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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.

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 (Aleixos 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; Liming 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 continues 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, webcam 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

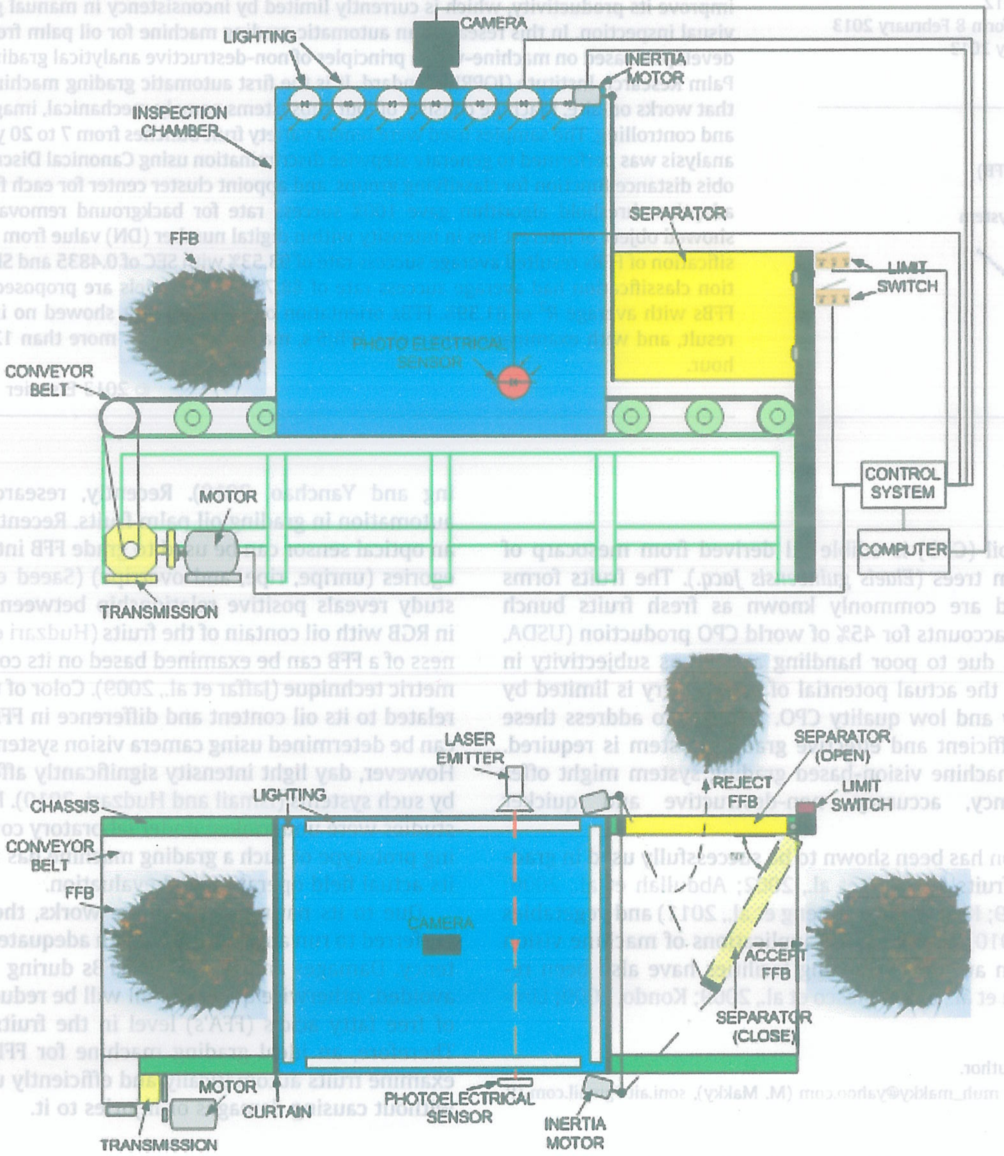


Fig. 1. Concept of automated FFB grading machine.

features from images to calculate weight, maturity, and classification of the FFBs. The detection device consists of a pair of laser emitter and light dependant resistor (LDR) as photoelectrical sensors to detect the FFB presence in the inspection chamber; and two limit switches to turn off inertia motors after the separator reaches the rotation limit in each direction.

