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OIL PALM AGE CLASSIFICATION ON SATELLITE IMAGERY USING FRACTAL-BASED COMBINATION

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ABSTRACT

Palm oil tree is one of the sources of vegetable oil and it has become the world's biggest need of vegetable oil comparing to other plant. The use of satellite imagery to manage the plantation is very helpful for the stakeholders in supervising the development. To find out the age of oil palm trees from the satellite imagery is done by using the extraction of fractal based texture features. This study purpose an feature extraction methods to recognize the age of palm oil tree on the imagery of panchromatic icons using algorithm of segmentation-based fractal texture analysis (SFTA) which is combined with local features and local binary pattern (LBP). The classification will be done by using multi-layer perception method into four classes, which are the age of adult, young, old palm, and the ones which are not palm. Extraction feature is done in fractal-based using SFTA algorithm, giving accurate result of 72.5 %. The combination of feature extraction using SFTA with the local features give accuracy of 74.5 % and the combination of SFTA and LBP gives the accuracy of 76 %.

Keywords: *Classification, Oil Palm Age, Ikonos-Panchromatic, Segmentation Based Ffractal Fexture Analysis (SFTA), Local Features, Local Binary Pattern (LBP)*

1. INTRODUCTION

Palm oil tree as one of the vegetable oil resource which has become the world's need has to be processed wisely, from the side of cultivation, benefit and plantation management. Palm oil tree is very suitable to be planted in a tropical climate area, whether in mountain or hill range. The monitoring of plantation terrain development is quiet hard to do because palm oil trees are planted in group, forming cerntain pattern and in a wide area. The use of technology in plantation sector will be so helpful in monitoring the growth. One of the needs of palm oil tree plantation's is to find out the age of palm oil tree. The observation of plant's condition is rarely done because the size of plantation land and limited human resources, so there are usually some loss in: falling or rotten palm kernels because of the old age, harvesting young palm kernels which need to be stored in the warehouse for a certain time, so that the warehouse function is not at best and the production of crude palm oil is hampered. By utilizing the satellite imagery and digital image processing technology we expect the loss can be decreased.

The development of technology is so rapid, as same as the development of digital image processing technique. By utilizing digital image processing technique, satellite imagery can be used for the land management, such as forest management, natural potency identification, forest plant species identification, dense of forest tree, forest structure identification, etc [1, 2, 3]. Beside that the use of satellite image also used for city planning [4, 5] and also for monitoring and classifying plantation field.

Utilization of high resolution satellite imagery-based objects has been carried out by utilizing the visible and Nir band [6, 5, 7, 8, 9]. IKONOS satellite imagery is a multi-spectral image consisting of five bands with a size of 1: 4m for visible and NIR band while for panchromatic has resolution of 1: 1m [10]. Research using panchromatic band of various kinds of satellites have been made to the mapping of forest structure, classification of plants and so on [2, 11, 3]. Visible and Nir band usage is less efficient, the use more texture features significantly correlated with forest structure [6, 9] and can improve the accuracy [12].

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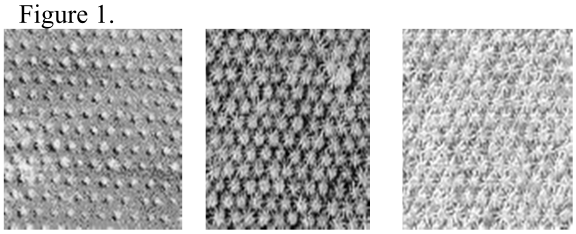
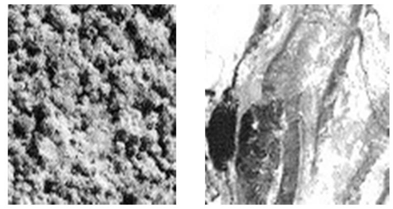
Oil palm plantations in the tropics are rarely accompanied by extreme weather changes, so that the use of satellite imagery is deemed relevant. The use of local feature gives pretty good results [11, 13, 3]. This method of feature extraction local binary pattern (LBP) is an efficient descriptor in texture analysis. Oil palm is planted to form a pattern that represents characteristic area of the oil palm plantation. The exact pattern of these plants forms a fractal, so the use of fractal-based methods is considered suitable to recognize the oil palm plantations. This study is designed to use fractal-based method combined with the local feature extraction and local binary pattern. Therefore, this study is aimed to identify the age of oil palm trees with a fractal-based methods classifier based multilayer perceptron. Thus, the questions of this study are whether the age classification of oil palm trees can be done using fractal-based methods? Does the addition of texture-based methods such as Local binary pattern (LBP) and the local feature extraction improve the accuracy? This research is to take advantage of the panchromatic band in recognizing the age of oil palm trees by digging the information and classifies it using multi-layer perceptron.

