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Deep Learning-based Method for Multi-Class Classification of Oil Palm Planted Area on Plant Ages Using *Ikonos* Panchromatic Imagery

Soffiana Agustin[a,1,c], Handayani Tjandrasa[a,2], R.V. Hari Ginardi[b]

[a]*Department of Informatics, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya, 60111, Indonesia*
E-mail: [1]asoffi@gmail.com; [2]handatj@its.ac.id

[b]*Department of Information Technology, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya, 60111, Indonesia*
E-mail: hari.ginardi@gmail.com

[c]*Department of Informatics, Muhammadiyah Gresik University, Gresik, Indonesia*
E-mail: soffiana@umg.ac.id

***Abstract*— Oil palm has many advantages, such as biofuels, cosmetics, food ingredients, etc. The amount of oil contained in oil palm fruit is very dependent on the age of the plant, so automatic detection of oil palm plantation area based on plant ages is required to estimate the amount of oil. The use of high-resolution satellite images in oil palm detection has shown promising results for small dimensions, and previous studies have used more than one band of the satellite images data. This will be a burden in terms of cost and processing. Previous studies regarding oil palm area detection usually focused on detecting land cover to distinguish oil palm and non-oil palm areas. This study proposes a method based on deep-learning convolutional neural networks to classify oil palm plantations at a productive age. The images used in this study are the *Ikonos* satellite image with panchromatic bands only, which have a spatial ratio of 1m. The plantation area is classified into the non-oil palm, oil palm areas with young, mature, and old ages. This study proposes a multi-class classification method for oil palm plantations based on plant ages using convolutional neural networks (CNN). This study performs two fine-tune models on a pre-trained CNN and then classified using SVM and CNN. The performance of CNN architectures such as AlexNet, VGG16, and VGG19 was compared. The highest accuracy is 94.74% when using the CNN classifier and fine-tune model-2 of the VGG19 pre-trained network.**

***Keywords*— multi-class classification; oil palm; plant ages; *ikonos* panchromatic images; fine-tune; convolutional neural network; support vector machine**

I. INTRODUCTION

Palm oil is an industrial plant which widely used to produce cooking oil, industrial oil, fuel, etc. Oil palm plantations can improve the welfare of the surrounding population and are currently a developing economic sector [1]. Oil palm plants grow well in tropical areas with humidity of 80-90 degrees and begin to produce fruit at three until twenty-five years old. At 3-8 years old, oil palm has 3.5-13 kg/bunch of fruit weight. At 8-16 years old, fruit growing up to 14-24 kg/bunch and 16-25 years produces 25-35 kg/ bunch. After more than 25 years old, palm oil will experience a decline in function and quality [2], [3]. The quality of oil palm is influenced by many factors, such as age, rainfall, varieties, treatment methods, and other indicators, but age is most often used as a point of reference for results [4], [5].

Oil palm is usually planted on large plantations, even though the monitoring of plantation land must always be carried out. Plantation monitoring accomplishes to obtain field data this activity is usually done manually and therefore requires a lot of time and energy. With the development of technology, the use of satellite imagery has been widely used to help get the required field data. Remote sensing data were obtained from aerial photographs or satellite imagery.

Satellites can provide information about conditions for very large areas, such as oil palm plantations. Satellite output belongs to spatial data that is stored in many bands according to the type of satellite used. Spatial information from detailed data can be used for industry and plantations, such as detecting land cover changes and monitoring oil palm plantations.

Research on monitoring oil palm plantations by utilizing satellite imagery to map land cover, detection, calculation, and estimation of oil palm ages. Most of this research uses digital image processing and computer vision techniques, including deep learning techniques. A method for mapping of oil palm plantations in Cameroon using satellite imagery using the Phased Array type L-band Synthetic Aperture Radar (PALSAR) by recognizing the type of land cover in four classes, namely: oil palm, forest, water, and another land cover. This study's learning machines: Support Vector Machine (SVM), Decision Tree, and K-Means [6]. SVM's are used by combining three bands to separate oil palm from forests, other plants, shrubs, and heaps or empty land [7] and gave quite good results [8] using WorldView-2 satellite imagery for classifying the oil palm area and a non-oil palm area.