The image processing program was developed to record the FFB images using native Win32 application programming interface (API). The program also reads sensors and controls the actuator through interfacing with single-chip-microcomputer (SCM). To capture image, the program first activates camera, record the frame to clipboard and save the recorded image to file. The recorded image will have 640 × 480 pixels with 24 bit RGB colors. All images were recorded in the inspection chamber under same lighting condition.

White LEDs were chosen as light source inside the inspection chamber. The LEDs have 5 mm diameter through hole with 6500 K white color temperature and 30° viewing angle. The LEDs color spectrum, measured by spectrometer (Ocean Optics, USB2000+Series, USA), spans from 420 nm through 665 nm. The LEDs emit cool white light through clear lens with intensity of 1 lumen. The LEDs were arranged inside the chamber facing 45° angle to the bottom of box. A total of 168 LEDs emit 502.2 lux of white light as measured by digital light meter (Krisbow, KW0600288, Indonesia).

2.1.3. Control system

The control system (Fig. 2) consists of a Single Chip Microcontroller (SCM) with In System Programmable (ISP) capability. It receives signals from photoelectrical sensor to detect FFB presents in the chamber. Signals from limit switches were read to control separator device that performs grading. The control system communicates with computer through universal serial bus (USB) port, bringing input to the program to control the conveyor motor, inspection chamber's lightning, and the inertia motor, through an array of electronic switches.

2.2. Working principle of the automated FFB grading machine

The FFBs are fed to the conveyor belt before they enter the inspection chamber, which is covered by double ply flexible curtain, in order to prevent direct sunlight entering the chamber that might alter result of image processing. A laser light emitter is 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

Images acquired by the camera (Fig. 3a) are sent to the computer in digitized form. The RGB digital number value in image is then extracted by the software and presented as histogram (Fig. 3b). Since the contrast between the object (FFB) and the background (conveyor belt) is enhanced by applying white homogenous color to the belt, the belt RGB values are accumulated in higher range of the histogram.

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,

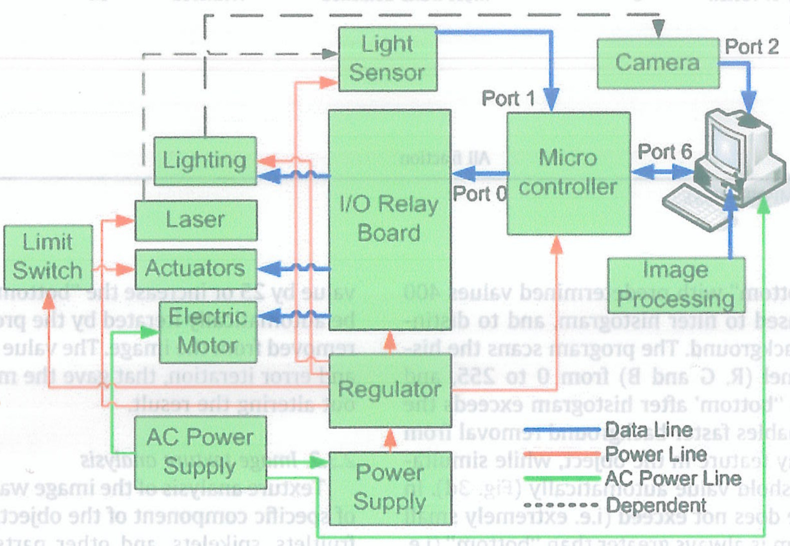
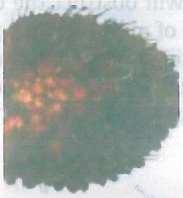
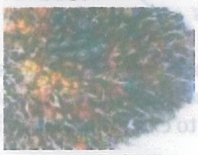
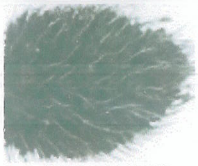


Fig. 2. The control system.

