyor floor helped to increase background segmentation efficiency in image processing. Belt conveyors are not doable for moving oil palm FFB due to variations in FFB weights. This conveyor unit was made to be able to withstand the weight of an oil palm FFB of more than 40 kg.

Video Recording

The process of fruits or other objects counting using video frames has three stages, *i.e.*, detection, tracking, and counting (Khude and Pawar, 2013). The counting program consisted of two main components, a detector and a tracker. The tracker had a counting step at the end of its algorithm. Video recording using an RGB camera was conducted in video mode live view. The camera utilised in video mode had a frame rate of 20 frames per second (FPS) and a video resolution of 640 x 480 pixels. We took 10 videos with different numbers of oil palm FFB in each video, numbers of FFB in a bucket and dates. The results of the video recording were RGB images. These images were later converted into HSV images. The counting algorithm allowed the counting process of moving FFB to be seen in real-time.

Detection Algorithm

The detection process consist of some stages. First, the OpenCV library read the image stream from the camera and converted the RGB matrix pixel into a grayscale pixel. Next, thresholding was applied to remove noise from the matrix pixel to obtain only the target pixels. After that, segmentation step used a background subtraction technique to extract the object from the background. The location of the extracted object was acquired using the contouring stage. The object location appeared as a bounding box of x, y, w, and h in dimensions. The bounding box information was later sent to the tracker algorithm.

Figure 2 shows the algorithm of the detection process in detail. Pixels on the RGB channel were converted to HSV channels using cv2. cvtColor(frame, flag) command. The flag in the command script was the target channel, and the frame was the frame chosen to convert its colour channel to the colour of the target channel. The colour characteristics used were extracted from the histogram matrix of the saturation colour image or s channel. The conversion results of the RGB image to the s channel image were then thresholded to obtain a binary image. The purpose of this conversion and thresholding was to produce a still and stable background that is sensitive to foreground changes. The next step was to smooth pixel components in oil palm FFB images with dilation and erosion operations to anticipate the poor image quality of the resulting binary image.

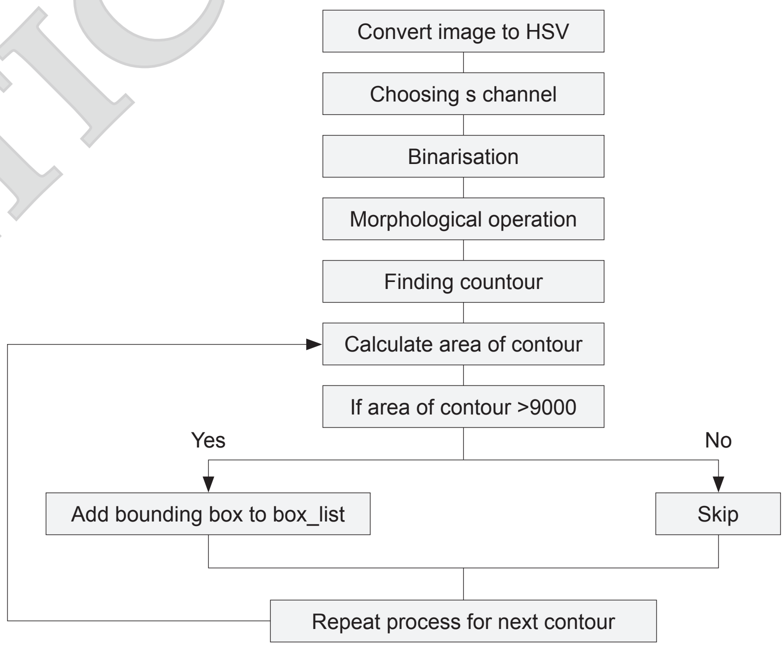


Figure 2. Object detection algorithm.

The next stage of the detection process was the morphological operation (Auroux *et al.*, 2011). The result of the morphological operation of the binary image would then be contoured. If the contour area was in the range above the value of 9000, then the object would be detected and added to the contour box list. The detection process would find the coordinates or region of interest (ROI). The output of the detection process was a centroid point needed for the tracking process.

