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Development of an automatic grading machine for oil palm fresh fruits bunches (FFBs) based on machine vision

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ABSTRACT

Despite being the main oil palm (*Elaeis guineensis* Jacq.) producer in the world, Indonesia still has scope to improve its productivity, which is currently limited by inconsistency in manual grading through human visual inspection. In this research, an automatic grading machine for oil palm fresh fruits bunch (FFB) is developed based on machine-vision principles of non-destructive analytical grading, using Indonesian Oil Palm Research Institute (IOPRI) standard. It is the first automatic grading machine for FFBs in Indonesia that works on-site. Machine consists of four subsystems namely mechanical, image processing, detection and controlling. The samples used were tenera variety fruit bunches from 7 to 20 year old trees. Statistical analysis was performed to generate stepwise discrimination using Canonical Discriminant with Mahalanobis distance function for classifying groups, and appoint cluster center for each fraction. Results showed adaptive threshold algorithm gave 100% success rate for background removal, and texture analysis showed object of interest lies in intensity within digital number (DN) value from 100 to 200. Group classification of FFBs resulted average success rate of 93.53% with SEC of 0.4835 and SEP of 0.5165, while fraction classification had average success rate of 88.7%. Eight models are proposed to estimate weight of FFBs with average R^2 of 81.39%. FFBs orientation on conveyor belt showed no influence on the sorting result, and with examination time of 1 FFB/5 s, machine performs more than 12 tons FFBs grading per hour.

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1. Introduction

Crude palm oil (CPO) is edible oil derived from mesocarp of fruits of oil palm trees (*Elaeis guineensis* Jacq.). The fruits forms large bunch and are commonly known as fresh fruits bunch (FFB). Indonesia accounts for 45% of world CPO production (USDA, 2007). However, due to poor handling as well as subjectivity in manual grading, the actual potential of the country is limited by low productivity and low quality CPO. In order to address these challenges, an efficient and effective grading system is required. An automated machine vision-based grading system might offer better consistency, accuracy, non-destructive and quicker performance.

Machine vision has been shown to be successfully used in grading process for fruits (Alexos et al., 2002; Abdullah et al., 2006; Blasco et al., 2009; Kondo, 2009; Zheng et al., 2011) and vegetables (Barnes et al., 2010). Furthermore, applications of machine vision based systems in automatic grading facilities have also been reported (Abdullah et al., 2006; Blasco et al., 2009; Kondo, 2009; Lim-

ing and Yanchao, 2010). Recently, researches have begun in automation in grading oil palm fruits. Recent studies indicate that an optical sensor can be used to grade FFB into three maturity categories (unripe, ripe, and overripe) (Saeed et al., 2012). Another study reveals positive relationship between red colors channels in RGB with oil contain of the fruits (Hudzari et al., 2010). The ripeness of a FFB can be examined based on its color using photogrammetric technique (Jaffar et al., 2009). Color of the bunch can also be related to its oil content and difference in FFBs spectral responses can be determined using camera vision system (Ismail et al., 2000). However, day light intensity significantly affects images captured by such systems (Ismail and Hudzari, 2010). Nonetheless, all these studies were undertaken under laboratory conditions, and a working prototype of such a grading machine has not yet developed for its actual field operation and evaluation.

Due to its nature of repetitive works, the grading machine is preferred to run automatically, with adequate accuracy and consistency. Damages and injuries to FFBs during inspection should be avoided; otherwise quality of oil will be reduced due to increment of free fatty acid's (FFA's) level in the fruits (Hadi et al., 2009). Therefore, an ideal grading machine for FFBs should be able to examine fruits automatically and efficiently using machine vision, without causing damages or injuries to it.

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This research was focused on development of an automatic machine for grading FFBs using principles of machine vision, equipped with a suitable algorithm to estimate FFBs maturity, weight, and classification, with minimal or no injuries to the fruits on continuous real time basis. The machine was designed for field operation and tested for its performance under real condition.

2. Materials and methods

2.1. Components of the grading machine

The automated FFBs grading machine (Fig. 1) was designed using computer aided design (CAD), and machine dimensions were set to accommodate inspection chamber and separator. The machine could be considered consisting of four subsystems: mechanical system, image processing system, detection system and controlling system.

2.1.1. Mechanical system

The mechanical system consists of a chassis (4 mm thick L-shape 50 mm × 50 mm steel bar), a conveyor and a separator.

The conveyor (double ply heavy duty flat belts, 650 mm wide and 4500 mm long) was used to transport FFBs, which had idle rollers arranged 20 cm apart. It had the provision of adjusting its height from ground to make the rollers be aligned with the loading ramp stopper. This enables the bunch to smoothly slide onto the loading ramp. The loading ramp then feeds FFBs to processing mills.

The separator with a 60° restricted horizontal rotation was connected to two inertia motors by steel cables to implement gradation. It worked by blocking the conveyor path and made sub-stranded FFBs to fall on the side of grading machine, and unblocking the conveyor path and made accepted FFBs to be transported by conveyor belt to the loading ramp.

2.1.2. Image processing system

The image processing system consists of a camera (Tefcon, web-cam 2.0 16MP, Taiwan) to acquire images; a closed inspection chamber with LED lighting, arranged along the inner perimeter of the top side of the chamber; a computer to process the images captured using image processing program; and an image processing program to analyze image, remove background and extract

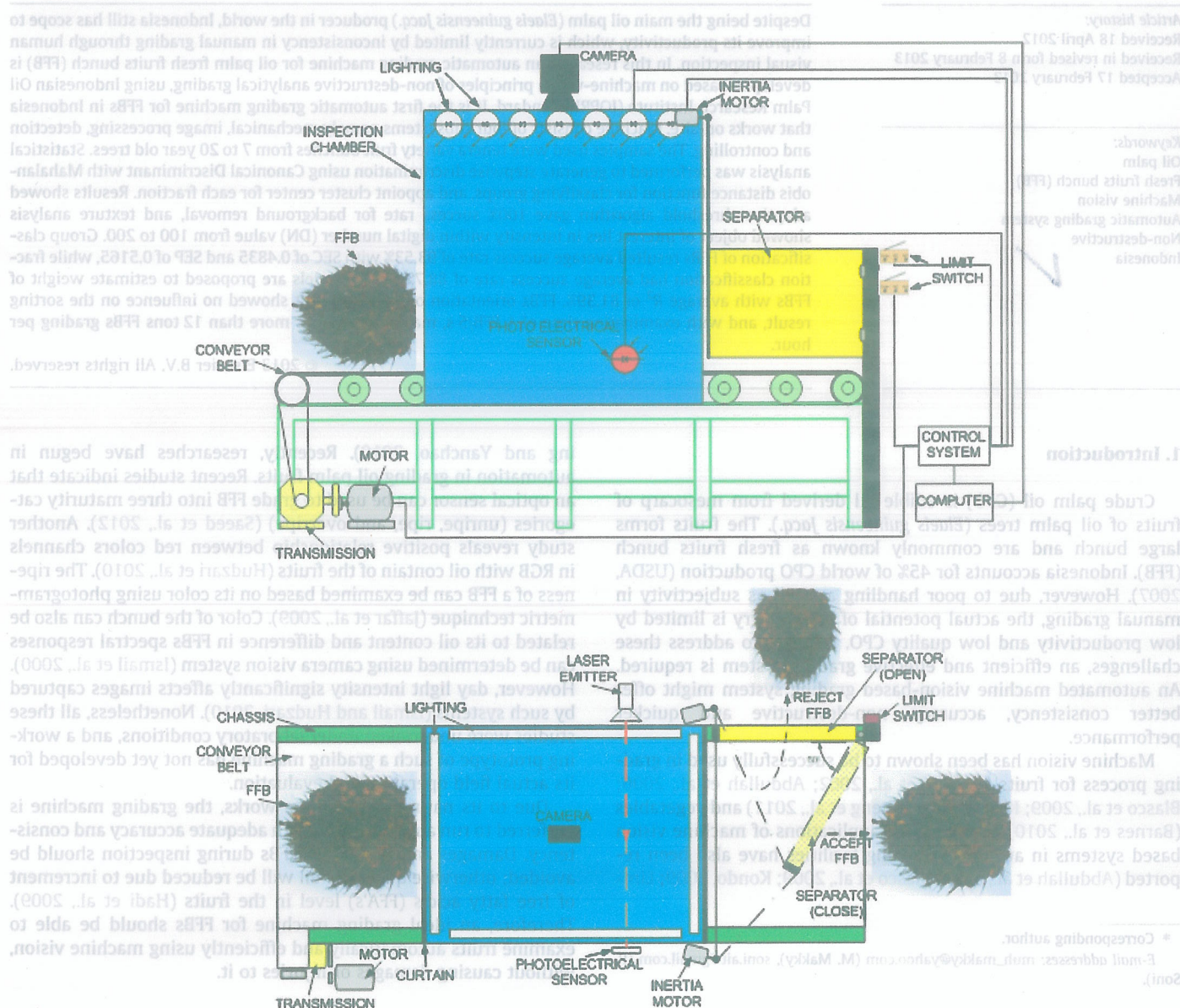


Fig. 1. Concept of automated FFB grading machine.

placed in the chamber illuminating a photoelectric sensor (LDR). Whenever a FFB passes between the laser emitter and LDR, and obstructs the laser light for more than 100 ms, the sensor sends signal to SCM, and activate the computer to capture the FFB image in the chamber using the camera. The image then will be automatically threshold using adaptive thresholding procedure.