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

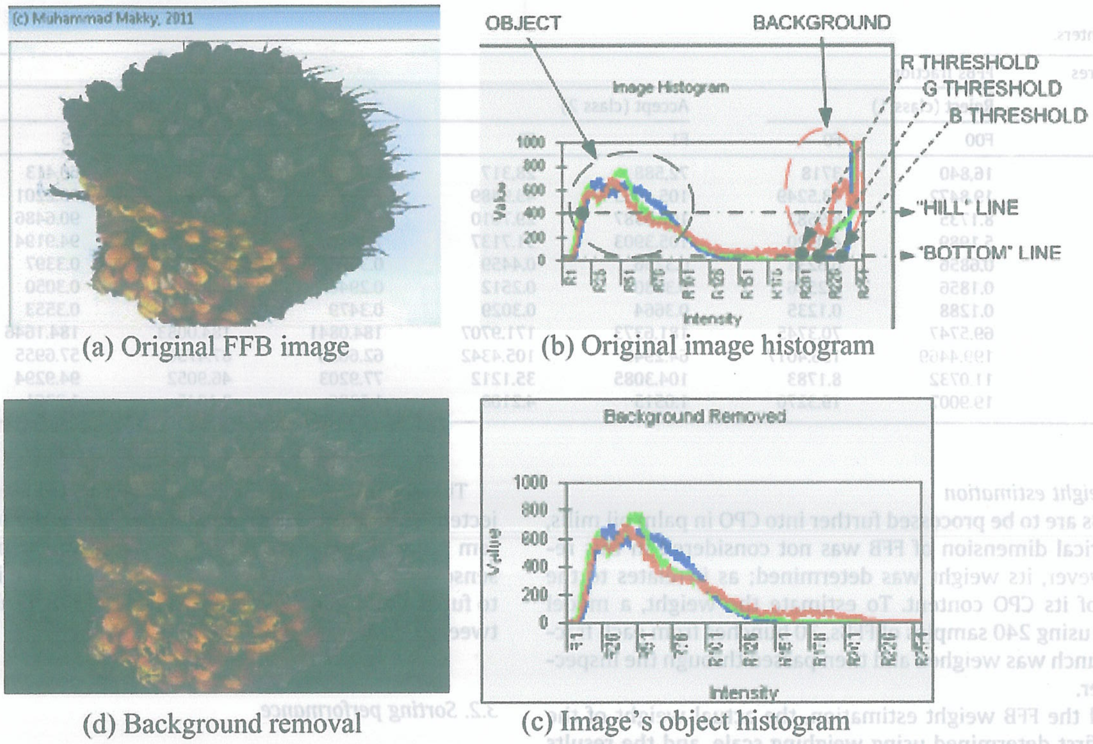


Fig. 3. FFB image thresholding.

(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

$$r = \frac{R}{R+G+B} \tag{1}$$

$$g = \frac{G}{R+G+B} \tag{2}$$

$$b = \frac{B}{R+G+B} \tag{3}$$

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

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

Classification of the FFB class was done by stepwise discriminate 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:

$$d(I_i, C_i) = (p_1 - q_1)^2 + (p_2 - q_2)^2 + \ldots + (p_n - q_n)^2 \tag{5}$$

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.

