International Journal of Scientific Research in Multidisciplinary Studies
Vol.8, Issue.1, pp.56-62, January (2022)
Research Paper
E-ISSN: 2454-9312
P-ISSN: 2454-6143

Identification and Classification of Oil Palm Maturity Using Machine Learning Techniques

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Available online at: www.isroset.org

Received: 24/Nov/2021, Accepted: 28/Dec/2021, Online: 31/Jan/2022

***Abstract*—** Oil palm is the main plantation crop in Indonesia, oil palm is the most efficient producer of vegetable oil. Oil palm fruit is one of the fruits that has a certain level of maturity in a relatively fast time. The distribution of oil palm fruit in various regions makes it important to identify and classify the maturity of oil palm fruit based on its maturity level. The degree of ripeness of the bunches at harvest is closely related to the oil content contained in the fruit. Accuracy problems are often encountered in research related to image classification. One challenge that arises is finding an appropriate representation of the data so that important structures of the data can be seen easily. One of the processes carried out to get better accuracy is the segmentation process. Through the use of proper segmentation techniques, the desired accuracy will be obtained. One of the techniques used in the segmentation method is to use the swarm optimization technique and its derivatives. In this study, identification and classification will be implemented using particle swarm optimization (PSO) at thresholding image segmentation in order to obtain better segmentation results when compared to the previous method. The classification is based on existing machine learning techniques, namely support vector machine (SVM). the accuracy rate for the classification of palm fruit maturity based on texture using the Support Vector Machine (SVM) method is obtained, which reaches 92.5%. From the accuracy obtained, it can be concluded that the method used to identify and classify in this study is good.

Keywords—Classification, Particle Swarm Optimization, Support Vector Machine

I. INTRODUCTION

Indonesia is an agricultural country that has abundant natural resources and a suitable climate for this agricultural sector. It is known as an agricultural country because most of the population has a livelihood in the field of agriculture or farming. According to data from the Central Bureau of Statistics Indonesia (BPS) in February 2016, it was noted that 31.74% of the workforce in Indonesia or around 38.29 million worked in the agricultural sector. Indonesia is a producer of various kinds of export commodities, including rice, corn, vegetables, various chilies, sweet potatoes and cassava. In addition, Indonesia is also known as a country with good exports of plantation products, including rubber, oil palm, tobacco, cotton, coffee and sugar cane.

Oil palm is the main plantation crop in Indonesia, oil palm is the most efficient producer of vegetable oil. Oil palm fruit is one of the fruits that has a certain level of maturity in a relatively fast time. The distribution of oil palm fruit in various regions makes it important to identify and classify the maturity of oil palm fruit based on its maturity level. The degree of ripeness of the bunches at harvest is closely related to the oil content contained in the fruit. The ripeness of the fruit is judged based on the colour of the fruit, the characteristics of the raw fruit are purple to black, while the base of the fruit is slightly pale. After the fruit is ripe, the colour will turn yellowish red. If the oil palms are harvested before the fruit is ripe or the fruit is too ripe, there will be lots of bad palms at the time of sale. Palm oil that is not well ripe will experience a price decline because the yield of oil from under ripe or overripe palm will reduce the yield and quality of the oil produced.

There are several types of ripeness in oil palm fruit such as overripe, ripe, under ripe and unripe in oil palm plants that require automatic techniques to recognize them. Machine learning is a framework that is intrinsically suitable to solve problems like this. A variety of techniques have been introduced for the identification and classification of image processing using machine learning. Where these automation techniques can be used to carry out the identification and classification monitoring process, the results of which are accuracy and robustness that still need to be improved [1]. Image segmentation is a process of dividing digital images into several regions or objects. The object provides a lot more useful information than just single pixels. Image segmentation plays an important role in the field of analysis. One of the most frequently used image segmentation methods is thresholding [2-4]. The thresholding technique is divided into two types, namely the optimal thresholding method and property-based thresholding. Several techniques have been proposed related to optimal thresholding using bi-level thresholding which can eventually be expanded into multilevel thresholding.

This paper is organized into five sections. Section I introduces the problems and the reason why identification and classification of oil palm maturity is proposed. Section II explains related works and the review of segmentation and classification strategies will be explained in Section III. Section IV explains the experiment and discusses the result in this paper. The conclusion of this work is presented in Section V.