According to the FFB standard grading characteristics (Table 1), initially image processing program classifies the FFBs into two classes: one as the “accepted” class (class 2), consist of FFBs in fraction 1, 2, and 3; and the other as “rejected” class (class 1), consist of FFBs in fractions 00, 0, 4, 5, and 6. Then the actual fraction for each bunch is determined and is displayed on the screen. The processed images and its analysis results were stored in a database file for record. Once a FFB is classified as class 1 (rejected), the computer sends signal to SCM to activate the appropriate inertia motor for closing the separator device. The separator will obstruct the conveyor path, and make the FFB fall to the side of machine, thus prevents the rejected FFB to be fed into the loading ramp. Only class 2 FFB (accepted) will be allowed to pass through the machine, and be delivered to the end of machine to be fed into loading ramp for further processing in the oil palm mill.

2.3. Real-time image acquisition and analysis

The image processing program mainly performed two tasks: (i) controlling subprogram to operate and communicate with SCM; and (ii) run the image analysis subprogram to extract features from images and perform grading.

2.3.1. Algorithm for background removal

Even though there are several algorithms available to extract object from background, but due to the complexity of FFB color variation, these could not be used in this research. In fact, rather than assigning an exact RGB value for segmentation or performing time-consuming complex algorithm, a dedicated and simple algorithm called “adaptive thresholding” was used. In this algorithm,



Fig. 2. The control system.

Table 1
Quality requirements of FFB acceptance in mills.

Ripeness state	Ripeness fraction	Detached fruitlets	Bunch color	Mesocarp color	Permissible proportion in the lot
Under raw bunch	00	None	Black	Pale	0%
Raw bunch	0	Up to 12.5% of outer fruits	Purple black	Yellowish	<3%
Under ripe bunch	1	12.5–25% outer fruits	Reddish purple	Yellowish orange	>85%
Ripe bunch I	2	25–50% outer fruits	Reddish orange	Orange	
Ripe bunch II	3	50–75% outer fruits			
Over ripe bunch I	4	75–100% outer fruits	Darkish red	Orange	<10%
Over ripe bunch II	5	Inner fruits start to detached			<2%
Empty or rotten bunch	6	Most fruits detached	Withered		0%
Free fatty acid (FFA)		All fraction			2.5–3.5%

Compiled from; IOPRI (1997) and MPOB (2003).

two variables: "hill" and "bottom" with predetermined values 400 and 50 respectively, were used to filter histogram, and to distinguish between object and background. The program scans the histogram in each color channel (R, G and B) from 0 to 255, and removes value smaller than "bottom" after histogram exceeds the "hill" value (Fig. 3c). This enables faster background removal from the image without losing any feature in the object, while simultaneously generates RGB threshold value automatically (Fig. 3d). In rare case, where "hill" value does not exceed (i.e. extremely small FFB) or value of the histogram is always greater than "bottom" (i.e. very large FFB), the program will automatically decrease the "hill"

value by 25 or increase the "bottom" value by 25. This process will be automatically iterated by the program until background is fully removed from the image. The value of 25 was chosen based on trial and error iteration, that gave the minimum computing time without altering the result.

2.3.2. Image texture analysis

Texture analysis of the image was done to classify the RGB value of specific component of the object, in order to distinguish among fruitlets, spikelets, and other parts. Removed background image were put into a 3D surface contour graph where pixel coordinates

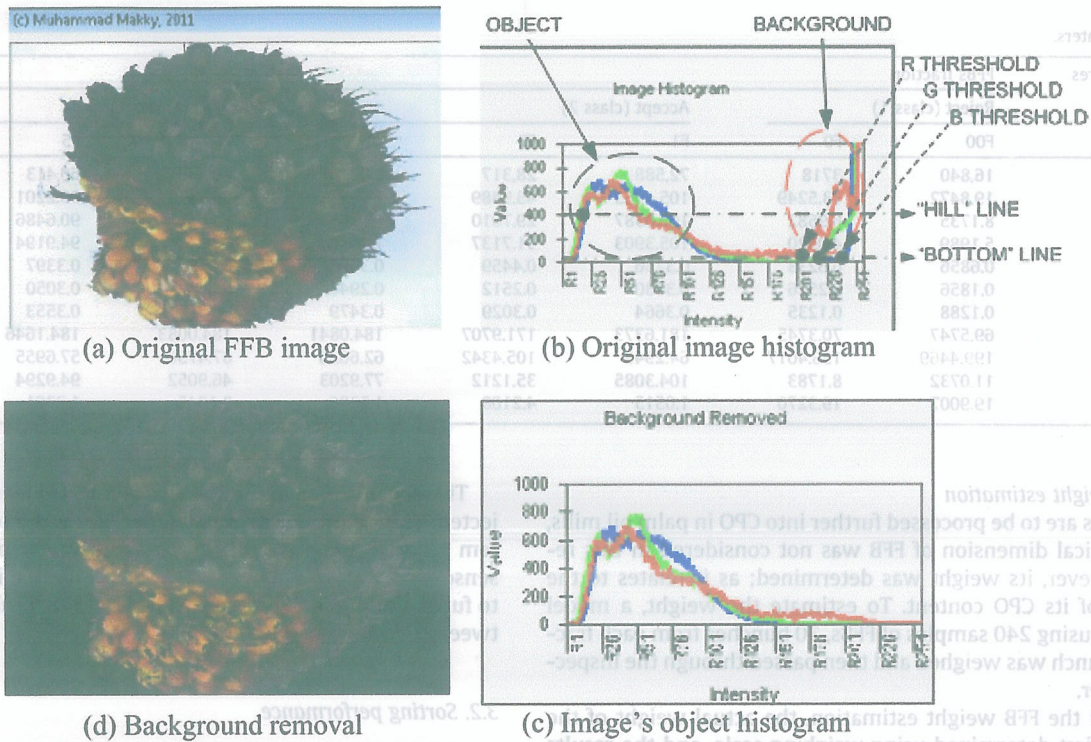


Fig. 3. FFB image thresholding.

the test. This includes the success rate of algorithm used to extract object features from images and accuracy of program in determining (row and column) and its RGB intensity values were used as data in X, Y and Z axes respectively. Result of this analysis was used to determine RGB value corresponding to fruitlets in the image object, and used for further decision making.

2.3.3. Classification of ripeness and quality of FFB

To make image more suitable for further image processing, image was transform from RGB color model into HSI (Hue (H), Saturation (S), and Intensity (I)) color model (Gonzalez and woods, 2008). Each recorded image was then processed to quantify the RGB and HSI values by the program. Furthermore, the image was normalized by converting RGB color model into r (red), g (green), and b (blue), where

$$r = \frac{R}{R+G+B} \quad (1)$$

$$g = \frac{G}{R+G+B} \quad (2)$$

$$b = \frac{B}{R+G+B} \quad (3)$$

Another indicator used to highlight the difference between ripened and unripen FFB is classification using ripeness index (RI) (Roseleena et al., 2011), where

$$\text{Ripness index (RI)} = \frac{R^2}{G \cdot B} \quad (4)$$

Classification of the FFB class was done by stepwise discriminant analysis using Canonical Discriminant Function with Mahalanobis distance. The variables used in the statistical analysis were mean values of the object's pixel, R, G, B, r, g, b, H, S, I and RI, all extracted from FFB image properties.