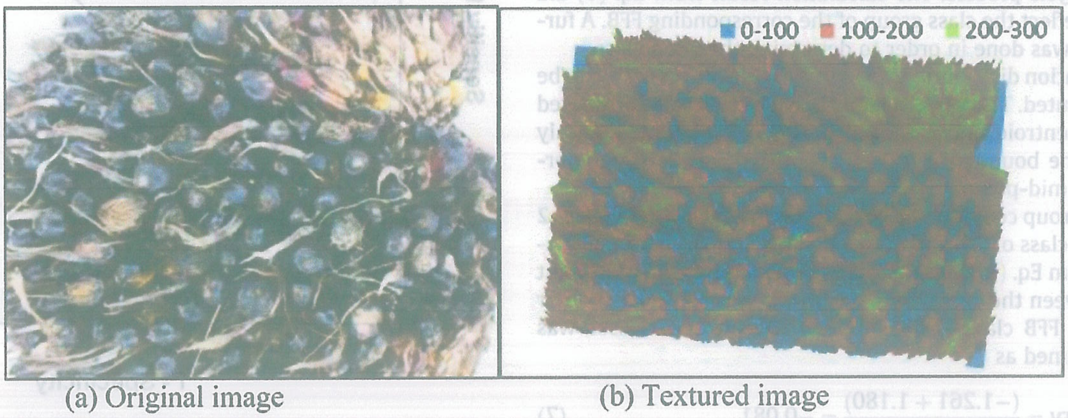


Fig. 5. Texture analysis of FFB's image.

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 multinomial 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 discriminate analysis using Canonical Discriminant Function calculation from Table 5 as below

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.

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

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 4
Wilks' lambda.

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

Table 5
Canonical Discriminant Function coefficients.

	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

Table 7
FFBs classification results.

		Class	Predicted group membership 1	Predicted group membership 2	Total
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

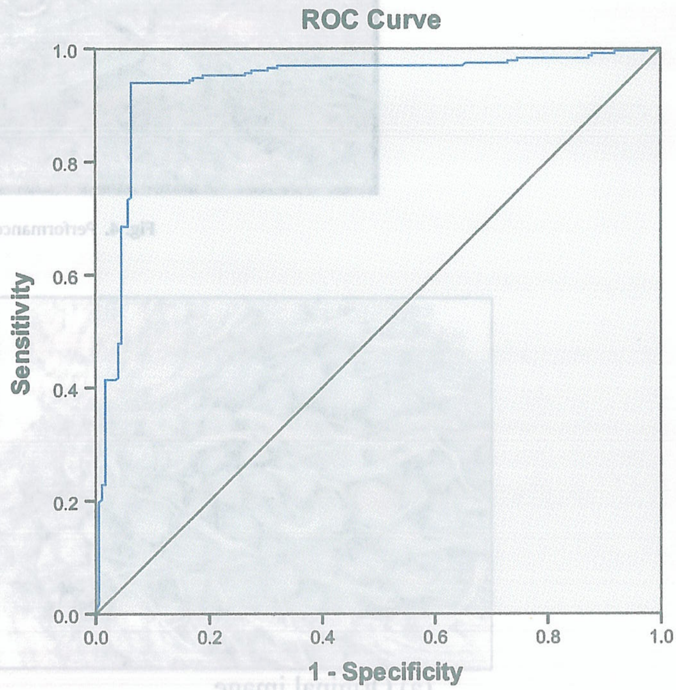


Fig. 6. ROC curve analysis for the classification performance, diagonal segments are produced by ties.

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 programing 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	−1.261
2	1.180

Unstandardized Canonical Discriminant Functions evaluated at group means.