Previous studies on oil palm area detection usually focus on detecting the plantation areas to distinguish between oil palm and non-oil palm. However, the amount of oil contained in oil palm fruit is very dependent on the age of the plant, so automatic detection of oil palm plantations area based on plant ages is required to estimate the amount of palm oil. Several studies have been done to detect and estimate the age of oil palm. The detection of oil palms using worldview-2 with nine visible bands to near-infrared and panchromatic (1: 0.5m) was used to estimate tree age based on the shape of the tree crown by measuring the diameter of the tree crown. This study gives a pretty good result of delineation for oil palm aged 8 to 13 years [9]. Age detection is performed on light detection and range (LiDAR) by estimating tree height using linear regression with a block size of 3x3 pixels [10]. The detection of the age of oil palms was proposed in [11] to detect areas of oil palm at young and adult ages.

The satellite image used was the worldview-3 RGB band with a 0.3m resolution. The image dimension used was 991 x 1155 pixels, where each image was divided into blocks with dimensions of 26 x 26 pixels in areas containing young oil palm trees and 31 x 31 pixels for areas containing mature oil palm trees. Then areas without young or adult oil palm trees will not be detected (no training or testing). The deep learning used in this research is LeNet architecture.

Previous studies on age detection of oil palm focus only on two categories: young and adult. However, there are three categories of oil palm ages, namely young, mature, and old. In addition, they use worldview-2 and worldview-3 imagery for oil palm detection. A Convolutional Neural Network (CNN) is one a deep learning that applies neural networks. On CNN, connectivity between neurons is carried out with several 2-dimensional parallel filters. When high performance is required, its implementation cannot be realized on standard microprocessors. This requires high hardware specifications, especially Graphical Processing Units (GPU) and Field Programmable Gate Arrays (FPGAs) [12]. Detection of oil palm based on deep learning was carried out by using a U-Net type neural network. The satellite images used were worldview-2 for the Jambi, Indonesia research area, and worldview-3 for India's Bengaluru region. Detection was carried out in the area of oil palm plantations to determine oil palm trees [13]. Quickbird satellite imagery was used in [14], [15] to detect oil palm trees. The categories used in the study were classified into four classes, namely: oil palm trees, background, other vegetation / bare land, and impervious/ cloud classes. The method proposed in this research was to use the AlexNet architecture [14] and by using a two-stage Convolutional Neural Network (CNN) [15].

The *Ikonos* imagery has a spatial resolution of 4 m for the multispectral band and 1 m for the panchromatic band. It has better visualization capabilities and is more effective than Quickbird satellite imagery, which has a resolution of 0.6 m [16]. In our previous study, panchromatic *Ikonos* was used to identify oil palm plantations using conventional digital processing methods. The parameters used are taken from the spatial domain and frequency. Spatial parameters are determined by calculating first-order statistical values, local features, and the Gray Level Co-occurrence Matrix (GLCM). The frequency-domain feature is taken from the power spectrum value, the Radially Average Power Spectrum Value (RAPSV) [17], and segmentation-based fractal texture analysis (SFTA) with local features LBP [18].

In summary, the previous studies have not classified the oil palm according to plant age. Besides, they used images with not too complicated tree crowns (an oil palm crown is not intersecting), and most previous studies use images with small dimensions. This study used large-scale images and simple to complex backgrounds (tree crowns are connected) of panchromatic bands only from *Ikonos* imagery.

This study proposes a multi-class classification method using a Convolutional Neural Network (CNN) to classify the oil palm plantation area based on the plant ages on the *Ikonos* panchromatic imagery. The main contributions of this study are as follows:

- We adapted several CNN architectures to classify the oil palm planted area, which is classified into four categories, i.e., non-oil palm, oil palm areas with young, mature, and old ages. In comparison, most other studies classified the plantation into two categories.
- We used large-scale images and simple to complex backgrounds (crowns connected tree) of the *Ikonos* imagery with panchromatic bands. It is expected that by using only one band (panchromatic), the computing and effort issued can be minimized.