2. RELATED WORKS

IKONOS satellite imagery is a high-resolution satellite imagery operated by GeoEye. IKONOS satellite imagery records multi-spectral data of four channels at a resolution of 4m, red, green, blue and Near Infra Red (Nir) channels and a panchromatic channel with a resolution of 1: 1m [10]. The use of high resolution satellite imagery has been helping a lot in resolving issues, such as forest management, mapping of settlements, and others [2, 5, 14, 13, 1, 4] Channels that are often used are visible channels. This study tries to identify the age of the plant oil palm using IKONOS satellite imagery in the panchromatic band without using visible channels. In panchromatic IKONOS satellite image, the image has the same intensity value in each channel red, green and blue. Examples of panchromatic IKONOS satellite imagery used can be seen in Figure 1.



(a) (b) (c)



(d) (e)

Image 1. IKONOS panchromatic satellite imagery of (a) young palm oil trees (b) adult palm oil trees (c) old palm oil trees (d) forest trees (e) not palm oil plantation.

Fractal-based feature extraction using SFTA algorithm divides the two parts of the process: gray-segmented image input is used to adjust the image based on the method of Otsu and fractal features is taken from each binary image [15]. The combination of a feature color and fractal or texture and fractal are also used for flower classification, MRI and CT scans [16, 17, 18].

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Research on forest management stated that the use of texture parameter is more significant than forest structure [13, 9]. The use of maximum local which accompanies Gabor filter on the segmentation of residential areas such as research of Beril Sırmacek is considered as good and reliable [11]. The addition of the local feature of pixel based is also suggested in some studies to improve the accuracy [3, 13, 19, 11]

Methods of local binary pattern (LBP) was first proposed by Ojala, et al., [20] has become one descriptor that is most widely used for the extraction of texture features because it is resistant to changes in lighting, the computational complexity is low, and the ability to encode the fine details. LBP can reflect the texture feature more comprehensively and can keep the information edge [21].

3. METHODOLOGY

This study proposes a framework to classify the age of oil palm plants using fractal-based extraction features which is combined with texture-based extraction features and local feature-based multilayer perceptron. The data set used in this study was taken in 2009. The image will be cropped to the size of 30x30 pixels as many as 100 images in each class, so there are 400 images. Imagery will be classified into four classes, namely palm oil with 3-8 years of age will be graded into plantations of young age, plantations of 8-16 years of age will graded into adult palm, palm trees with more than 16 years of age will be graded into old and the other one will collect

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imagery of plants which are not included in oil palm plantations.

In IKONOS panchromatic satellite imagery, the age of oil palm trees can be seen from the texture they are formed. Young palm trees form a smoother texture than the texture is formed from an adult palm tree or old grown oil palm tree. Adult oil palm trees form smoother texture than the texture is formed from old oil palm trees and coarser than the texture is formed of young palm trees. Palm tree with old age forming coarser texture than the other two classes, while the forest trees form a coarser texture than old oil palm trees. For image 1 (d) and (e) will not be included in the class of the palms.

This study will be divided into three main steps, namely preprocessing, feature extraction using texture and fractal then classify it using a multilayer neural network perceptron. The proposed method is depicted in image 2.