2.3.4. FFB fraction classification using K-means clustering and Squared Euclidean distance Analysis

For fraction classification, first the FFBs were grouped based on its fraction and image data (mean values of the object pixel, R, G, B, r, g, b, H, S, I and RI). Using statistical analysis (K-means clustering) the FFBs were grouped into 8 fractions, namely, F00, F0, F1, F2, F3, F4, F5 and F6. The initial condition of the cluster centre was initiated by the program, and the program achieved convergence, after 53 iterations. The final cluster centers are presented in the Table 2.

The final cluster centers were used as database to examine FFB image, by comparing its image properties with all clusters using Squared Euclidean distance analysis. The distance between image (I) and cluster database (C) can be described using equation below:

$$d(I_i, C_i) = (p_1 - q_1)^2 + (p_2 - q_2)^2 + \dots + (p_n - q_n)^2 \quad (5)$$

where I_i is image number, C_i is clusters member, p_i (1, 2, 3...n) are the image data (object pixel, R, G, B, r, g, b, H, S, I, RI), and q_i are the cluster center data. The squared Euclidean distance was used in order to place progressively greater weight on data that are farther apart. It is frequently used in optimization problems in which distances only have to be compared.

The examined FFBs were first classified into 2 classes (accepted, rejected). Then based on its class, further analysis was done by measuring the distance between image data (I) and cluster database (C). For instance, if the FFB is classified as class 2 (accepted), then distances will be measured between image data (I) and cluster data F1, F2 and F3 only (Table 2). And if the FFB is classified as class 1 (rejected), then distances will be measured between image data (I) and the rest of clusters. The closest cluster distance to an image data (I) made the currently examined FFB become the member of that cluster, and the fraction of the FFB will be determined based on its cluster membership.

Table 2
Final cluster centers.

Object features	FFBs fraction							
	Reject (class 1)		Accept (class 2)			Reject (class 1)		
	F00	F0	F1	F2	F3	F4	F5	F6
Object pixel	16,840	3718	72,588	28,317	51,223	36,838	60,413	44,202
R	19.8472	13.5249	105.4963	43.9489	85.3135	56.6473	99.2201	72.2914
G	8.1735	6.9582	102.0387	29.7010	72.3678	40.4516	90.6486	55.5701
B	5.1989	4.0520	105.3903	31.7137	76.0797	43.6166	94.9194	58.0091
r	0.6856	0.6238	0.3256	0.4459	0.3576	0.4096	0.3397	0.3829
g	0.1856	0.2526	0.3080	0.2512	0.2946	0.2653	0.3050	0.2799
b	0.1288	0.1235	0.3664	0.3029	0.3479	0.3251	0.3553	0.3372
H	69.5747	70.3745	181.6373	171.9707	184.0841	184.0083	184.1646	182.2264
S	199.4469	196.4017	64.2948	105.4342	62.6626	87.4796	57.6955	73.2333
I	11.0732	8.1783	104.3085	35.1212	77.9203	46.9052	94.9294	61.9569
R.I	19.9007	19.3270	1.0515	4.2108	1.5386	3.1045	1.2361	2.0371

2.3.5. FFB weight estimation

Since FFBs are to be processed further into CPO in palm oil mills, the geometrical dimension of FFB was not considered in this research. However, its weight was determined; as it relates to the estimation of its CPO content. To estimate the weight, a model was created using 240 samples of FFBs, 30 bunches from each fraction. Each bunch was weighed and then passed through the inspection chamber.

To model the FFB weight estimation, the actual weight of the bunch was first determined using weighing scale, and the results were then correlated to its area measured in the segmented image using polynomial fit. Since the FFB samples in this study represented different ripeness conditions, ripeness-specific weight estimation models for each ripeness stage were suggested; which in turn enhanced estimation accuracy. As the bunch has been classified using the FFB fraction classification model, the area of its segmented image was recorded as object pixel variable. This variable was plotted against the measured weight to obtain trend-line equations. These equations were then used in the program as FFB weight estimation algorithm. Eight models were developed, each for fraction 00 through fraction 6 (F00 to F6). Based on its class membership and ripeness fraction, the bunch weight was estimated corresponding to its area in the image using these models.

3. Results and discussion

The developed automatic grading machine was subjected to a series of tests during November–December 2011 (Fig. 4) with total of 465 FFBs of tenera variety randomly taken from oil palm trees aged 7–20 years. The FFBs used in the test were picked up from Cimulang plantation, Bogor. Results were used to validate the machine's accuracy and the functions of its all mechanical, control and software systems.

3.1. Performance of the grading machine

All four subsystems smoothly functioned as designed when tested under field condition during day time. The conveyor belt could accommodate three to four FFBs, depending on their individual size. The sagging of the belt between idle rollers, if any, can be fixed by adjusting the belt tension. The inspection chamber could accommodate all sizes of tested FFBs.

Vibrations generate by motor and transmission could influence the quality of image taken by camera. This was addressed by applying natural rubber isolators on both motor and transmission mounting. The flexible curtain at the entrance and exit side of the inspection chamber successfully prevented direct sunlight entering into the chamber.

The separator successfully diverted the FFBs classified as “rejected” to fall aside of the machine. During the tests, control system worked properly, with minor adjustment of photoelectrical sensor position. The camera was securely housed in a casing; while to further attenuate vibrations, a layer of foam rubber was put between the camera and holder.

3.2. Sorting performance

Overall performance of the grading machine was observed in the test. This includes the success rate of algorithm used to extract object features from images and accuracy of program in determining the FFB's class, ripeness (fraction), and weight. The adaptive threshold algorithm used in the software to remove background from the acquired image showed success rate of 100%.

Texture analysis of the image classified the RGB value of specific features of the object (in order to distinguish among fruitlets, spikelets and other parts). Analysis result showed that by converting RGB data to intensity, features in the image can be grouped into three (Fig. 5). The first group had intensity value from 0 to 100, representing the space between fruitlets, background, non-ripe fruitlets and contaminant (dirt, dust). The second group had intensity value from 100 to 200, and mainly represents ripe fruitlets. And the third group had intensity value from 200 to 255, denoting spikelets, calyx, and fruitlets stem. Given the result, only information from second group was used for further feature extraction in image processing.

The objective of FFB grading in a palm oil mill is to examine a bunch whether it is a suitable candidate to be processed further, for oil extraction (Table 1). In the tests, FFBs were successfully classified in two classes, namely “rejected” (class 1) and “accepted” (class 2). The classification was based on object image features, which are object pixel, average R, average G, average B, average r, average g, average b, average H, average S, average I and average of ripeness index.

With 240 samples for calibration, a Stepwise discriminate analysis using Canonical Discriminant Function with Mahalanobis distance was performed using statistical software.

The means of each variable (R, G, B, H, S, I, r, g, and b) extracted from recorded images were considered as input variable, while the actual class of related FFB, based on the assessment agreed by a group of trained and experienced grader, was considered as target variable. Data were analyzed using the discriminant classification analysis. The target classes were put as grouping variable of class 1 or class 2, while the input variables were considered as independents. A stepwise method for discriminant analysis was used together with data analysis descriptions using three methods, namely means, ANOVA and Box M method. The discriminant



Fig. 4. Performance test of the grading machine.

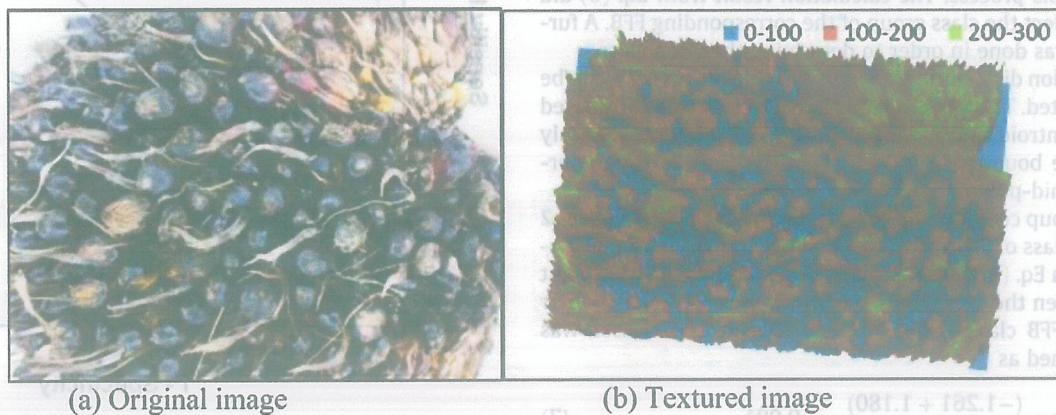


Fig. 5. Texture analysis of FFB's image.

factors were obtained using Fisher and unstandardized functions coefficients, and Mahalanobis distance analysis was employed using F value of 3.84 and 2.71 as entry and exit values respectively. The Eigenvalues (Table 3) represent special set of scalars related to linear system of equations that also known as characteristic roots or characteristic values (Hoffman and Kunze, 1971), proper values, or latent roots (Marcus and Minc, 1988). The Eigenvalues are important since they are equivalent to the diagonal matrix and arise as stability analysis. The Eigenvalues are calculated and used in deciding how many factors to extract in the overall factor analysis, and with the Eigenvalue of 1.490 it satisfies the validity of the equation generate by statistical software.