Tracking and Counting Algorithms

The last part of the counting program was a tracker. *Figure 3* shows the tracker algorithm. The centroid-based tracker has three processes, register, update and deregister. The register step is a process to check whether the dictionary is empty. If the dictionary is found empty, it will assign an ID and a centroid to HashMap. All the bounding boxes will experience this process. Next, the update step is a process to check the centroid of each bounding box. If the distance of the centroid is close, then the centroid for the ID will be updated. However, if the centroid distance is too far, then the bounding box is assumed to be unrecognisable, so an ID will be reassigned. The last step is the deregister, which is deleting ID and centroid from the HashMap. An ID will be erased from the HashMap only if the ID is no longer detected in N consecutive frames.

This tracker algorithm also has a counting process. Centroid counting will be executed on each oil palm FFB on each frame. The final or overall centroid point information and object position will be saved as a benchmark by the tracker. If in the next frame a centroid value of the object is found and has a close distance to the previously detected centroid, then the object is assumed to be the previously detected object. The next process after updating the centroid tracker is implementing a loop of the resulted centroid tracker update in order to extract the ID and centroid of the oil palm FFB.

Confusion Matrix Analysis

The effectiveness and performance of the counting system were analysed using a confusion matrix or known as an error matrix (Novakovic *et al.*, 2017). The parameters used included Recall, F-Score, Accuracy, and Precision. The

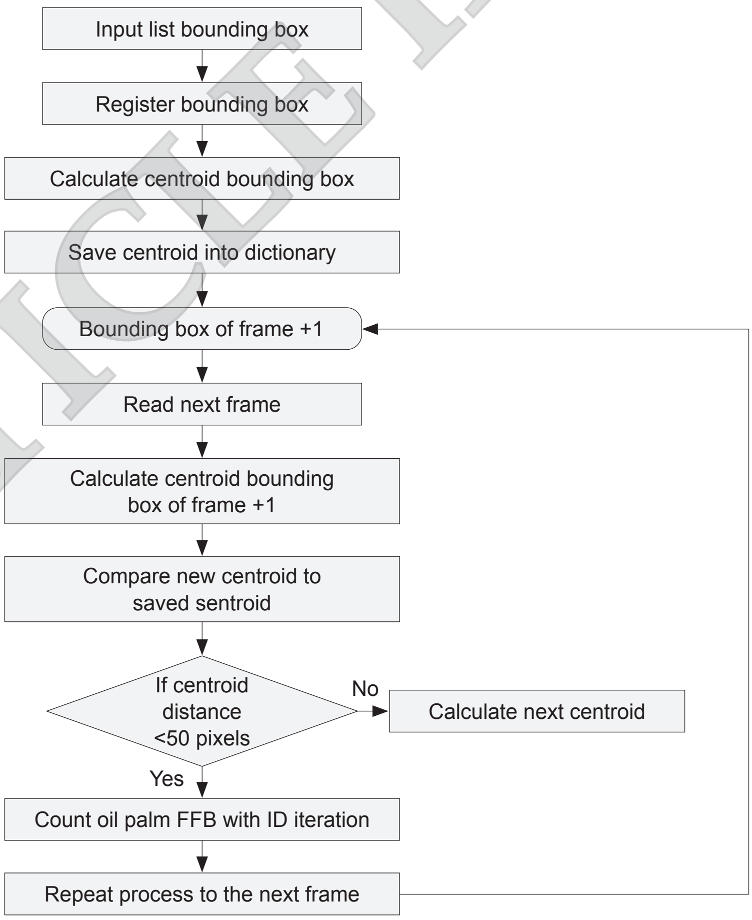


Figure 3. Object tracking and counting algorithm.

recall is a comparison or ratio of true positive (TP) predictions with the total number of data, consisting of TP and false negative (FN) data as in Equation (1).

$$\text{Recall} = \frac{TP}{TP + FN} \quad (1)$$

F-score is a measure or value that represents the performance level of the algorithm implemented on the system as measured using Equation (2).

$$\text{F-score} = \frac{2\ x\ (\ Precision\ x\ Recall)}{Precision + Recall} \quad (2)$$

The accuracy is the ratio value representing true-positive data to the overall data calculated using Equation (3).

$$\text{Accuracy} = \frac{TP}{TP + FN + FP} \times 100\% \quad (3)$$

Precision is a comparison between the true-positive predictions to the overall results that were predicted positive in Equation (4).