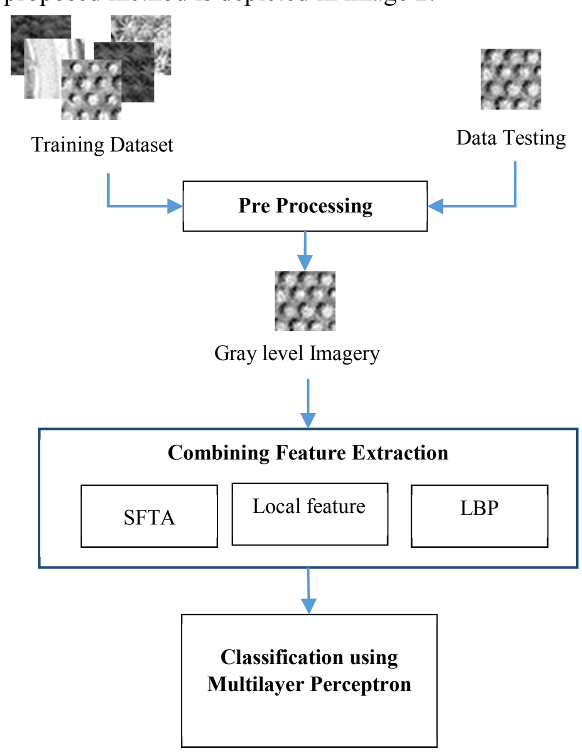

Image 2. The Method Proposed In The Classification Of The Age Of Oil Palm Plants

3.1. Preprocessing

IKONOS panchromatic image size is very large, in a format of RGB image with the same value of red, green and blue. In this study, IKONOS imagery is cut to the size of 30x30 pixels then converted into a grayscale color. Changing the image into the grayscale will be done by taking the intensity value of the green channel.

3.2. Feature Extraction

Feature extraction is performed is a fractal-based using algorithm segmentation-based Fractal Texture Analysis (SFTA) [15] combined with local features and texture-based feature extraction using Local Binary Pattern (LBP).

SFTA algorithm divides the process into two main parts, namely the decomposition of the image into two binary images and calculating the fractal dimension. The image that will be processed in the algorithm SFTA is a grayscale image. Binary image formation in SFTA algorithms does Two-threshold Binary Decomposition (TTBD) by applying Otsu multilevel algorithm [22] The image will be formed into two sets of binary image consisting of the foreground image and background image. After getting the binary image, the next step is to calculate the fractal dimension. The results of the SFTA algorithm has vector features that show the size of binary image, the average intensity value of grayscale and fractal dimension of the respective boundary binary image formed is shown in algorithm 1.

Algorithm 1 SFTA extraction algorithm.

Require: Grayscale image I and number of thresholds nt.
Ensure: Feature vector VSFTA.
T ← **MultiLevelOtsu**(I, nt)
TA ← {{ti ,ti+1}:ti,ti+1∈T,i∈[1..|T|−1]}
TB ← {{ti nl} : ti∈T,i∈ [1..|]]}
i ← 0
for {{t`, tu} : {t`, tu} ∈ TA ∪ TB} **do**
Ib ← **TwoThresholdSegmentation**(I, t`, tu)
Δ(x, y) ← **FindBorders**(Ib)
VSFTA[i] ← **BoxCounting**(Δ)
VSFTA[i + 1] ← **MeanGrayLevel**(I, Ib)
VSFTA[i + 2] ← **PixelCount**(Ib)
i ← i + 3
end for
return VSFTA

Local feature extraction used is statistic features calculated on certain windows. Local features are done by calculating the entropy value, range and standard of deviation in the grayscale image. The calculation of statistical values operated on the intensity values that enter in the windows of a certain size.