Wilks' lambda (Table 4) used in this Discriminant analysis to measure the class centers separation. Since the classes are multi-

nomial with identical means, the Wilk's lambda value of 0.402 means groups are well separated, and their means are significantly different. The Chi-square (Table 4) represents whether distributions of categorical variables (numerical and categorical) differ from one another. The result of Chi-square 1239.189 with 9 degree of freedom showed that both class are individual and no association exists between the two variables.

The canonical table (Table 5) described discriminant function coefficients, as the basis for discriminating the FFB grouping classes. The FFB class can be calculated by means of stepwise discriminant analysis using Canonical Discriminant Function calculation from Table 5 as below

$$Y = -0.019R - 0.041G + 0.013B + 40.241r + 29.105g + 0.041H - 0.037S - 0.004RI - 29.848 \quad (6)$$

where y is the intermediate calculation result, R, G, B, r, g, H, S and RI are means of red, green, blue, normalized red, normalized green, hue, saturation and ripeness index, respectively. This equation was formulated using coefficients generated by the statistical analysis, where non-significant variables were eliminated in the

Table 3
Eigenvalues.

Function	Eigenvalue	% Of variance	Cumulative (%)	Canonical correlation
1	1.490 ^a	100.0	100.0	0.774

^a First 1 Canonical Discriminant Function was used in the analysis.

Table 4
Wilks' lambda.

Test of function(s)	Wilks' lambda	Chi-square	df	Sig.
1	0.402	1239.189	9	0.000

Table 5
Canonical coefficients.

Discriminant	Function
	1
Object pixel	0.000
R	−0.019
G	−0.041
B	0.013
r	40.241
g	29.105
H	0.041
S	−0.037
RI	−0.004
(Constant)	−29.848
Unstandardized coefficients	

stepwise analysis process. The calculation result from Eq. (6) did not directly reflect the class group of the corresponding FFB. A further analysis was done in order to determine the FFB's class.

The population distributions in both classes were assumed to be evenly distributed. The groups' mean in each class was considered as the group centroid, and as the populations were assumed evenly distributed, the boundary between these two classes was determined as the mid-point between two group centroids.

With the group center of −1.261 for class 1 and 1.180 for class 2 (Table 6), the class of FFB can be decided by comparing its calculation result from Eq. (6) with the group boundary. As the mid-point distance between the two groups' centroids was set as the border between two FFB classes; the border between two classes was hence determined as

$$\text{Class boundary} = \frac{(-1.261 + 1.180)}{2} = -0.081 \quad (7)$$

For each FFB sample, its class was determined by calculating its variables (R, G, B, r, g, b, H, S, I, RI) extracted from the image, into Eq. (6) and compared the result (y) to the Eq. (7). The sample becomes member of class 1 if the calculation result (y) was equal to or less than −0.081, or of class 2 if y was greater than −0.081.

Processing time is an important factor that determines the practical utility of a machine vision based inspecting system. Although there are many textural features possible in image processing, this research considered only means of the color channels. In previous studies (Ismail and Razali, 2010; Saeed et al., 2012) as well as in this research, means of the color channels was selected as the feature in image processing since it offers the advantages of low complexity in programming and low computing time required while maintaining high accuracy levels in the results. Selection of means of the color channels has successfully overcome major challenges

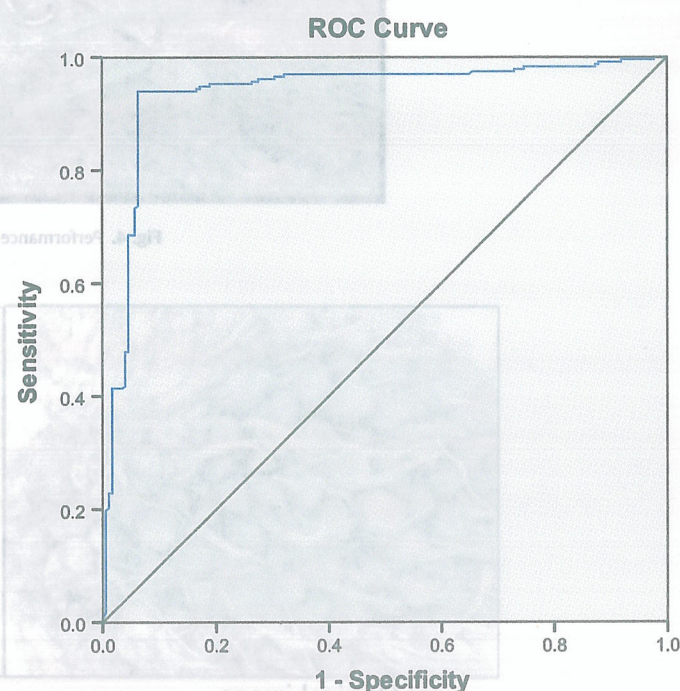
Table 6
Functions at group centroids.

Class	Function
1	−1.261
2	1.180

Unstandardized Canonical Discriminant Functions evaluated at group means.

Table 7
FFBs classification results.

		Class	Predicted group membership		Total
			1	2	
Original	Count	1	140	10	150
		2	5	85	90
	%	1	93.33	6.67	100
		2	5.56	94.44	100
Cross-validated	Count	1	143	10	153
		2	20	292	312
	%	1	93.46	6.54	100
		2	6.41	93.59	100

**Fig. 6.** ROC curve analysis for the classification performance, diagonal segments are produced by ties.

in this research, where analyses of complex data in the images with large numbers of variables were involved. This feature in image processing enabled construction of combined data while still being able to describe the data with sufficient accuracy. It reduced the requirement of large number of resources for accurately describing a large set of data.

Combination of 11 variables (Object pixel, R, G, B, H, S, I, r, g, b and RI), extracted from the image, provided an acceptable working system for grading the FFB and improved the accuracy of results. Since the software in this research could only compute a single row of matrix data, only mean values of the variables were chosen to be used in the classification exercise.

During calibration (Table 7), model correctly classified 93.33% of class 1 FFBs and 94.44% of class 2 FFBs with standard error calibration (SEC) of 0.4835, while on cross validation tests, model correctly classified 93.46% of class 1 and 93.59% of class 2. Overall, model correctly classified 93.53% of FFBs original class with standard error prediction (SEP) of 0.5165. The classification performance analysis was done using the receiver operating characteristic (ROC) curve analysis as presented in Fig. 6. The area under the curve is 0.935 with 99.99% confidence interval.

After the FFBs class classification, the program grouped the bunch according to its fraction (00,0,1,...,6). The object features

Table 8
FFB fraction classification result.