II. Materials and Methods

In 2019/2020, Indonesia produced 43 million tons of palm oil, an increase of 1.5 million tons from 2018/2019. This is due to the large number of oil palms that grow in mature age [19]. Hence, this study chooses an area in Indonesia. The area studied is monoculture plantations in Riau and Kalimantan, Indonesia. This area is generally a plantation area with another land cover, such as roads, warehousing areas, swamps, bare land, forest trees, or other vegetation types.

This study uses IKONOS satellite images with panchromatic bands. This image has a spatial resolution of 1:1m. This means that one pixel represents 1m in the real world. The use of panchromatic *Ikonos* imagery is quite good at visualizing the land and is useful for identifying objects in more detail, even though it has a lower resolution [20], [16].

In our previous studies, the dataset training and dataset testing were 30x30 pixel dimensions, which consisted of 100 data for each class. Dataset training and dataset testing were selected randomly using a ten-fold validation [17], [18]. In this study, dataset training is taken by cropping the image with a size of 30x30 pixels, and the dataset testing was taken by cropping satellite images randomly with varying dimensions. The selection of training images is carried out at random images to represent each class's image condition, which consists of 1,883 non-palm data, 569 young palm data, 511 mature palm data, and 508 old palm data. The dataset test is divided into three categories according to the accompanying land cover (background). The three datasets test categories are:

- Dataset test-1 contains 11 images with image sizes between 100x100 pixels and 300x300pixels, where the background conditions tend to be homogeneous.
- Dataset test-2 contains 33 images with a size larger than dataset test1 and heterogeneous land cover conditions
- Dataset test-3 contains 166 images with sizes larger than dataset-test2 and land cover conditions are very diverse (heterogeneous).

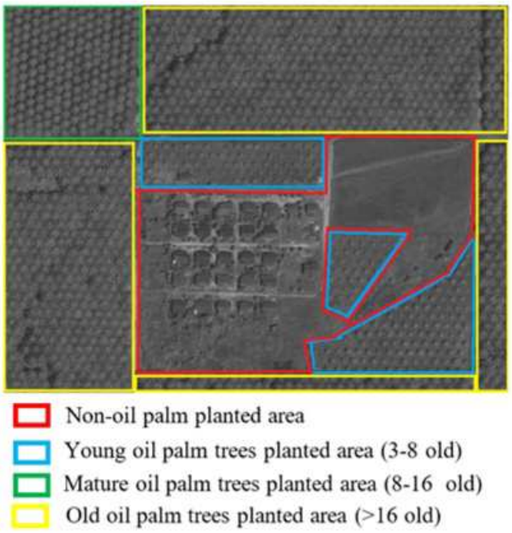

Fig. 1 The subset of study area

This study aims to classify the area of oil palm plantations into several regions using only the Panchromatic band of *Ikonos* satellite imagery. This image is categorized into oil palm plantations and non-oil palm plantations. The oil palm area is classified into specific categories of age according to planting age. To recognize a certain age of oil palm in the plantation area requires thoroughness. The area of oil palm plantations is classified into multi-classes, namely the area of area of young oil palm, mature oil palm, and the area of old oil palm, as shown in Fig. 1.

This category refers to the age of oil palm tree planting. Oil palm trees aged 3-8 years are categorized as young oil palm, palm trees aged 8-16 years are categorized as mature oil palm and oil palm trees up to 16 years are categorized as old oil palm [3], [17], [18]. The framework proposed in this study is shown in Fig. 2. This study proposes the use of an SVM and a Convolutional Neural Network (CNN) with several fine-tune models of CNN pre-trained network to classify the area of oil palm plantations in multi-class classification. The CNNs used in this study are the AlexNet and Visual Geometry Group (VGG).

This study is performed in three stages, namely pre-processing, processing and classification. The pre-processing stage performs reads and image resizing. The processing stage developed transfer learning, constructing the CNN model, arranging optimization parameters, and training the network. Classification stage: classification is done using SVM and CNN classifier. This stage converted the classification output into a color map to show the oil palm plantation area's class.

1) Pre-processing: At this stage, the image is read and the dimensions are resized according to the type of CNN architecture used. The input dimension of the image in this study is 30x30 pixels. This study uses CNN with architectural types: AlexNet and Visual Geometry Group (VGG). AlexNet requires input data dimensions of 227x227 pixels and VGG requires input data dimensions is 224x224 pixels.