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

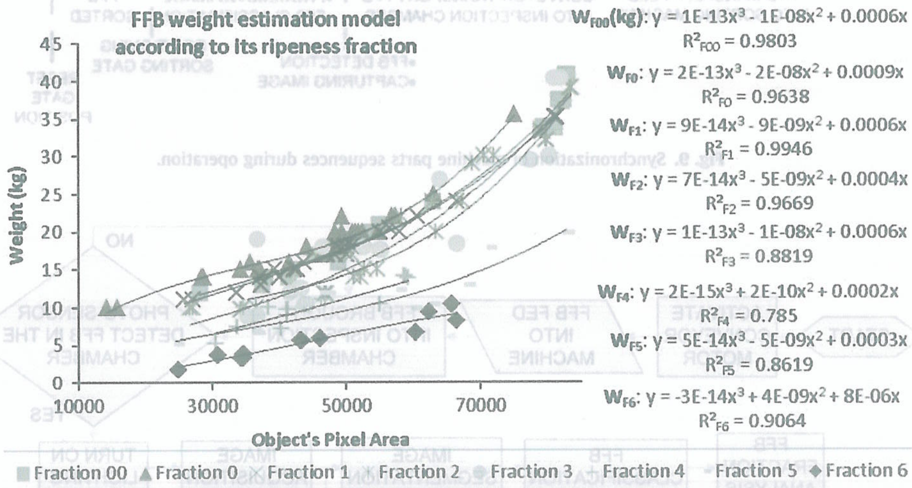


Fig. 7. FFB weight estimation model.

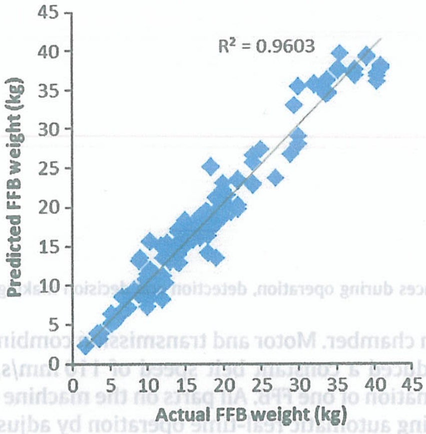


Fig. 8. FFB's weight estimation for all fractions.

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 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

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

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

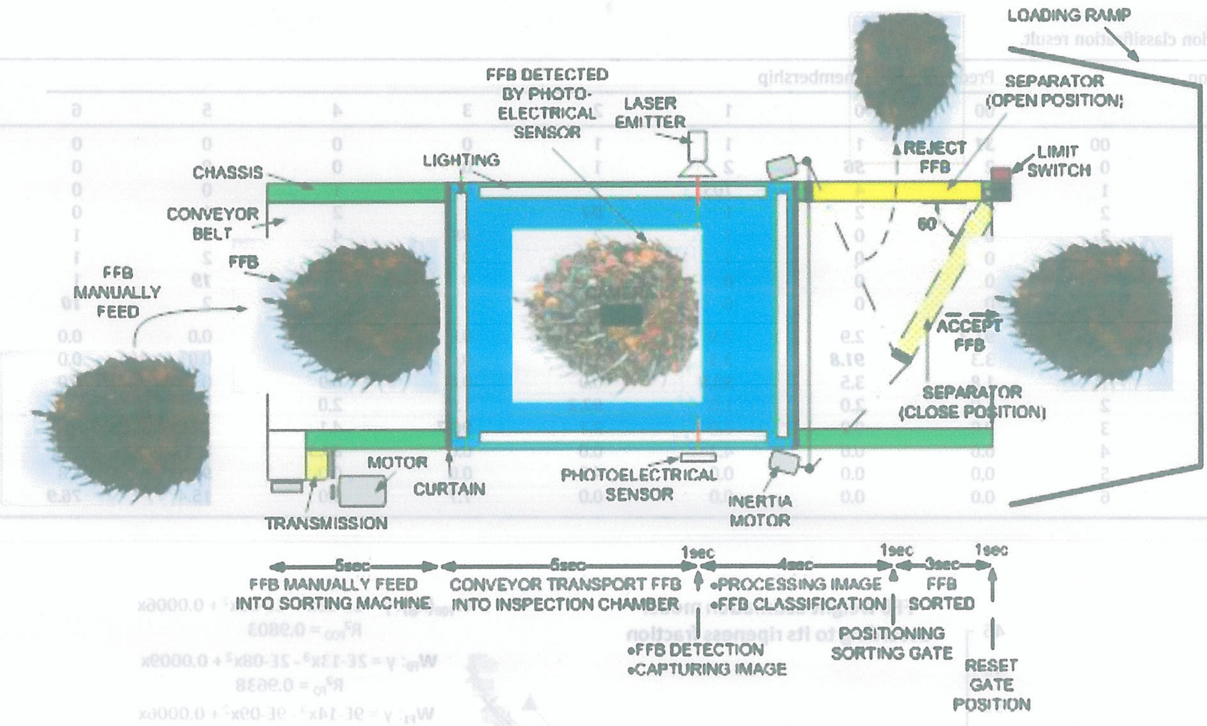


Fig. 9. Synchronization of machine parts sequences during operation.