II. RELATED WORK

Thresholding is the simplest and most widely used image segmentation method. Thresholding can be bi-level or multilevel. Both types can be classified into a parametric approach rather than a parametric approach write surveys regarding thresholding techniques for image segmentation. From the survey, it is evident that the Otsu method is often used for image segmentation using thresholding. This method finds the optimal threshold through maximizing the number of weights between the class variance (between-class variance) [3]. Even so, the process of finding a solution is an exhaustive search and it takes a long time because its complexity grows exponentially with many thresholds. One technique that is widely used is to use a bio-inspired algorithm, namely particle swarm optimization (PSO) and its derivatives [5]. Several modified particle swarm optimizations, among others[5], [6], [7]. Application of PSO have been proposed in [8-13] , [[15-16].

A. Particle Swarm Optimization (PSO)

The particle swarm optimization (PSO) technique was first introduced in 1995, which is a stochastic optimization technique that is the same as the behavior of a flock of birds or the sociological behavior of a group of humans [5]. The original PSO algorithm is written in the form of velocity updated and position updated as shown in equation (1) and equation (2), respectively [4].

$$v_{id}^{t+1} = w.v_{id}^{t} + c_1 .r_1 .(p_{id}^{t} - x_{id}^{t})c_2 .r_2(p_{gd} - x_{id}^{t}) \quad (1)$$
$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \quad (2)$$

Where c_1 and c_2 are positive constant, namely acceleration coefficients. r_1 and r_2 are two random number with the value in range [0,1]. w is inertia weight. The large inertia weight will facilitate a global exploration while the small inertia will facilitate a local exploitation. Particle-i represented by $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ .The best position previous from particle-i is save and represented by $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$. Position provides the best fitness value. The index of the best particle among all the particles in the population is represented by the symbol g. The rate of change in position (velocity) for particle i is represented as $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. During the update process, the velocity of each dimension of a particle is limited to v_{max}. D is the dimension of each search space.

B. Texture Features

Texture analysis is important and useful in the field of machine vision. Most natural surface textures are displayed and a successful vision system must match the surrounding texture objects. In texture analysis, an intensity pair matrix is needed, which is a matrix that describes the frequency of appearance of two pixel pairs with a certain intensity within a certain distance and direction. One technique for texture analysis is the use of gray level co-occurence matrix (GLCM) [17 - 20]. Texture properties can be taken from the gray level intensity value statistics in the image, namely the average (mean). The mean value of a gray image value distribution can be searched without the aid of a pair matrix, but to extract other properties in the pair matrix texture analysis is needed to help calculate the properties to be extracted from the image. Other features that can be obtained using the GLCM method are standard deviation (SD), Entropy, Root mean Square (RMS), Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy and Homogeneity [14]. A feature for measuring the randomness of the intensity distribution is called Entropy and is defined as:

$$entropy = -\sum_{i1}\sum_{i2} p(i_1, i_2)\log p(i_1, i_2) \quad (3)$$

The maximum entropy value will be if all the elements are the same, namely the matrix associated with the image where there is no specific arrangement in the intensity pair with a certain vector distance d.

Energy, a feature used to measure the concentration of pairs on the co-occurrence matrix is defined as:

$$energy = \sum_{i1}\sum_{i2} p^2(i_1, i_2) \quad (4)$$

The energy value will get bigger if the pixel pairs that meet the co-occurrence intensity matrix requirements are concentrated on several coordinates and decrease if the location is spread out. Contrast is used to measure the strength of the difference in intensity in an image and is expressed by the equation:

$$contrast = \sum_{i1}\sum_{i2} (i_1 - i_2)^2 p(i_1, i_2) \quad (5)$$

The contrast value increases when the variation in intensity in the image is high, and decreases when the variation is low. Whereas the opposite of contrast is homogeneity, which is used to measure the variation in intensity in an image, and is defined as:

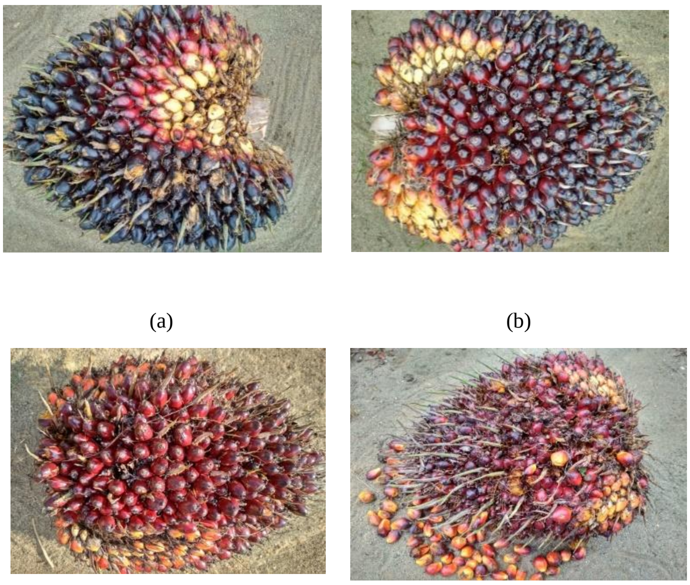
$$homogeneity = \sum_{i1}\sum_{i2} \frac{p(i_1, i_2)}{1 + |i_1 - i_2|} \quad (6)$$

The homogeneity value will increase when the intensity variation in the image decreases and vice versa the value will decrease when the intensity variation in the image grows.

C. Oil Palm

Oil palm is an industrial / plantation plant that is used as the largest producer of industrial oil and fuel. Oil palm trees consist of two species, namely *eleais oleifera* and *elaeis guineensis* which are used for commercial agriculture by producing palm oil. Oil palm became popular after industrial revolution at the end of the 19th century which caused a high demand for oil for the foodstuff and soap industry (Indonesian Plantation Service, 2007). Oil palm is a tree-type plant, reaching 24 meters in height. The flowers and fruit of the palms are in the form of bunches and have many branches. The fruit is large, dark black when raw and then when ripe it will turn reddish yellow. The skin and pulp contain oil. The oil produced by palm oil can be used as an ingredient in cooking oil, margarine, soap and wax. The pulp from oil palm can be used for animal feed, in particular it can be used as an ingredient in chicken feed. Palm fruit has different ripeness criteria, namely raw, ripe, under ripe and over ripe fruit.

Unripe fruit is a fresh fruit bunch, with the criteria that the fruit is not loose (the fruit is separated from the bunch), dark black. Slightly ripe fruit is fruit bunches with the criteria of 12.5-25% loose fruit (the fruit is released from the bunch), reddish in color. Ripe fruit is fresh fruit bunches with the criteria for the most suitable fruit to be harvested is fruit that is completely ripe. The characteristics of ripe fruit are 26-50% of the outer fruit stalk (the fruit is released from the bunch), shiny red. Fruit through ripe is fruit bunches with the criteria of 51-100% outer fruit or part of the inner fruit. The condition of the fruit can be seen in Figure 1.



(a) (b) (c) (d)

Figure 1. Image of Oil Bunches: Raw Palm Oil (a), Palm Oil Slightly Mature (b), Matured Palm Oil (c), Trough Matured (d).

III. METHODOLOGY

The entire The main steps in identifying and classifying oil palm fruit maturity using machine learning techniques are shown in Figure 2.

Broadly speaking, research using machine learning techniques to identify and classify oil palm maturity consists of two main activities. The two activities are training and testing.

(1) dataset Image Input. The color image input used is an RGB color image which includes 3 channels of red, green and blue (RGB) images from the oil palm image. Palm fruit image taken using a HP camera.

(2) pre-processing image The goal at this stage is to get an image that is ready to be used for the next process. This process includes:

a. Image cropping

Image cropping according to identification needs with a standard size of 250x250 pixels

b. image enhancement

Image repair is a technique for more detailing an image. The process of improving image quality aims to obtain images that can provide information in accordance with the objectives of image processing. This image enhancement process includes repairing images which during the acquisition process experience significant disturbances such as noise, geometric, radiometric disturbances and several other natural factors disturbances. An image enhancement approach method used here is to use contrast stretching.

c. Image transformation Image transformation from RGB color space to HSV color space (Hue, Saturation, Value) and image contrast enhancement (contrast enhancement).