Original operator of local binary pattern (LBP), was first introduced in [20] is the texture descriptors which is efficient. This method also

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gives quiet good results in content-based image retrieval (CBIR) on satellite imagery [23]. Pixel label operator is calculated based on the mean of each image using a particular window. Image 3 shows the process of LBP using 3x3 window. C value at the center point of the window is used as a threshold to convert the neighbor values into bitwise. If the value of the neighbors is greater than the threshold value then it will be assigned a value of 1 and vice versa, if the neighbor value is smaller than the threshold they will be given a value of 0.

Invariant rotation is one variant of LBP extended which robust against rotation. Input image rotation has two effects: each local environment rotated to other pixel locations, and in every environment, sampling points on a circle around the center point rotated to different orientations. Other critical variant of LBP is taking uniformity pattern formed from ordinary LBP [20]. Uniformity pattern is calculated from the number of bitwise transition from 0 to 1 or vice versa when the bit pattern is considered circular.

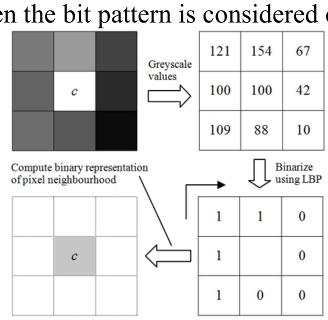

Image 3. LBP Process Using 3x3 Windows

4. RESULTS AND DISCUSSIONS

This study aims to identify the age of the palm according to fractal-based method combined with local textures. This combination is done to improve performance in a fractal-based recognition. In IKONOS panchromatic imagery, the image will gives grayscale intensity values without any other color value so the information of shape or texture can't be used to distinguish the age of the oil palm tree. Texture information gives contribution more significant compared with the information in recognizing the shape and color of the oil palm tree age [7, 12, 24, 4].

SFTA algorithms transform grayscale image into a binary image using multiple threshold, Otsu then calculating the fractal dimension using algorithm 1, *T* is the threshold value that is generated from Otsu multi threshold, *I* is a grayscale image and there are two *nt*'s used in this research. *Lb* is result of a binary image from otsu multi threshold. *Tl* is the smallest threshold value, *tu* is the highest threshold value, *fractal dimension* is the box counting algorithm, and VSFTA is SFTA feature vectors. The result of SFTA feature extraction results is presented in Table 1.

Local feature extraction will calculate statistical entropy value, standard deviation and range of a grayscale image, using a window size of 3x3 for the local feature extraction of standard deviation and range, while for the local feature of entropy using windows in a 9x9 [25]. The resulting value is then averaged to produce three features for each grayscale image. Local feature extraction results in this study are presented in Table 2.

Table 2. Feature Extraction Results Using Local Features

Classification	Local Entropy		Local Range		Local Standard of Deviation	
Data Set	MIN	MAX	MIN	MAX	MIN	MAX
young oil palm	4.2670	5.4852	31.8811	129.2755	10.8350	43.5859
adult oil palm	4.9278	5.5223	56.3577	135.82	18.7990	46.1121
old oil palm	4.9468	5.4700	59.4011	141.9289	20.1063	48.3392
not oil palm	4.2707	5.4107	32.8556	120.8433	11.0040	40.8189

This study uses LBP texture of feature based extraction with mapping of uniform invariant rotation. The size of the windows used is 3x3, so the value of LBP operated on 8 neighborhoods. Varian of LBP used is robust against rotation (invariant rotation) and variants that take pattern of uniformity (uniform). Rotation is done in 8 different degrees, and the pattern of uniformity is taken to see the transition of bitwise binary pattern. Local binary pattern is called uniform if the size uniformity is valued 2 at most. For example, pattern 00000000 (0 transition), 01.11 million (second transition) and 11,001,111 (two transitions) while the uniform pattern of 11,001,001 (4 transitions) and 01,010,011 (5 transition) is called non-uniform. The results of feature extraction LBP-uniform rotation invariant are presented in Table 3.