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

RESULTS AND DISCUSSION

Counting of oil palm FFB was done using a counting system consisting of a RGB camera, a conveyor system, and a Python-based counting program. The program used video frames to detect and track oil palm FFB moving on a conveyor. Here, we presented the results and evaluated the performance of the counting process.

Segmentation Results

A colour feature was added to the counting algorithm to differentiate the oil palm FFB from other fruits. HSV colour space was used instead of RGB images such that the conversion of RGB to HSV images became essential. *Figure 4* shows the conversion results. The resulting HSV images have more contrast than the RGB images as seen in *Figure 4a*. The object and the background could be differentiated easily, therefore improving the quality of the segmentation result.

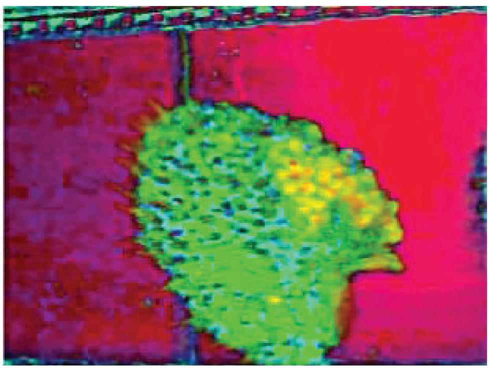
Figure 5 shows the signature of an oil palm FFB as a white blob after the thresholding step implemented on the HSV image. The image represented by white is the resulting detected oil palm FFB, while the black image shows the object's background. *Figure 5a* shows the resulting binary image. It shows that the image has thickened. The morphological operations have improved the contrast. It shows that the thresholding step has differentiated more between the object and the background.

In this study, contouring was executed using a minimum threshold to an area aiming to detect oil palm FFB successfully. The minimum threshold value for the contour area used in this study is 9000. If the contour area is >9000, then the contour is considered as a signature blob of the oil palm FFB.

The Counting Performances

Testing the performance of the counting system can be done by adding more oil palm FFB in one bucket. *Figure 6* shows some cases of the resulting images of the detection and tracking from the video frames. As seen in *Figure 6a*, the counting system will respond to every oil palm FFB movement in real-time detection. In the resulting image, the green bounding box is a marker that the oil palm FFB is detected. The bounding box will automatically follow the movement of the oil palm FFB in the ID iteration process.

(a) RGB image

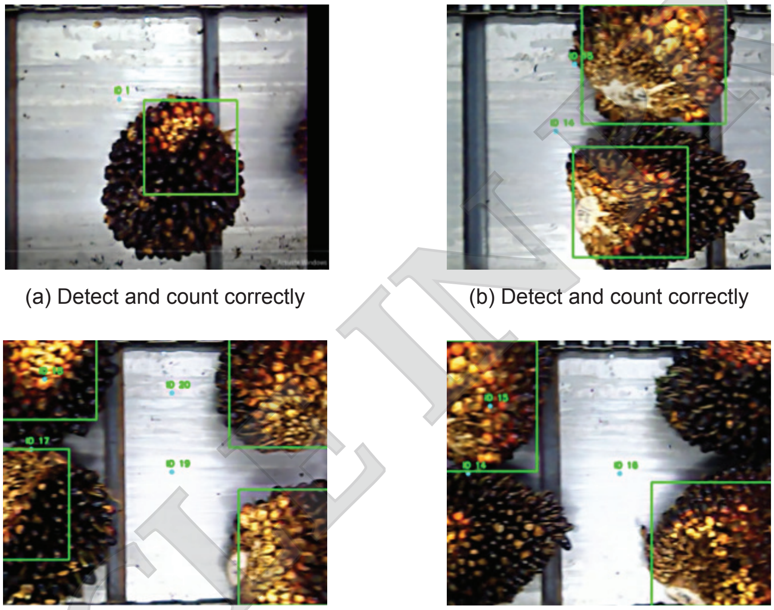


(b) HSV image

Figure 4. Converting (a) RGB image to (b) HSV image.