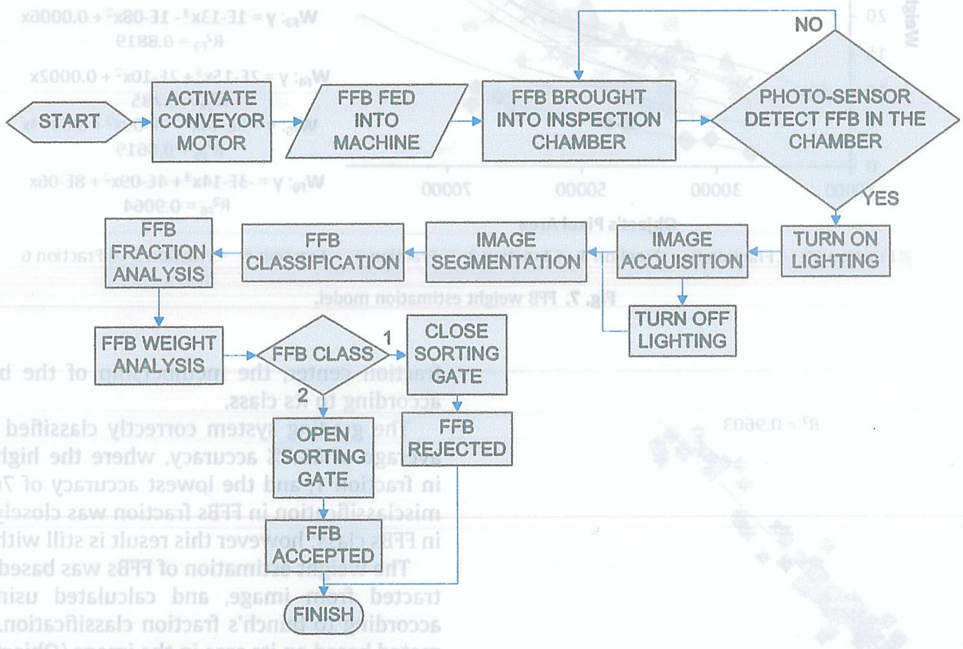


Fig. 10. Flow chart of machine operation, synchronization of machine parts sequences during operation, detection and decision making.

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	• Oil palm FFBs class • Ripeness • Weight	• Adaptive thresholding • Texture analysis • Discriminant analysis • K-means clustering • Squared Euclidean distance analysis	• 93.53% (FFB classification) • 92.2% (FFB ripeness fraction) • 96.03% (FFB weight)	• RGB • HSI • rgb • Ripeness index (RI)	• LEDs	• Automatic real-time operation	5 s
Roseleena et al. (2011)	• Oil palm FFBs ripeness	• K-means clustering using MATLAB®	• 90%	• RGB DN • Ripeness index (R^2/GB)	• Four 8 W fluorescent	• Real time	25 s
Jamil et al. (2009)	• Oil palm FFBs ripeness	• RGB digital numbers (DN) & Neuro fuzzy	• 49% (RGB DN), • 73.3% (Neuro-fuzzy)	• RGB digital numbers	• Sunray	• Analysis of recorded image	Not mentioned
Abdullah et al. (2002)	• Oil palm fruitlets ripeness	• Wilk's Λ & • Discrimination analyses	• 90%	• Hue channel HSI (30–100°)	• Fluorescent	• 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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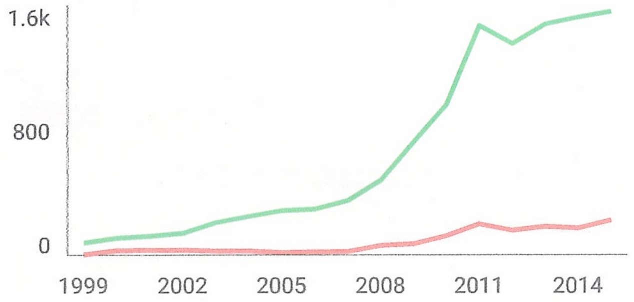