The study will be performed using fractal-based feature extraction algorithms of SFTA, local feature extraction of statistical entropy value, standard of deviation and range, and texture-based feature extraction using feature extraction of LBP-uniform invariant rotation feature as well as combinations of these. In Table 1, 2 and 3, the value SFTA produce 12 traits, local feature extraction produces three traits and result of LBP has 10 traits (image 5). Multi layer perceptron was

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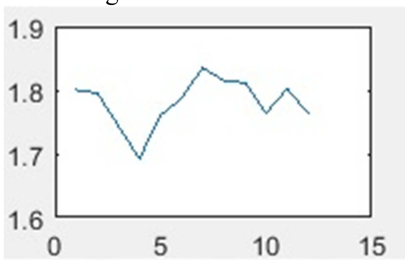
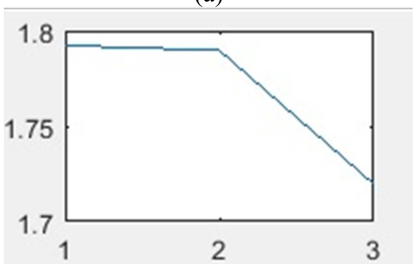
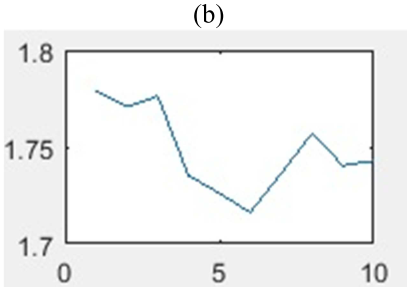
performed using 15 traits of merger of SFTA characteristics and local characteristics and 22 traits of the merger from SFTA and LBP result.



(a)



(b)



(c)

Image 5. Data Composition From The Feature Extraction Used (A) Feature Extraction Using SFTA Algorithm (B) Feature Extraction Using Local Feature And (C) Feature Extraction Using LBP

Training data and testing data are randomly selected using a 10 fold cross validation. The measurement of classification accuracy will be done using confusion matrix and the percentage of calculation accuracy.

Confusion matrix is a 2x2 matrix with a number of diagnostic, indicating the classification results of the test data to the reference data. This matrix contains the results of classification of test images into the correct classes and other classes. The results are presented in confusion matrix tables 4. The calculation of accuracy percentage is calculated using the formula (1).

$$\text{accuracy} = \frac{\text{correct data amount}}{\text{total data amount}} * 100\% \qquad (1)$$

Table 4. Confusion Matrix From Each Method

Methods	Classification	adult oil palm	young oil palm	old oil palm	not oil palm
SFTA	adult oil palm	78	4	14	4
	young oil palm	4	80	4	12
	old oil palm	14	4	74	8
	not oil palm	9	21	12	58
Local feature	adult oil palm	69	5	20	6
	young oil palm	18	11	33	38
	old oil palm	25	9	62	4
	not oil palm	5	13	29	53
Lbp-uniform invariant rotation	adult oil palm	59	11	19	11
	young oil palm	18	62	7	13
	old oil palm	9	6	79	6
	not oil palm	13	21	24	42
Sfta + local feature	adult oil palm	75	5	16	4
	young oil palm	3	79	4	14
	old oil palm	11	3	81	5
	not oil palm	10	19	9	62
Sfta + lbp	adult oil palm	76	1	15	8
	young oil palm	2	81	4	13
	old oil palm	12	3	77	8
	not oil palm	5	17	8	70
Sfta + local feature + lbp	adult oil palm	76	2	16	6
	young oil palm	6	83	1	10
	old oil palm	14	2	77	7
	not oil palm	7	16	9	68

The accuracy results show that the classification of oil palm age using feature extraction of SFTA and LBP are better than MLP classification which is done by using feature independently as presented in table 5.

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Table 5. Comparison Of The Accuracy Of Each Method Of Feature Extraction

Proposed Method	Accuracy Result
sfta+lbp+local	75.50%
sfta+lbp	76%
sfta+local	74.25%
Lbp	60.50%
Local	48.75%
Sfta	72.50%

Local feature extraction provides the lowest accuracy, namely 48%, feature extraction using LBP provide 60.5% of accuracy and SFTA provides an accuracy of 72.5% results. The use of a combination of feature extraction SFTA with local features could increase the accuracy of 1.75% which result 74.24% of accuracy and combination SFTA-LBP improve the accuracy of 3.5% to 76%. The combination of these three methods improves the accuracy of 3%.