(3) Image Segmentation. The purpose of this stage is to divide the image into regions based on the same pixel intensity (ROI). The image segmentation technique performed here uses the Particle Swarm Optimization Technique, namely Adaptive Chaotic Inertia Weight Particle Swarm Optimization (ACIW-PSO)[5]. Figure 3 shows a flow chart of the image segmentation process. In the segmentation process, the input image in the form of an RGB image is converted into the HSV image space. The HSV image information is then clustered using the PSO algorithm. The PSO variant used here is Adaptive Chaotic Inertia Weight Particle Swarm Optimization (ACIW-PSO).

(4) Feature Extraction. The purpose of this stage is to extract features from the segmented image area. The technique used is to use the Gray Level Co-Occurrence Matrix. The features used are 11 features, namely: mean, standard deviation, variance, entropy, root mean square (RMS), IDM, kurtosis, contrast, correlation, energy and homogeneity.

(5) Image Classification. The aim is to obtain classes on the maturity level of oil palm. In this study, the Support Vector Machine (SVM) technique will be used. Where k = 1 and the kernel used in SVM is a linear kernel. There are 4 classes, namely slightly ripe, overripe, ripe and raw.

(6) Classification Accuracy. Test image accuracy using a configuration matrix. In the measurement of the configuration matrix, the parameter values to be looked for include: True Positive (TP) which is the number of positive data detected correctly, True Negative (TN) is

the number of positive data detected incorrectly, False Positive (FP) is the amount of negative data that is detected detected is true, and False Negative (FN) is the number of negative data detected is false.

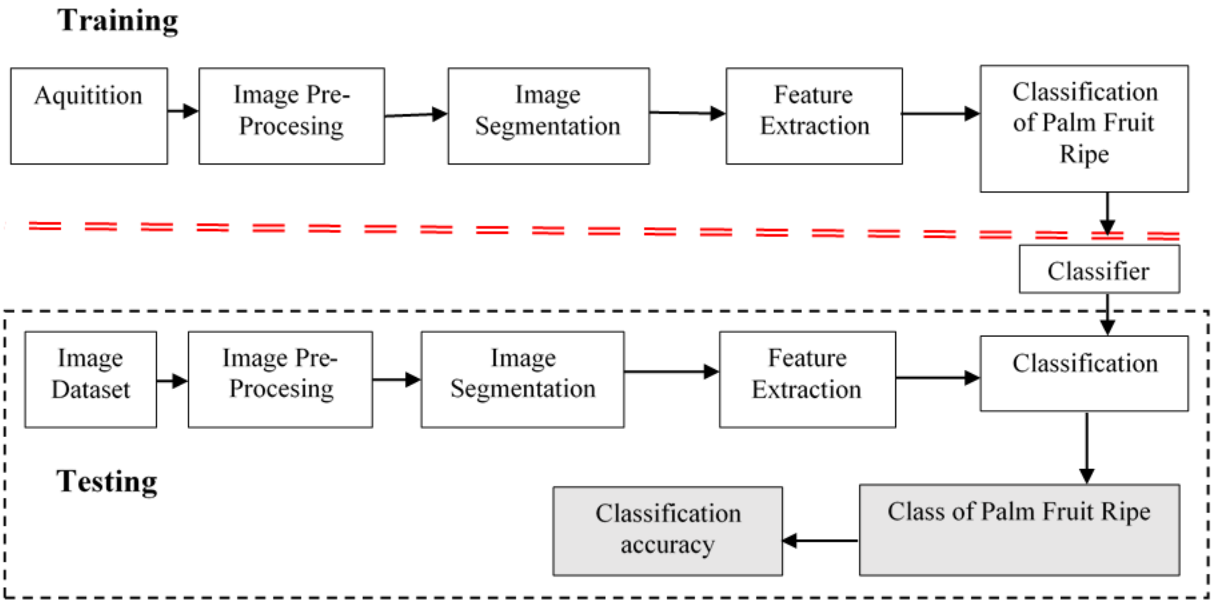


Figure 2. Flowchart of Machine Learning Techniques for Identification and Classification of Oil Palm Maturity

IV. Results and Discussion

In accordance with Figure 2, the process in this study includes training and testing. In the training process, several important things are: image acquisition, image processing, image segmentation, feature extraction and classification.

The image acquisition is obtaining from shooting the palm sign, where the original image is in the RGB image format (3 bands). In this study, the research data used were 120 images of oil palms. The image data is taken based on oil palm fruit bunches taken from oil palm trees. 120 image data consists of 80 training images and 40 testing data. The format of the 120 images is *.JPG. Of the 40 images that will be tested, they are divided into 10 images in each class, namely raw, slightly ripe, ripe and overripe. The original image is taken using a HP camera, then the initial processing is carried out in the form of cropping the image according to identification needs. The cropping size is 250 x 250 pixels. The result is as shown in Figure 3.