(a) Binary image (b) Thresholding result

Figure 5. Result of binarisation and thresholding process.



(a) Detect and count correctly (b) Detect and count correctly

(c) Detect and count correctly (d) Detect incorrectly

Figure 6. Detection, tracking and counting performance.

Figure 6 shows the counting performance. *Figure 6a* shows the algorithm has counted correctly. The same is true in *Figure 6b* where the counting system has detected two oil palm FFBs correctly. *Figure 6c* shows the counting system was capable of detecting and tracking accurately four oil palm FFB at once with ID and bounding box. However, counting four oil palm FFB in a bucket can lead to a failure shown in *Figure 6d*, where only three oil palm FFB were detected. This case was due to the distance between two adjacent oil palms affecting the system. Oil palm FFB with close centroid points were detected as the same object by the system, therefore failing to count four oil palm FFB correctly.

There were some other errors found in detecting and tracking oil palm FFB. One error was an error in assigning an ID, where sometimes an oil palm FFB has two ID numbers. This error could arise because of too high room light intensity during image acquisition that one oil palm FFB has a contour area above 9000 (Septiarini *et al.*, 2020). It also could be caused by the physical characteristics of the oil palm FFB especially colours, masses, and shapes (Razali *et al.*, 2012).

Confusion Matrix evaluated the accuracy of the counting performance. This matrix is in the form of a table that describes the performance information of a classification model on a series of testing data to the actual classification results. *Table 1* shows the Confusion Matrix results for 10 videos and the values of TP, false positive (FP), and FN. In *Table 1*, the 5^{th} video recording had the highest TP because all the oil palm FFB were counted right by the program, the same as the actual number. Therefore, the recall, precision, and F-score have values of 1 as shown in *Table 2*. The accuracy is 100%. The 10th video recording has the highest FP, which means the program has counted far more than the actual number of oil palm FFB. The 9th video recording also has a higher FP. FN tells that the program has made mistakes in counting the oil palm FFB and that the number of oil palm FFB counts was less than it should be. This happened to the 1st and 2nd video recordings.

Table 2 shows the summary of the accuracies of the counting system. The recall and precision values in *Table 2* are the ratio of the TP, FN, and FP of each video recording. The accumulation of the recall and precision results defines the algorithm's performance, represented by F-Score values. In *Table 2*, The highest F-scores values were found at the 5th and 8th video recordings. Here, the values were influenced by the room light intensities and the physical characteristics of the oil palm FFB. Due to the additional colour feature added to the detection algorithms, the room light intensities can affect the accuracies. In addition, the oil palm FFB came in different shapes, masses and ripeness. Each video has oil palm FFB with different shapes, mass, and ripeness. But we observed that most of the miscalculation was due to the orientation of the FFB surface on the bucket. Oil palm FFBs have ellipsoidal shapes and can be divided into three parts: basal, middle, and top. The FFB top part has a darker colour than the basal part. The basal part has a lighter colour, unfertile fruitlets. It also can be divided into two faces, front and back. The back face or surface has a lighter colour than the front (Owolarafe *et al.*, 2007; Razali *et al.*, 2012). The miscalculation happened when the FFB part and surface seen by the camera is dark. This is due to the detection algorithm of HSV conversion that has a certain limit and causes ID and centroid unidentified. These errors can be avoided by using the YOLO algorithm in the detection program (Yi *et al.*, 2021).