2) CNN architecture: This phase aims to build a Convolutional Neural Network (CNN). Deep learning is a reliable method of recognizing objects, using images directly to learn, and recognizing images, and solving multiclass problems. The CNN architecture is composed of convolution layers, Rectifier Linear Units (ReLU), pooling layers and fully connected component layers. At the convolution layer, convolution will be carried out by a few filters or kernels. From this convolution, we will get a map feature that contains prominent features of the input image.

This map feature is then normalized by removing negative values by changing it to 0 in the ReLU layer. In the pooling layer, the feature map is subsampled by taking the largest value in the window (max pooling) or the window's mean value (mean pooling). In this research, max-pooling was used. In the last stage of the CNN, the fully connected layer produces output in the form of categories according to the classes used in the dataset. This study proposes the use of CNN to classify the area of oil palm plantations in multi-class classification. The CNNs used in this study are the AlexNet and Visual Geometry Group (VGG).

Transfer learning refers to a learning technique. It is also applied for training a model used in the following steps: the process begins with randomly initiating weights, then begins training with the initiation of random weights and updates weight values so that tasks can be completed with fewer errors (optimal). After the results are considered satisfactory, the weight of the network is saved. The network weights can be used directly for similar problem conditions, no need to do network training anymore so that it can save time and simplify computing. AlexNet and VGG trained more than thousands of images and were able to recognize 1000 categories of objects. It is very useful if this pre-trained network is still used. For this reason, this study arranges the transfer learning by reusing pre-trained and doing some fine-tuning on the pre-trained network.