Previous research suggests that the classification of oil crops using image matching techniques by correlation on FORMOSAT-2 imagery using a combination of multispectral channels and texture information give an accuracy of 76.8% [12]. Some determine the age of the palm of a high-resolution image worldview satellit-2 with 9 bands is visible to near infra-red and panchromatic (1: 0.5m). The detection of the tree's age based on the shape of the crown of the tree is done by measuring the diameter of the crown tree (tree crown). This study provides delineation results which were good enough for palm aged 8 to 13 years [7].

Identification of oil palm plantations using rapsv method gives an accuracy of 84.75% and the addition of local feature add an accuracy of 0.5% to 85.25% while the addition of the local feature in the SFTA method improves accuracy of 1.75% to 74.25% [19]. SFTA feature extraction is also used with classification accuracy of 73.6% in flowers [26], but the use of the local binary pattern feature extraction for oil palm age detection has not been used yet. Recently, LBP is widely used for the extraction of face based on texture features and leaves with fairly good results [27, 28].

Compared to the previous studies, the age classification of oil palm plant gives better results because this is more economical, accurate, and efficient. the best classification using the proposed method is in the classification of young oil that is equal to 83% and the ugliest on the classification of non-oil, by 68%. this was due to the diversity of patterns of not oil palm object.

5. SUMMARY

Panchromatic band provides texture information better than the visible or NIR band. It can be maximized by using the appropriate feature, such as texture or fractal-based. At the age classification of oil palm trees fractal-based method is used on a satellite imagery IKONOS panchromatic band. Classification method used is a multi-layer perceptron with feature extraction based using SFTA algorithm combined with local features and local binary pattern. SFTA classification based Multi layer perceptron provide 72.5% of accuracy results, multilayer based classification of local feature gives results amounted to 48.75% of accuracy while the multi-layer perceptron based classification using feature extraction LBP-uniform invariant rotation provides an accuracy of 60.5% in results.

Classification of the oil palm plant age with multi layer based perceptron can be done by either using the texture information which is provided in the IKONOS panchromatic satellite imagery. Limitations of the band panchromatic in terms of color doesn't affect significantly in the results of classification. The use of feature extraction as proposed in this study is able to increase the accuracy to 76 %.

REFERENCE

[1] A. Räsänen, M. Kuitunen, E. T. b and A. Lensu, "Coupling high-resolution satellite imagery with ALS-based canopy height model and digital elevation model in object-based boreal forest habitat type classification," *Science Direct - ISPRS Journal of Photogrammetry and Remote Sensing* , vol. 94, p. 169–182, 2014.

[2] B. Beguet, D. Guyon, S. Boukir and N. Chehata, "Automated retrieval of forest structure variables based on multi-scale texture analysis of VHR satellite imagery," *Science Direct - ISPRS Journal of Photogrammetry and Remote Sensing,* vol. 96, p. 164–178, 2014.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[3] H. Fadaei, T. Sakai, T. Yoshimura and M. Kazuyuki, "ESTIMATION OF TREE DENSITY WITH HIGH-RESOLUTION IMAGERY IN THE ZARBIN FOREST OF NORTH IRAN (CUPRESSUS SEMPERVIRENCE VAR. ORZONTALIS),," *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science, Kyoto Japan,* vol. XXXVIII, no. 8, pp. 679 - 684, 2010.

[4] S. Talebi, A. Z. S. Sadeghian and H. Arefi, "DETECTION OF TREE CROWNS BASED ON RECLASSIFICATION USING AERIAL IMAGES AND LIDAR DATA," *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* Vols. XL-1/W3, 2013, SMPR 2013, 5 – 8 October 2013, Tehran, Iran, pp. 415 - 420, 2013.