Image enhancement is a technique for more detailing an image. The process of improving image quality aims to obtain images that can provide information in accordance with the objectives of image processing. An image enhancement approach method used here is to use contrast stretching. The result is as shown in Figure 4 (a).

Before the segmentation process is carried out, the RGB image is first transformed into an HSV image. This is done to facilitate the classification process. In some cases, the RGB color space does not match, therefore it is transformed into the HSV color space. This transformation results in the hue, saturation and value features. One of the important processes in classification is segmentation.

The segmentation process using appropriate techniques will produce high accuracy values in the classification process. Therefore, the technique used in this research is a good technique. The image segmentation technique performed here uses PSO based-clustering. We use namely Adaptive Chaotic Inertia Weight Particle Swarm Optimization. The result is as shown in Figure 4 (b).

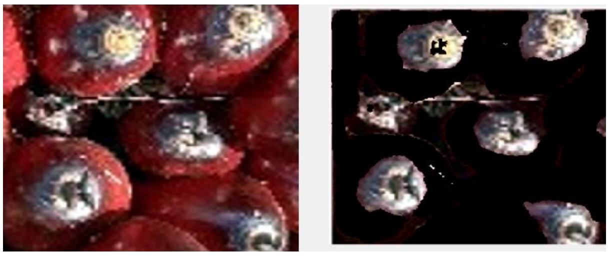
After the image segmentation process, then feature extraction is carried out. This process aims to obtain features that will be used in the classification process. The technique used to get texture features is using gray level co-occurence matrix (GLCM) [20]. There are 11 features used in this study. These features are: F1 is mean, F2 is standard deviation, F3 is entropy, F4 is root mean of square (RMS), F5 is kurtosis, F5 is skewness, F6 is contrast, F7 is correlation, F8 is contrast, F9 is correlation, F10 is energy, and F11 is homogeneity. the value of each of these features is shown in Table 3.

The aim this research is to obtain oil palm maturity levels. In this study, the Support Vector Machine (SVM) technique will be used. Where k = 1 and the kernel used in SVM is a linear kernel. There are 4 classes, namely slightly ripe, through ripe, ripe and raw. The experimental results were obtained through testing on 40 oil palm images. After analyzing the results of the oil palm fruit maturity level test conducted by the system and experts, the results showed that the image of the oil palm fruit had compatibility between the system and Expert Judgment. Where the N value is the total number of oil palm fruit images, namely

40 images consisting of 10 raw fruit images, 10 ripe fruit images, 10 ripe fruit images and 10 mature fruit images.

(a) (b)

Figure 3. Ripe Oil Palm Image Result of Cropping (a), Mature Image of Oil Palm Contrast Stretching Result (b)



(a) (b)

Figure 4. Ripe Oil Palm Image Result of Contrast Stretching (a), Image of Mature Oil Palm as a Result of Segmentation (b).

In this research, the test image classfication accuracy using a configuration matrix [21-22]. Matrix of confusion classification palm fruit is show in Table 1.

Table 1. Matrix of confusion classification palm fruit

		Prediction Class				Total
		raw	Slightly ripe	ripe	Over ripe	
Real Class	raw	10	0	0	0	10
	Slightly ripe	1	9	0	0	10
	ripe	0	1	8	1	10
	Overripe	0	0	0	10	10

Table 2 shows that from a total of 40 experimental images divided into four classes, namely: raw, slightly ripe, ripe and overripe. Each class consists of 10 images. From the results of the experiments conducted, it was found that the raw class between the prediction and the real class as a whole is suitable. In the slightly ripe and overripe class of the 10 images used, there is one image that is not suitable. Likewise, in the ripe class there are 2 inappropriate images. Table 2 shows the results of data classification testing obtained in this experiment. Accuracy can be calculated using the formula:

$$\frac{\textit{the number of suitable image}}{\textit{total image dataset}}\, x\ 100\% = \frac{37}{40} x100\% = 92{,}5\%. \qquad (7)$$

Table 2. The Result of Testing Data for Classification Palm Fruit

Testing Data		
Input	**suitable**	**not suitable**
raw	10	0
Slightly ripe	9	1
ripe	8	2
Overripe	10	0

From Table 1, the accuracy rate for the classification of palm fruit maturity based on texture using the Support Vector Machine (SVM) method is obtained, which reaches 92.5%.