Ambient light is one of the factors that can affect counting performance (Sengupta and Lee, 2014). Therefore some studies on counting fruits have used a controlled artificial light or worked nighttime (Song *et al.*, 2014; Wang *et al.*, 2012). The counting system in this study was conducted in a laboratory

TABLE 1. CONFUSION MATRIX RESULTS

Video label	Actual count	Count by the system	True positive (TP)	False positive (FP)	False negative (FN)
Video 1	14	13	12	1	2
Video 2	15	13	13	-	2
Video 3	15	16	15	1	-
Video 4	3	6	3	3	-
Video 5	15	15	15	-	-
Video 6	11	13	11	2	-
Video 7	3	4	3	1	-
Video 8	11	11	11	-	-
Video 9	15	24	15	9	-
Video 10	15	25	15	10	-

TABLE 2. COUNTING ACCURACY OF EACH VIDEO

Video samples	Duration (min)	Light intensity (lux)	Recall	Precision	F-Score	Accuracy (%)
Video 1	1′11″	120	0.86	0.92	0.89	80.00
Video 2	1′02″	160	0.87	1.00	0.93	86.67
Video 3	0′52″	235	1.00	0.94	0.97	93.75
Video 4	0′11″	40	1.00	0.50	0.67	50.00
Video 5	0′57″	190	1.00	1.00	1.00	100.00
Video 6	0′37″	140	1.00	0.85	0.92	84.61
Video 7	0′36″	100	1.00	0.75	0.86	75.00
Video 8	0′47″	200	1.00	1.00	1.00	100.00
Video 9	1′05″	80	1.00	0.63	0.77	62.50
Video 10	1′05″	60	1.00	0.60	0.75	60.00

where its room light was not adjustable. The samples of oil palm FFB used came from a plantation in the vicinity that sometimes arrived late in the evening. Therefore, the room light intensity varied each time in each video recording. The RGB camera has auto exposure or white balance hence creating a colour difference in the camera during video recordings (Lumenera, 2017).

In *Table 2*, the highest level of accuracy of 100% resulted in the light intensity of 190 and 200 Lux. Low light conditions gave an accuracy of about 50%, such as in video 4 with an intensity level of 40 Lux. Too bright room light conditions also resulted in low accuracies, such as in Video 3, which had less than 95% accuracy with the intensity of 235 Lux. The room light intensity affects the counting system of recognising and detecting oil palm FFB. This system can work well at light intensity levels of around 180-210 Lux.

Table 2 also shows the duration of each video recording that varies for the same amount of oil palm FFB. We believe the problems with the intensity variations were due to the room light conditions and the characteristics of the webcam. The camera position and the distance from the camera to the conveyor base were unchanged during each video recording. However, due to the long working distance and no controlled lighting around the oil palm FFB, the room lighting in the laboratory caused the intensity to vary. The camera specifications also affect the computer vision system performance. At the time of video recording, the conveyor speed and the frame rate were not matched. We used a low-cost webcam with a resolution of 640 × 480 pixels and a maximum frame rate of 30 FPS. The sensor size is the smallest which is 1/3". The unmatched conveyor speed and the frame rate values could cause the program's accuracy. The sensor will detect an object if the light reflected by the object enters the sensor area. The sensor has difficulty receiving light due to faster moving objects (Lumenera, 2017).

CONCLUSION

This study has investigated the possibility of using a computer vision method for counting moving oil palm FFB on a conveyor. There is a potential to use the counting system in sorting and grading machine vision where masses of the oil palm FFB are also measured. The capacity of the oil palm mill then can be estimated non-destructively and faster using mass measurement and counting. The built counting system has reached the accuracy of 100% depending on the oil palm FFB surface colours and the intensity of the room light and, a lighter surface can be calculated accurately. The orientation of an oil palm FFB in a conveyor bucket sometimes caused the darker part of the oil palm FFB to face the camera, hence it led to misdetection due to HSV colour conversion in the detecting algorithm. A suitable lighting condition and the higher camera specifications are the key factors to overcome the light intensity effects for the counting system. For future works, the counting system could add more features in addition to the colour and a deep learning algorithm. Nonetheless, it has shown the potential of using the computer vision-based counter for oil palm FFB.

ACKNOWLEDGEMENT

The authors would like to acknowledge the Indonesia Endowment Fund for Education (LPDP), the Ministry of Finance, and the Universitas Riau Institution of Research and Community Services for supporting this study through research grant of PRJ/57/2020.

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