Fraction		Predicted group membership								Total
		00	0	1	2	3	4	5	6	
Count	00	31	1	1	1	0	0	0	0	34
	0	2	56	2	1	0	0	0	0	61
	1	2	4	105	1	0	1	0	0	113
	2	1	2	1	94	1	2	1	0	102
	3	0	0	1	2	88	4	1	1	97
	4	0	0	1	0	0	20	2	1	24
	5	0	0	0	1	0	0	19	1	21
	6	0	0	0	0	1	0	2	10	13
%	00	91.2	2.9	2.9	2.9	0.0	0.0	0.0	0.0	100
	0	3.3	91.8	3.3	1.6	0.0	0.0	0.0	0.0	100
	1	1.8	3.5	92.9	0.9	0.0	0.9	0.0	0.0	100
	2	1.0	2.0	1.0	92.2	1.0	2.0	1.0	0.0	100
	3	0.0	0.0	1.0	2.1	90.7	4.1	1.0	1.0	100
	4	0.0	0.0	4.2	0.0	0.0	83.3	8.3	4.2	100
	5	0.0	0.0	0.0	4.8	0.0	0.0	90.5	4.8	100
	6	0.0	0.0	0.0	0.0	7.7	0.0	15.4	76.9	100

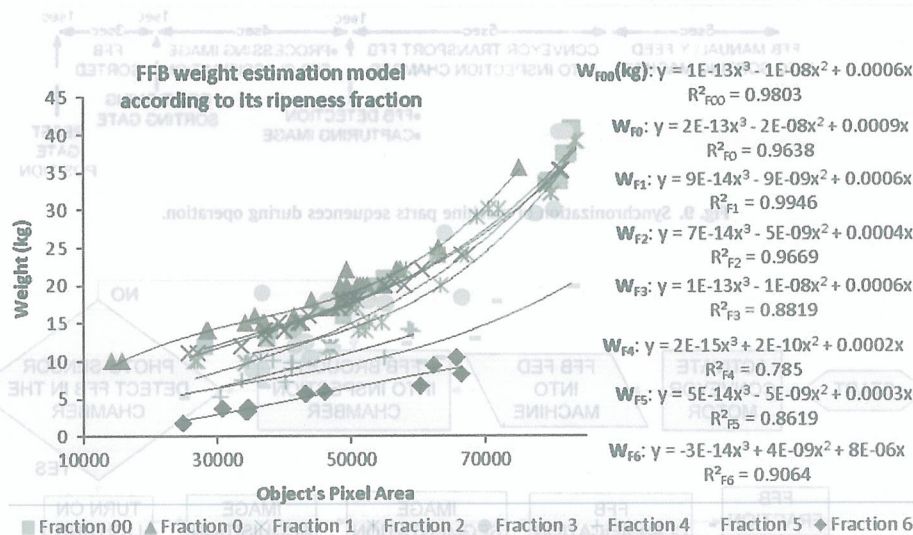


Fig. 7. FFB weight estimation model.

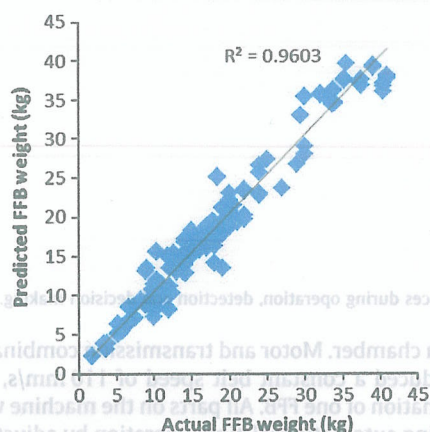


Fig. 8. FFB's weight estimation for all fractions.

fraction center, the membership of the bunch will be decided according to its class.

The grading system correctly classified FFBs fraction with an average of 88.7% accuracy, where the highest accuracy of 92.9% in fraction 1, and the lowest accuracy of 76.9% in fraction 6. The misclassification in FFBs fraction was closely related to misclassify in FFBs class; however this result is still within the mill's tolerance.

The weight estimation of FFBs was based on object features extracted from image, and calculated using appropriate model according to bunch's fraction classification. The weight was estimated based on its area in the image (Object pixel), using equation described in the Fig. 7. For instance, if the inspected FFB was determined as class 2 (Accepted) and its ripeness fraction was estimated as fraction 1 (F1), then the FFB weight was estimated using model corresponding to F1, hence FFB weight was

$$W_{F1}(kg) = (9E-14x^3) - (9E-09x^2) + 0.0006x \quad (8)$$

where x is Object's pixel.

Other FFB weight estimation models for the respective ripeness fractions are shown in Fig. 7. In general, the machine correctly estimated the FFBs weight in all fractions with R^2 of 0.9603 (Fig. 8). The miscalculation perhaps caused by the miss classification of the FFBs in the previous step due to confusing or border resemblance to other class, especially between fractions 0 and 1, or

on image is compared to cluster centre in each fraction (Table 3) which has been produced by classifying data of FFBs sample using K-means clustering. Using Squared Euclidean distance analysis, the nearest position of FFBs to any fraction cluster center will automatically make related bunch to become the member of that fraction (Table 8). In case the distance of a FFB is equal to more than one

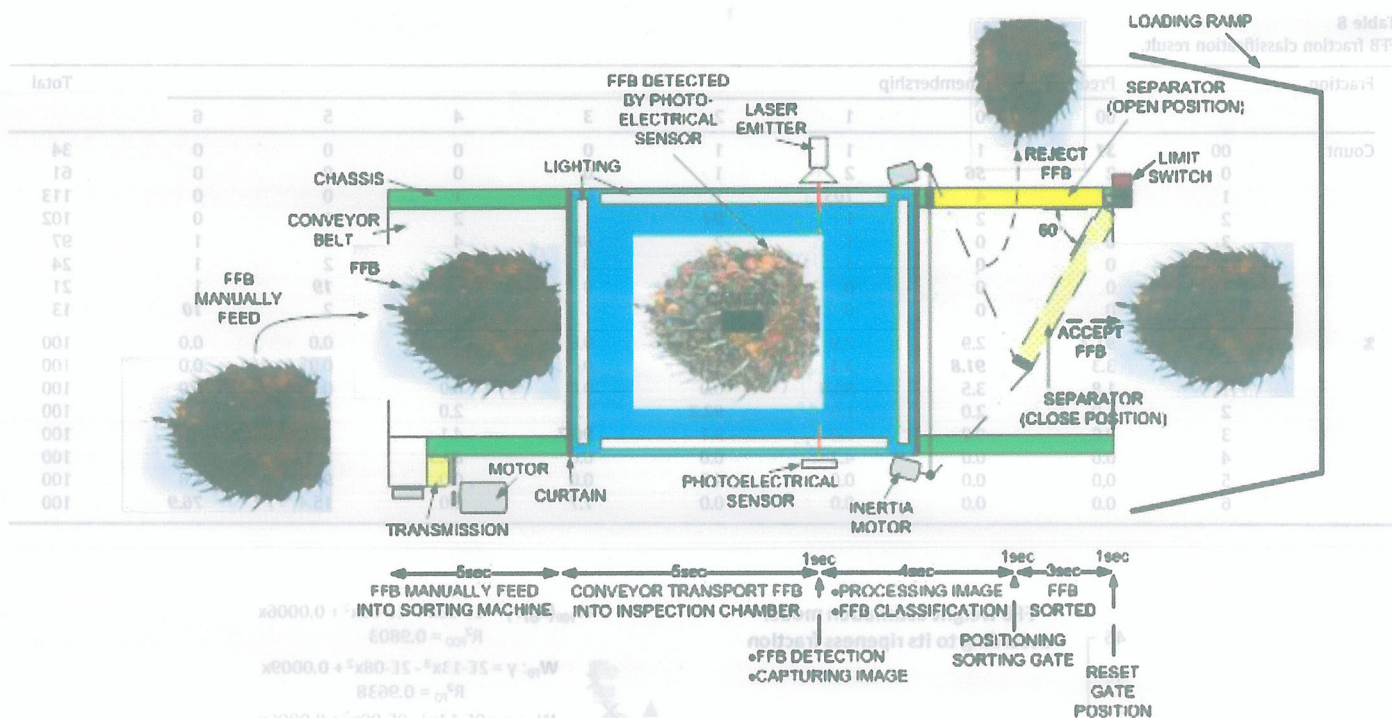


Fig. 9. Synchronization of machine parts sequences during operation.