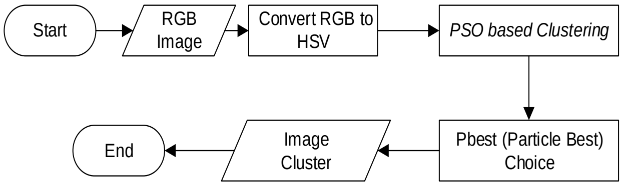


Figure 5. Flow Chart based- Color Image

ACKNOWLEDGMENT

We would like to thank LPPM (The Research Institution of Universitas Ahmad Dahlan) that has been funding through the Competitive Research Grant scheme in 2020. Number: PD-001/SP3/LPPM-UAD/2020.

V. CONCLUSION

This paper proposes the use of an image segmentation algorithm based on particle swarm optimization and support vector machine. Oil palm fruit can be classified well into four classes, namely, raw, half ripe, ripe and overripe. The classification results indicate that the method used is good for the identification and classification process. The classification accuracy rate reaches 92.5%.

In this study, the features used are color features. The accuracy in this research is expected to be further improved by adding texture and shape features. These features can be added for the identification process. Likewise, the identification process can use other optimization techniques to improve segmentation results. Good segmentation results will greatly affect the classification accuracy achieved

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Murinto pursed Bachelor of Science from Universitas Sebelas Maret, Indonesia in 1998, Master of Computer Science from Universitas Gadjah Mada, Indonesia in year 2004 and Doctor of Philosophy (Ph.D) in Computer Scinces from Universitas Gadjah Mada, Indonesia in year 202. The currently is working as Assistant Professor in Department of Informatics engineering, Department of Informatics Engineering, Universitas Ahmad Dahlan Yogyakarta, Indonesia, since 2004. He is a member of IEEE & IEEE computer society since 2012, He has published more than 15 research papers in reputed international journals including Thomson Reuters (SCI & Web of Science) and conferences including IEEE and it’s also available online. His main research work focuses on image processing, computer vision, and machine learning. He has 16 years of teaching experience and 8 years of Research Experience.

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Table 3. Classification Results for Palm Oil Using a Support Vector Machine