[5] S. Bhaskaran, S. Paramananda and M. Ramnarayan, "Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data," *science direct - Applied Geography,* vol. 30, p. 650–665, 2010.

[6] D. Neves and C. Carneiro, "Semi-automatic Use of High Resolution Images and Digital Elevation Models for Counting and Identification of Forest Trees".

[7] A. Chemura, Determining oil palm age from high resolution satellite imagery, Sweeden: Master of Science Thesis - University of Twente, Faculty of Geo-Information Science and Earth Observation, 2012.

[8] K. Jusoff, "Mapping of Individual Oil Palm Trees Using Airborne Hyperspectral Sensing: An Overview," *CCSE,* vol. 1, no. 1, pp. 15-30, 2009.

[9] I. Ozdemira and A. Karnielib, "Predicting forest structural parameters using the image texture derived from WorldView-2 multispectral imagery in a dryland forest, Israel," *Science Direct - International Journal of Applied Earth Observation and Geoinformation,* vol. 13, p. 701–710, 2011.

[10] S. Nana, "Resolusi Spasial, Temporal dan Spektral pada Citra Satelit Landsat, Spot dan Ikonos," *Widya,* vol. 1, pp. 167 - 174, 2013.

[11] B. Sırmacek and C. Unsalan, "Urban Area Detection Using Local Feature Points and Spatial Voting".

[12] L. Gandharum and C.-F. Chen, "Pemanfaatan Informasi Tekstur untuk Klasifikasi Tanaman Sawit Menggunakan Citra FORMOSAT-2," pp. 57 - 65.

[13] M. Laba, B. Blair, R. Downs, B. Monger, W. Philpot, S. Smith, P. Sullivan and P. C. Baveye, "Use of textural measurements to map invasive wetland plants in the Hudson River National Estuarine Research Reserve with IKONOS satellite imagery," *Science Direct - Remote Sensing of Environment ,* vol. 114, p. 876–886, 2010.

[14] P. C. F. F. Christophe Proisy, "Predicting and mapping mangrove biomass from canopy grain analysis using Fourier-based textural ordination of IKONOS images," *Elsevier - Science Direct,* vol. 109, no. Remote Sensing of Environment, p. 379–392, 2007.

[15] A. F. Costa, G. Humpire-Mamani and A. J. M. Traina, "An Efficient Algorithm for Fractal Analysis of Textures," in *25th Conference on Graphics, Pattern and Images*, Brazil, 2012.

[16] A. Y. Sari and N. Suciati, "Flower Classification using Combined a* b* Color and Fractal-based Texture Feature," *International Journal of Hybrid Information Technology,* vol. 7, no. 2, pp. 357-368, 2014.

[17] R. Korchiyne, S. M. Farssi, A. Sbihi, R. Touahn and M. T. Alaoui, "A COMBINED METHOD OF FRACTAL AND GLCM FEATURES FOR MRI AND CT SCAN IMAGES CLASSIFICATION," *Signal & Image Processing : An International Journal (SIPIJ),* vol. 5, no. 4, pp. 85-97, 2014.

[18] R. Usha and K. Perumal, "Content Based Image Retrieval using Combined Features of Color and Texture Features with SVM Classification," *International Journal of Computer Science & Communication Networks,* vol. 4, no. 5, pp. 169-174.

[19] S. Agustin, H. Ginardi and H. Tjandrasah, "Identification of Oil Palm Plantation in Ikonos Images using Radially Averaged Power Spectrum Values," in *International Conference on Information, Communication Technology and System*, Surabaya, Indonesia, 2015.

[20] M. P. T. Ojala and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *Pattern Analysis and Machine Intelligence, IEEE Transactions,*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

vol. 24, no. 7, pp. 971-987, 2002.

[21] S. W. Yu Xia, P. Jin and L. Yue, "A Novel Sea-Land Segmentation Algorithm Based on Local Binary Patterns for Ship Detection," *International Journal of Signal Processing, Image Processing and Pattern Recognition,* vol. 7, no. 3, pp. 237-246, 2014.