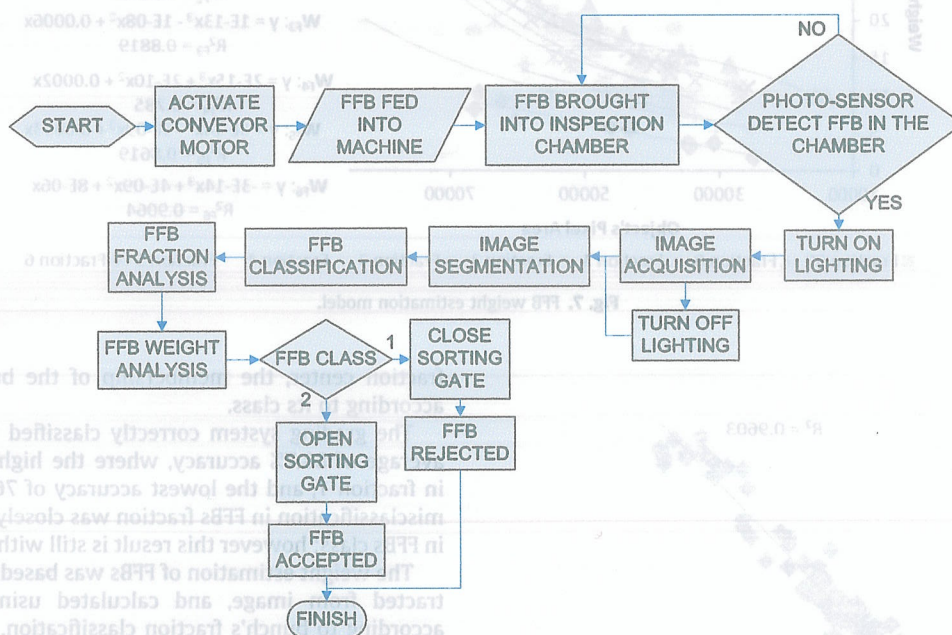


Fig. 10. Flow chart of machine operation, synchronization of machine parts sequences during operation, detection and decision making.

between fractions 3 and 4. Another cause might be the non-uniform color of bunch within the fraction, in case of overlapping fraction members, even an experienced trained grader commonly misjudge. However, the machine has the advantage of consistency and repeatability as compared to human grader.

3.3. Operation of the machine

In the tests, the placement of FFBs on conveyor belt was not governed, resulting different bunch orientations. However, this showed no influence on the sorting accuracy. The FFBs were fed manually by operator onto machine, with its handle facing toward

inspection chamber. Motor and transmission combination arrangement produced a constant belt speed of 110 mm/s, providing 5 s for examination of one FFB. All parts on the machine were synchronized during automatic real-time operation by adjusting coordination of the photo-electrical sensor, the single chip microcontroller (SCM), and the computer. These devices govern the sequence works of the detection system, the image acquisition system, the decision making and the segregation parts of the machine (Fig. 9). A flow chart to describe the operation of the machine is presented in Fig. 10.

With average FFB weight of 16.8 kg, the machine examined more than 12 tons FFBs per hour; which fairly satisfy mill's grading

Table 9
Comparative summary of previous attempts.

Reference	Objective	Methods	Success rate	Variables	Lighting	Inspection type	Inspection time
This research	<ul style="list-style-type: none"> Oil palm FFBS class Ripeness Weight 	<ul style="list-style-type: none"> Adaptive thresholding Texture analysis Discriminant analysis K-means clustering Squared Euclidean distance analysis 	<ul style="list-style-type: none"> 93.53% (FFB classification) 92.2% (FFB ripeness fraction) 96.03% (FFB weight) 90% 	<ul style="list-style-type: none"> RGB HSI rgb Ripeness index (RI) 	<ul style="list-style-type: none"> LEDs 	<ul style="list-style-type: none"> Automatic real-time operation 	5 s
Roseleena et al. (2011)	<ul style="list-style-type: none"> Oil palm FFBS ripeness 	<ul style="list-style-type: none"> K-means clustering using MATLAB® 	<ul style="list-style-type: none"> 90% 	<ul style="list-style-type: none"> RGB DN Ripeness index (R^2/GB) 	<ul style="list-style-type: none"> Four 8 W fluorescent 	<ul style="list-style-type: none"> Real time 	25 s
Jamil et al. (2009)	<ul style="list-style-type: none"> Oil palm FFBS ripeness 	<ul style="list-style-type: none"> RGB digital numbers (DN) & Neuro fuzzy 	<ul style="list-style-type: none"> 49% (RGB DN), 73.3% (Neuro-fuzzy) 90% 	<ul style="list-style-type: none"> RGB digital numbers 	<ul style="list-style-type: none"> Sunray 	<ul style="list-style-type: none"> Analysis of recorded image 	Not mentioned
Abdullah et al. (2002)	<ul style="list-style-type: none"> Oil palm fruit-lets ripeness 	<ul style="list-style-type: none"> Will's Δ & Discrimination analyses 	<ul style="list-style-type: none"> 90% 	<ul style="list-style-type: none"> Hue channel HSI (30–100°) 	<ul style="list-style-type: none"> Fluorescent 	<ul style="list-style-type: none"> Real time 	Not mentioned

capacity requirement. A comparison of the previous attempts is summarized in Table 9. All FFBS samples used in the test show no major bruise, and hence the grading process considered safe in handling the bunch without damaging it.

4. Conclusion

In this research, an automatic grading machine for FFB is built and tested through a series of field tests. All four machine subsystems have satisfactorily passed the tests with minor adjustments. The machine automatically graded the FFBS without causing injuries to the bunch. Using Stepwise discriminate analysis, machine correctly classified the FFBS into two classes, namely rejected (class 1), and accepted (class 2) with success rate of 93.53%. For fraction classification, IOPRI standard was used. In the algorithm K-means clustering and squared Euclidean distance analysis were applied, which showed the success rate of 88.7%. Eight models were used to estimate FFBS weight, one for each fraction, and showed average R^2 of 0.9603. Development of this automatic grading machine for oil palm FFB using real-time and non-destructive method provides the oil palm industries in Indonesia with the first FFB automatic grading machine that works on-site and grades the FFBS based on IOPRI grading standard.