No.	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	Result
1	44,6243	65,965	5,19681	11,2618	4267,56	6,74039	1,59223	2,17247	0,705726	0,309012	0,795667	slightly ripe
2	23,6115	50,4897	2,68267	7,01741	2210,59	7,62622	2,28985	1,42005	0,577187	0,491997	0,860531	slightly ripe
3	32,3164	666,8622	2,70799	7,29976	3765,77	5,96684	2,03809	1,92195	0,716569	0,493393	0,864877	slightly ripe
4	11,8694	32,5194	1,98302	6,37162	1002,75	15,9797	3,42127	0,545052	0.596485	0,677637	0,932539	slightly ripe
5	29,9696	64,8165	2,48529	6,95791	3636,44	6,38329	2,1341	1,88555	0,712592	0,532291	0,874992	slightly ripe
6	27,56	64,4712	2,23549	6,39818	3566,99	7,18886	2,32556	2,01414	0,68916	0,569489	0,881922	slightly ripe
7	20,1266	55,8104	1,66121	5,17388	2830,59	9,66077	2,79288	1,15913	0,786292	0,693235	0,874992	slightly ripe
8	34,2547	61,3907	3,77144	9,27331	3479,08	5,78411	1,9143	1,55787	0,739595	0,405339	0,835926	slightly ripe
9	50,1599	63,4984	5,66966	11,8756	3836,35	3,89612	1,30756	2,05646	0,67662	0,226057	0,772161	slightly ripe
10	21,5104	46,2593	2,76629	7,74147	2003,32	8,70694	2,44618	1,07485	0,658693	0,523846	0,888278	raw
11	62,7547	67,187	6,0484	12,6433	4091,38	2,90478	0,922131	1,91396	0,730461	0,149451	0,750928	overripe
12	22,6912	50,6594	2,64356	7,58731	2397,67	8,62421	2,47415	0,865671	0,723082	0,5248	0,89706	overripe
13	24,6217	52,9596	2,64317	7,42977	2585,75	7,44396	2,27206	1,3921	0,615407	0,504303	0,872842	overripe
14	47,4635	66,2175	4,81513	10,7114	4087,55	3,85289	1,33984	1,46314	0,782624	0,295146	0,828692	overripe
15	51,3363	69,5081	4,75533	10,6209	4546,93	3,26611	1,17809	1,80967	0,764814	0,280312	0,806431	overripe
16	70,0659	77,5665	5,42225	11,836	5876,16	2,07835	0,65886	2,36382	0,741572	0,208923	0,76118	overripe
17	63,4484	72,9522	5,49787	11,8479	5080,24	2,45398	0,826935	1,45702	0,830788	0,223117	0,793831	overripe
18	59,583	71,5469	5,60285	11,7543	4876,71	2,89569	1,01254	1,49893	0,823089	0,363708	0,800138	overripe
19	45,1546	72,1563	4,02781	9,61835	4885,05	3,88334	1,46674	2,07911	0,734743	0,396232	0,827265	overripe
20	37,0188	65,9401	3,23031	8,56821	4101,03	4,50436	1,64415	2,23237	0,621255	0,467398	0,832113	overripe
21	44,2275	75,5274	3,39209	8,93682	5470,81	3,82825	1,49611	2,58434	0,696854	0,380311	0,837132	overripe
22	60,4074	72,5383	5,29734	11,5214	5025,85	2,53496	0,89512	2,09914	0,211856	0,205778	0,765592	ripe
23	55,9541	69,6863	5,48152	11,5928	4268,32	3,15321	1,11415	2,18225	0,292975	0,211856	0,761491	ripe
24	48,2045	66,8451	4,86418	10,7835	4192,22	3,77489	1,3229	1,42529	0,308428	0,292975	0,829785	ripe
25	47,5337	68,5389	5,30921	10,2048	4490,2	3,51444	1,28257	1,99616	0,205032	0,308428	0,805809	ripe
26	68,5756	77,6016	4,67151	11,688	5885,62	2,07492	0,682574	1,87688	0,300928	0,205032	0,784511	ripe
27	55,7502	75,4963	5,39876	10,6709	5522,6	2,82227	1,07296	1,25823	0,247722	0,300928	0,829703	ripe
28	57,4015	71,1053	4,46213	11,5041	4791,36	2,96212	1,04878	1,33379	0,298059	0,247227	0,82078	ripe
29	62,7729	83,3609	5,58828	10,3988	6763,84	3,19368	0,885398	2,13816	0,200146	0,298059	0,813412	slightly ripe
30	56,2468	66,7723	4,80186	11,9215	4185,81	3,70518	1,07091	1,76809	0,290874	0,200146	0,775471	raw
31	57,9528	73,6025	4,76173	10,8221	4846,23	2,46695	0,910094	1,92024	0,242285	0,242849	0,779581	raw
32	28,2439	55,861	2,74059	7,89541	3028,52	5,74114	1,93739	0,778462	0,830048	0,528934	0,897868	raw
33	29,4235	58,811	2,74229	7,8596	3353,19	5,74276	1,95536	1,00113	0,801225	0,525531	0,871159	raw
34	26,7102	52,9835	2,80353	7,99794	2706,98	5,98653	1,98574	0,560401	0,863116	0,537824	0,907984	raw
35	30,4715	57,2087	2,9419	8,2418	3174,63	5,23235	1,80878	0,948499	0,789551	0,490402	0,864133	raw
36	62,9403	75,1464	5,5833	12,1465	5571,84	3,25436	1,10914	1,63264	0,820436	0,210019	0,815559	raw
37	38,378	59,5929	4,82048	10,3785	3325,25	5,63528	1,80103	1,56134	0,70183	0,3622	0,833559	raw
38	22,761	49,6392	2,41455	7,21569	2356,11	7,23384	2,23901	0,979917	0,677897	0,558267	0,888475	raw
39	41,7443	63,2704	4,60328	10,4604	3853,33	4,62918	1,5865	1,15798	0,809006	0,354925	0,826712	raw
40	46,7367	63,0234	5,49195	11,4266	3780,47	4,47875	1,48509	1,46415	0,76059	0,279978	0,826712	raw