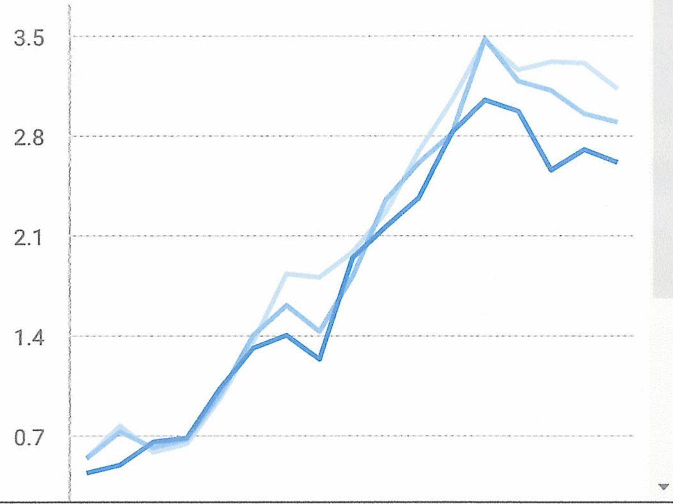

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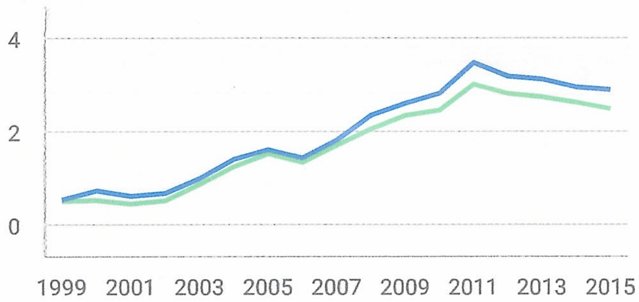

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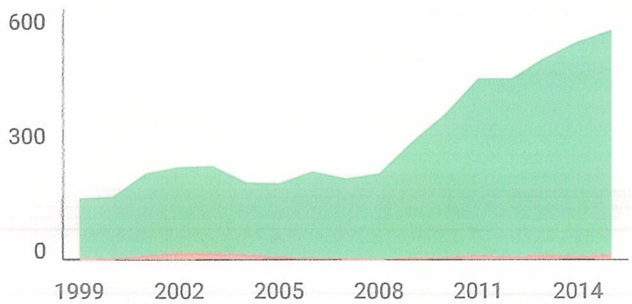

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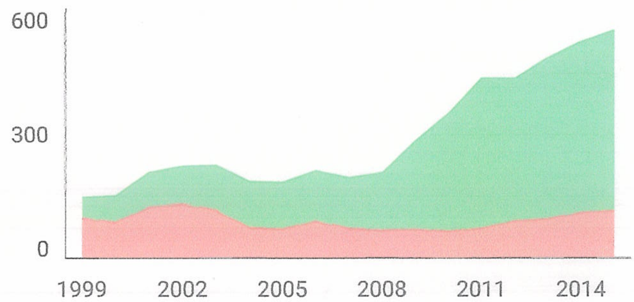

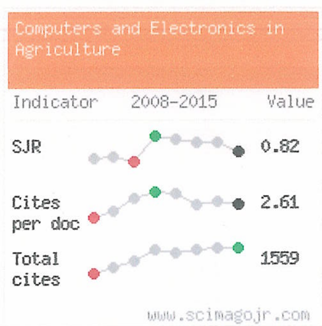

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