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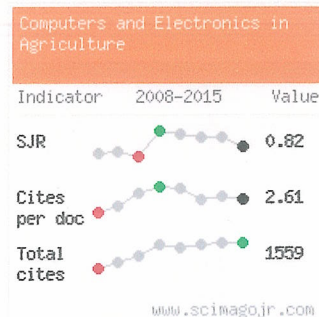
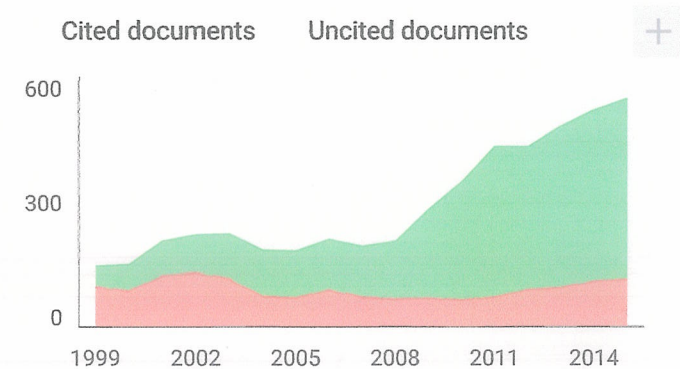
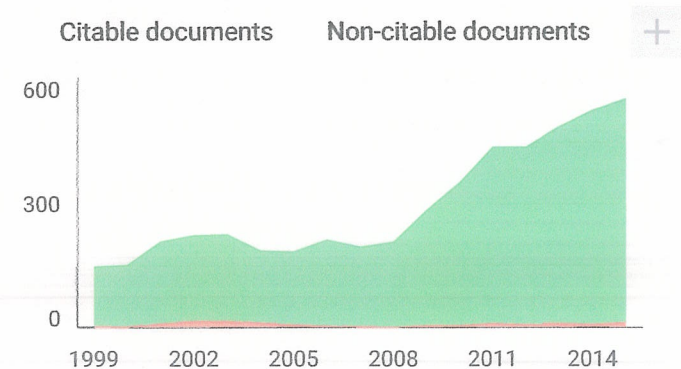
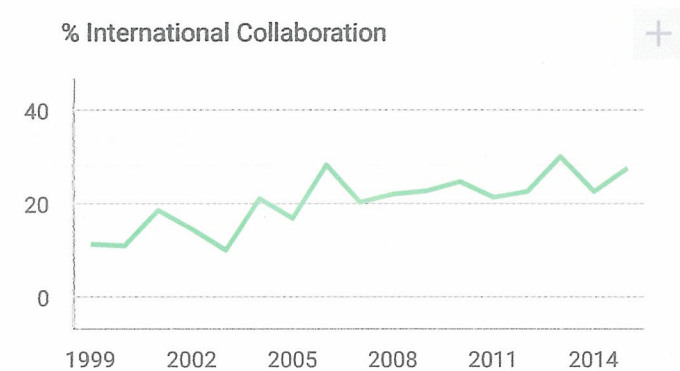
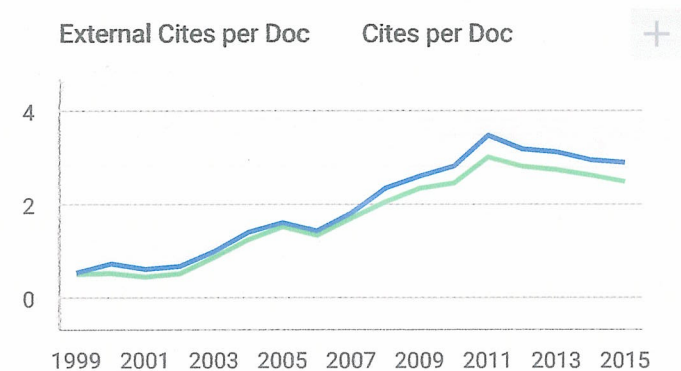
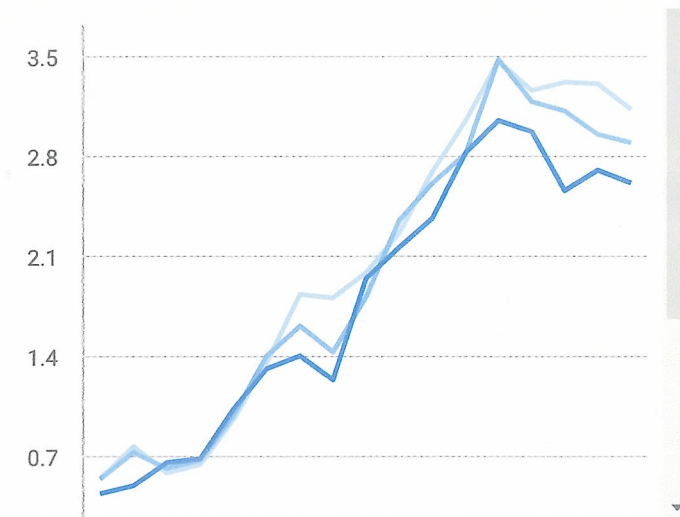
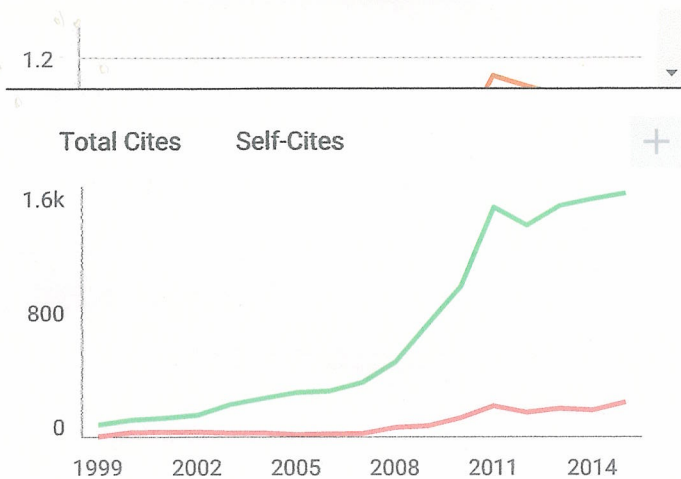
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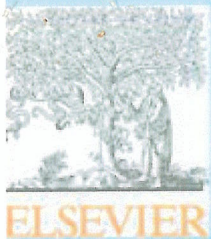
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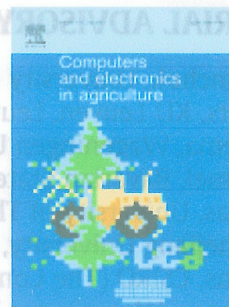
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Computers and Electronics in Agriculture

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Issue contains Open Access articles

1. Editorial Board

PDF (24 K)

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2. Editorial Board

PDF (17 K)

.....Page ii

3. Rectangular shape management zone delineation using integer linear programming

Nestor M. Cid-Garcia, Victor Albornoz, Yasmin A. Rios-Solis, Rodrigo Ortega

Abstract Close graphical abstract PDF (1024 K)

► We present a zoning method that optimally delineates rectangular homogeneous management zones. ► This zoning method, based on soil properties, uses relative variance to guarantee the homogeneity. ► It relies on an integer linear programming mathematical model that is efficiently solved to optimality. ► Experimental results on real and generated at random instances validate the method.

Original Research Article.....Pages 1-9

4. Sources of angle-dependent errors in terrestrial laser scanner-based crop stand measurement

Detlef Ehlert, Michael Heisig

Abstract Close graphical abstract PDF (1391 K)

► Laser rangefinders have a high potential for measuring crop stand parameters like crop height, biomass and contours. ► Up to now, certain existing error sources in such measurements are not well investigated. ► Influence of gap fraction and errors were analyzed and discussions were carried out in the paper. ► Experimental tests are indispensable for error analyzes.

Original Research Article.....Pages 10-16

5. Sow-activity classification from acceleration patterns: A machine learning approach

Hugo Jair Escalante, Sara V. Rodriguez, Jorge Cordero, Anders Ringgaard Kristensen, Cécile Cornou

Abstract Close graphical abstract PDF (1139 K)

► A supervised-learning approach to sow-activity classification is introduced. ► Acceleration patterns are used, time dependencies between measurements are ignored. ► The method is able to classify measurements recorded at an instance of time. ► The

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method allows the online monitoring of animals in (near) real-time. ► Experimental results outperform previous work by a considerable margin.
Original Research Article.....**Pages 17-26**

6. A simple model to assess the sensitivity of grassland dairy systems to scenarios of seasonal biomass production variability

A. Lurette, C. Aubron, C.-H. Moulin

[Abstract](#) [Close graphical abstract](#) [PDF \(1001 K\)](#)

► We model a dairy cattle farming system feeding almost exclusively on grass in France.
► A model was developed with some interactions with advisers and could be used by them. ► The model is used to understand sensitivity and adaptive capacities of the systems. ► The amount of forage bought was not only explained by the forage autonomy of farms. ► Farms with high forage autonomy can resist to repeated biomass growth variability.

Original Research Article.....**Pages 27-36**

7. A multi-objective analysis for import quota policy making in a perishable fruit and vegetable supply chain: A system dynamics approach

E. Teimoury, H. Nedaei, S. Ansari, M. Sabbaghi

[Abstract](#) [Close graphical abstract](#) [PDF \(678 K\)](#)

► A two-stage agricultural supply chain is modeled using system dynamics simulation.
► The model is validated by both quantitative method and behavior reproduction test. ► Three objectives are identified: price mean, price variation, and markup. ► The multi-objective analysis provides trade-off solutions for import quota policy making. ► Contour plots examination reveals some thresholds in Pareto frontier lines.

Original Research Article.....**Pages 37-45**

8. Automated sensing of hydroponic macronutrients using a computer-controlled system with an array of ion-selective electrodes

Hak-Jin Kim, Won-Kyung Kim, Mi-Young Roh, Chang-Ik Kang, Jong-Min Park, Kenneth A. Sudduth

[Abstract](#) [Close graphical abstract](#) [PDF \(825 K\)](#)

► An ISE-based, automated test stand for direct measurement of hydroponic nutrients is developed. ► The sensitivity and selectivity of PVC membranes for NO_3 , K, Ca, and Mg are tested. ► Tested ISEs provide good estimates for $\text{NO}_3\text{-N}$ and K in hydroponic solution.

Original Research Article.....**Pages 46-54**

9. Fusion of remotely sensed data from airborne and ground-based sensors to enhance detection of cotton plants

Huihui Zhang, Yubin Lan, Charles P.-C. Suh, John Westbrook, W. Clint Hoffmann, Chenghai Yang, Yanbo Huang

[Abstract](#) [Close graphical abstract](#) [PDF \(276 K\)](#)

► Data fusion of ground and airborne remote sensing data for distinguishing crops. ► Discriminant analyses on imagery, radiometer data, and fused data from both sensors. ► Fused dataset performed better than did the dataset using a single sensor alone. ► Data fusion can be an effective tool for detecting cotton plants. ► The method may be extended to the fusion of other data types for agricultural study.

Original Research Article.....*Pages 55-59*

10. Water harvesting for young trees using Peltier modules powered by photovoltaic solar energy

M.A. Muñoz-García, G.P. Moreda, M.P. Raga-Arroyo, O. Marín-González

Abstract Close graphical abstract PDF (1261 K)

► Water can be obtained from the moisture of the air using Peltier modules. ► The water obtained by electronic devices can be enough to save young trees. ► A computer based controller can optimize the energy consumption of a water condenser. ► A photovoltaic power source supplies more energy when the necessity is higher.