[22] P.-S. Liao, T.-S. Chen and P.-C. Chung, "A Fast Algorithm for Multi Level Thresholding," *Journal of Information Science and Engineering,* vol. 17, no. 5, pp. 713-727, 2001.

[23] S. Bouteldja and A. Kourgli, "Retrieval of High Resolution Satellite Images Using Texture Features," *JOURNAL OF ELECTRONIC SCIENCE AND TECHNOLOGY,* vol. 12, no. 2 , pp. 211-215, 2014.

[24] Z. Szantoia, F. Escobedob, A. Abd-Elrahmana, S. Smith and L. Pearlstinec, "Analyzing fine-scale wetland composition using high resolution imagery and texture features," *Science direct - International Journal of Applied Earth Observation and Geoinformation,* vol. 23 , p. 204–212, 2013.

[25] R. Gonzalez and R. E. Woods, Digital Image Processing, New Jersey: Prentice Hall, 2001.

[26] Y. A. S. a. N. Suciati, "Flower Classification using Combined a* b* Color and Fractal-based Texture Feature," *International Journal of Hybrid Information Technology,* vol. 7, no. 2, pp. 357-368, 2014.

[27] A. Kadir, L. E. Nugroho, A. Susanto and P. I. Santoso, "A local binary pattern based texture descriptors for classification of tea leaves," *International Journal of Computer Trensda and Technplogy,* vol. July to Aug, no. 2011, pp. 225-230, 2011.

[28] Md. Abdur Rahim, Md. Najmul Hossain, Tanzillah Wah and Md. Shafiul Azam, "Face Recognition using Local Binary Patterns (LBP)," *Global Journal of Computer Science and Technology Graphics & Vision,* vol. 13, no. 4, pp. 1-7, 2013.

[29] C. Zhang and Z. Xie, "Combining object-based texture measures with a neural network for vegetation mapping in the Everglades from hyperspectral imagery," *Science Direct - Remote Sensing of Environment ,* vol. 124 , p. 310–320, 2012.

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Table 1. The Result Of Features Extraction Using SFTA

Classification / Data Set	sfta-1		sfta-2		sfta-3		sfta-4		sfta-5		sfta-6		sfta-7		sfta-8		sfta-9		sfta-10		sfta-11		sfta-12	
	Min	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
young oil palm	1.71	1.86	74.46	162.84	342	562	1.76	1.84	86.40	196.55	372	527	1.62	1.83	68.37	149.01	234	505	1.76	1.84	86.40	197.39	372	527
adult oil palm	1.76	1.84	79.46	170.02	401	510	1.69	1.81	92.78	203.81	308	457	1.64	1.78	67.90	138.26	244	422	1.69	1.81	92.78	202.03	308	457
old oil palm	1.73	1.82	82.95	201.44	379	503	1.74	1.82	95.68	223.80	373	497	1.61	1.73	68.07	173.95	218	360	1.74	1.82	95.68	220.99	373	494
not oil palm	1.74	1.87	72.12	201.00	394	589	1.53	1.87	87.04	230.44	183	588	1.68	1.85	68.13	176.14	281	550	1.53	1.87	87.04	232.36	183	588

Table 3. Result Features Extraction – Lbp

Classification / Data Set	lbp1		lbp2		lbp3		lbp4		lbp5		lbp6		lbp7		lbp8		lbp9		lbp10	
	Min	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
young oil palm	70	135	71	104	39	71	39	105	44	126	44	122	49	81	82	112	80	149	152	194
adult oil palm	77	173	82	112	48	77	35	83	35	84	50	81	46	80	90	102	81	285	153	201
old oil palm	93	120	82	113	43	64	39	67	45	67	59	73	44	76	85	112	106	119	161	212
not oil palm	102	169	87	120	22	65	36	89	27	117	37	94	35	75	85	109	112	401	170	211