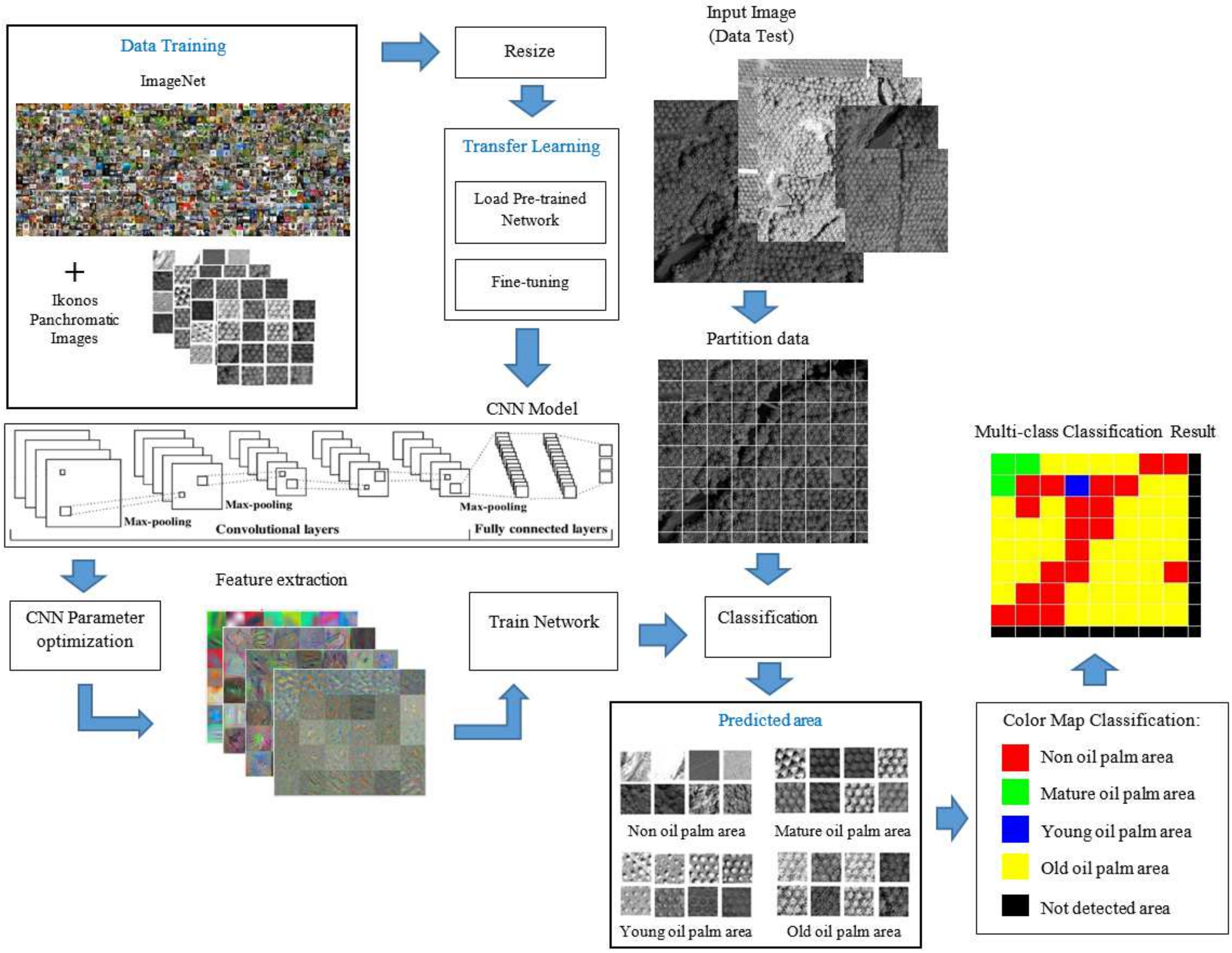

Fig. 2 Framework for multi-class classification of oil palm plantations

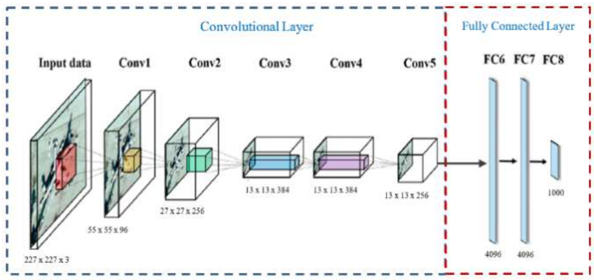

Fig. 3 AlexNet Architecture [14], [21]

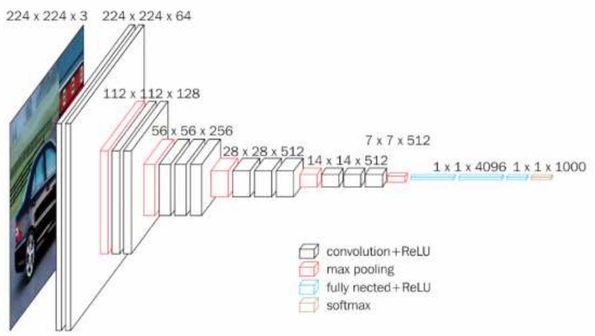

Fig. 4 VGG Architecture [23]

The AlexNet pre-trained network model has five convolution layers, three max-pooling layers, and three fully connected layers, as seen in Fig. 3. The Visual Geometry Group (VGG) network has a more regular standard than AlexNet. All convolutional filters used must have a size of 3x3, and after 2 or 3 times, convolution must do pooling. There are two famous architectures from VGG, namely VGG16 and VGG19. This naming is adjusted to the number of convolutional layers carried out in the architecture. VGG16 has 16 convolutional layers, while VGG19 has 19 convolution layers and three fully-connected layers [22]. VGG architecture is shown in Fig.4.

This study performs two types of fine-tuning models. The first model is replacing the last three layers ('fc8') of the pre-trained network with the new fully-connected layer to learn our feature data set. The second model replaces the last six layers of pre-trained to replace the new fully connected layer. The fine-tuned model used in this study can be seen in Fig.5. For the training options of AlexNet, mini-batches were set to 32 and max epochs of 45 and in training options for VGG16 and VGG19 reduce the mini batches' values to 10 and max epochs to 5 to ease the training process.