Original Research Article.....*Pages 60-67*

11. Application of kernel-genetic algorithm as nonlinear feature selection in tropical wood species recognition system

Rubiyah Yusof, Marzuki Khalid, Anis Salwa M. Khairuddin

Abstract Close graphical abstract PDF (1496 K)

► KDA with GA are used to generate nonlinear features of the wood features. ► Use dataset of 52 wood species, each has 70 images for training and 30 for testing. ► 157 wood features are extracted from the fusion of BGLAM and SPPD methods. ► Size of original training database is reduced by 61.75% using the proposed method. ► Accuracy of 98.6%, reduction of 3 times the memory space for storing the samples.

Original Research Article.....*Pages 68-77*

12. Comparisons of two numerical approaches to simulate slatted floor of a slurry pit model – Large eddy simulations

Wentao Wu, Chao Zong, Guoqiang Zhang

Abstract Close graphical abstract PDF (1872 K)

► LES was used to model slatted floor directly (LESD) and as porous media (LESP). ► LESP can estimate air velocity and turbulence in the core of the pit headspace. ► Vertical air motion in the slot was observed for LESD result but not for LESP. ► A dominant Strouhal number 0.23 was found for LESD result but not for LESP result. ► Turbulence transportation was the dominant removal mechanism for both LESD and LESP.

Original Research Article.....*Pages 78-89*

13. Residual biomass calculation from individual tree architecture using terrestrial laser scanner and ground-level measurements

A. Fernández-Sarriá, B. Velázquez-Martí, M. Sajdak, L. Martínez, J. Estornell

[Abstract](#) [Close graphical abstract](#) [PDF \(989 K\)](#)
 ► Biomass removed from pruning could be used as source of renewable energy. ► The amount of this residual biomass has been quantified for *Platanus hispanica*. ► Models for residual biomass estimation were developed from dendrometric parameters obtained by TLS.

Original Research Article.....**Pages 90-97**

14. Agriculture Land Suitability Evaluator (ALSE): A decision and planning support tool for tropical and subtropical crops

Ranya Elsheikh, Abdul Rashid B. Mohamed Shariff, Fazel Amiri, Noordin B. Ahmad, Siva Kumar Balasundram, Mohd Amin Mohd Soom

[Abstract](#) [Close graphical abstract](#) [PDF \(2235 K\)](#)

► ALSE as an intelligent system for land evaluation using the FAO-SYS model and management expertise. ► GIS-MCE support systems that assist decision-makers on land suitability evaluation. ► ALSE as a useful system for land planners to make complex decisions within a short period.

Original Research Article.....**Pages 98-110**

15. Automatic identification of marked pigs in a pen using image pattern recognition

Mohammadamin Kashiha, Claudia Bahr, Sanne Ott, Christel P.H. Moons, Theo A. Niewold, F.O. Ödberg, Daniel Berckmans

[Abstract](#) [Close graphical abstract](#) [PDF \(1582 K\)](#)

► Pigs are localised in a pen using ellipse fitting modelling. ► We paint fattening pigs with basic patterns to differentiate them. ► We introduce an elegant way to identify pigs in a farm pen. ► Algorithms are presented to detect location of pigs within a pen. ► We can analyse specific behaviours in pigs such as resting using identification and therefore localisation.

Original Research Article.....**Pages 111-120**

16. Tree feature extraction using image data obtained through virtual field server

Xuefeng Wang, Masayuki Hirafuji, Xiaodong Li

[Abstract](#) [Close graphical abstract](#) [PDF \(825 K\)](#)

► An indoor virtual field server monitored *Xanthoceras sorbifolia* tree seedling growth. ► A camera model and reconstruction formula were developed for the virtual field server. ► Images from two cameras were used to calculate tree crown widths.

Original Research Article.....**Pages 121-128**

17. Development of an automatic grading machine for oil palm fresh fruits bunches (FFBs) based on machine vision

Muhammad Makky, Peeyush Soni

[Abstract](#) [Close graphical abstract](#) [PDF \(1749 K\)](#)

► Machine vision is used to automatically grade fresh-fruits bunches of oil palm. ► Stepwise discrimination (Canonical and Mahalanobis functions) to classify groups. ►

Adaptive threshold algorithm showed 100% success rate for background removal. ► Group classification of FFBs resulted average success rate of 93.53%. ► Fraction classification, using Euclidean distance analysis showed 88.7% success rate.
Original Research Article.....**Pages 129-139**

18. A field-specific web tool for the prediction of Fusarium head blight and deoxynivalenol content in Belgium

S. Landschoot, W. Waegeman, K. Audenaert, P. Van Damme, J. Vandepitte, B. De Baets, G. Haesaert

[Abstract](#) [Close graphical abstract](#) [PDF \(937 K\)](#) [Supplementary content](#)

► We studied the Fusarium head blight incidence and DON content during 2002–2011.
 ► We modelled Fusarium head blight incidence and DON content. ► The best models are embedded in a web tool. ► The web tool returns predictions for Fusarium head blight and DON content together with an appropriate advice.

Original Research Article.....**Pages 140-148**

19. CFD in the Agri-Food Industry: A maturing engineering design tool

Tomás Norton

[PDF \(124 K\)](#)

.....**Pages 149-150**

20. Computational fluid dynamics applications to improve crop production systems

T. Bartzanas, M. Kacira, H. Zhu, S. Karmakar, E. Tamimi, N. Katsoulas, In Bok Lee, C. Kittas

[Abstract](#) [Close graphical abstract](#) [PDF \(2888 K\)](#)

► The majority of CFD studies for precision crop production focusing on greenhouses.
 ► Greenhouses designs and climate have been optimized with CFD. ► Application of CFD unresolved issues related to dynamic soil-tool interaction. ► CFD simulations improve pesticide sprayer efficiency for crops.

Original Research Article.....**Pages 151-167**

21. The past, present and future of CFD for agro-environmental applications

In-Bok Lee, Jessie Pascual P. Bitog, Se-Woon Hong, Il-Hwan Seo, Kyeong-Seok Kwon, Thomas Bartzanas, Murat Kacira

[Abstract](#) [Close graphical abstract](#) [PDF \(1954 K\)](#)

► The application of CFD is discussed in atmospheric, land and water management. ► The atmospheric processes are investigated in the fluid flow characteristics. ► The application of CFD is still limited in soil and water management. ► Future direction of the CFD applications in the agro-environment field was discussed.

Original Research Article.....**Pages 168-183**

22. The use of CFD to characterize and design post-harvest storage facilities: Past, present and future

A. Ambaw, M.A. Delele, T. Defraeye, Q.T. Ho, L.U. Opara, B.M. Nicolai, P. Verboven
[Abstract](#) [Close graphical abstract](#) [PDF \(1293 K\)](#)

► This article review the recent CFD approaches in post-harvest storage facilities. ► Airflow, heat and mass transfer in different post-harvest applications are considered. ► New trends and directions for future research are presented. ► There is progress towards using CFD on detailed geometrical models of products and packages. ► We are at the advent of a true multiscale approach to CFD simulation of post-harvest systems.

Original Research Article.....*Pages 184-194*

23. Advances in the use of CFD to characterize, design and optimize bioenergy systems

Binxin Wu

[Abstract](#) [Close graphical abstract](#) [PDF \(1155 K\)](#)

► CFD development of six major bioreactors is documented. ► Opportunities and challenges for CFD developing bioenergy are presented. ► Comments on model physical and biological processes in bioreactors are made.

Original Research Article.....*Pages 195-208*

24. Prediction of quality parameters for biomass silage: A CFD approach

T. Bartzanas, D.D. Bochtis, O. Green, C.G. Sørensen, D. Fidaros

[Abstract](#) [Close graphical abstract](#) [PDF \(1477 K\)](#)

► A validated CFD model for temperature distribution within silage stacks. ► A validated CFD model for oxygen concentration distribution within silage stacks. ► Prognosis system for silage quality parameters. ► Influence of infiltration rate on microclimate distribution in silage stack.

Original Research Article.....*Pages 209-216*

25. A computational analysis of a fully-stocked dual-mode ventilated livestock vehicle during ferry transportation

Tomás Norton, Peter Kettlewell, Malcolm Mitchell

[Abstract](#) [Close graphical abstract](#) [PDF \(2442 K\)](#)

► The CFD analysis of a livestock transporter was validated using a real-life transportation scenario. ► The mechanically ventilated deck exhibited environmental heterogeneity owing to its design. ► The naturally ventilated deck was found to have better environmental uniformity.

Original Research Article.....*Pages 217-228*

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