VGG19 Architechture

name	type
input	Image Input
conv1_1	Convolution
relu1_1	ReLU
conv1_2	Convolution
relu1_2	ReLU
pool1	Max Pooling
conv2_1	Convolution
relu2_1	ReLU
conv2_2	Convolution
relu2_2	ReLU
pool2	Max Pooling
conv3_1	Convolution
relu3_1	ReLU
conv3_2	Convolution
relu3_2	ReLU
conv3_3	Convolution
relu3_3	ReLU
conv3_4	Convolution
relu3_4	ReLU
pool3	Max Pooling
conv4_1	Convolution
relu4_1	ReLU
conv4_2	Convolution
relu4_2	ReLU
conv4_3	Convolution
relu4_3	ReLU
conv4_4	Convolution
relu4_4	ReLU
pool4	Max Pooling
conv5_1	Convolution
relu5_1	ReLU
conv5_2	Convolution
relu5_2	ReLU
conv5_3	Convolution
relu5_3	ReLU
conv5_4	Convolution
relu5_4	ReLU
pool5	Max Pooling
fc6	Fully Connected
relu6	ReLU
drop6	Dropout
fc7	Fully Connected
relu7	ReLU
drop7	Dropout
fc8	Fully Connected
prob	Softmax
output	Classification Output

VGG16 Architecture

name	type
input	Image Input
conv1_1	Convolution
relu1_1	ReLU
conv1_2	Convolution
relu1_2	ReLU
pool1	Max Pooling
conv2_1	Convolution
relu2_1	ReLU
conv2_2	Convolution
relu2_2	ReLU
pool2	Max Pooling
conv3_1	Convolution
relu3_1	ReLU
conv3_2	Convolution
relu3_2	ReLU
conv3_3	Convolution
relu3_3	ReLU
pool3	Max Pooling
conv4_1	Convolution
relu4_1	ReLU
conv4_2	Convolution
relu4_2	ReLU
conv4_3	Convolution
relu4_3	ReLU
pool4	Max Pooling
conv5_1	Convolution
relu5_1	ReLU
conv5_2	Convolution
relu5_2	ReLU
conv5_3	Convolution
relu5_3	ReLU
pool5	Max Pooling
fc6	Fully Connected
relu6	ReLU
drop6	Dropout
fc7	Fully Connected
relu7	ReLU
drop7	Dropout
fc8	Fully Connected
prob	Softmax
output	Classification Output

AlexNet Architechture

name	type
data	Image Input
conv1	Convolution
relu1	ReLU
norm1	Cross Channel Normalization
pool1	Max Pooling
conv2	Grouped Convolution
relu2	ReLU
norm2	Cross Channel Normalization
pool2	Max Pooling
conv3	Convolution
relu3	ReLU
conv4	Grouped Convolution
ReLU	ReLU
conv5	Grouped Convolution
relu5	ReLU
pool5	Max Pooling
fc6	Fully Connected
relu6	ReLU
drop6	Dropout
fc7	Fully Connected
relu7	ReLU
drop7	Dropout
fc8	Fully Connected
prob	Softmax
output	Classification Output

Fine Tune Model-2

Fine Tune Model-1

Fine Tune Model-2

Fine Tune Model-1

Fig. 5 Proposed fine-tuning on pre-trained network

3) Classification: In the classification process, the test data are partitioned into non-overlapping blocks. By applying sliding windows, each block extracts the features and classifies them according to match the features of the block with the trained features. Classification in this study is done using a Support Vector Machine (SVM) and a CNN classifier (AlexNet, VGG16 and VGG19). The number of classes used is 4 for predicting labels they are: label 1 is given for the non-oil palm planted area, label 2 is given for the mature oil palm planted area, label 3 is given for the young oil palm planted area and label 4 for the old oil palm planted area.

This label is presented in colors based on certain criteria. The classification results are described in a color map that shows the meaning of the area in the oil palm plantation. Areas such as swamps, roads, stowage areas, bare land, areas with forest trees, etc. are inclusive in non-oil palm planted area classes and given a red color. Label 2 is presented in green, label 3 is presented in blue and label 4 is presented in yellow, while blocks having less than 30 pixels in dimension are given a black color.

III. Result and Discussion

Ikonos satellite images produce data with very large dimensions. The data are extracted into training data with dimensions of 30x30 pixels for all classes, and labeling is done manually. The test data were extracted from *Ikonos* imagery with varying dimensions from 100x100 pixels up to 2400x1200 pixels. Experiments were carried out on several test data distributions using the fine-tune model for pre-trained networks that had been built before (fine-tune model-1 and model-2).

TABLE I
RESULTS OF MULTI-CLASS CLASSIFICATION USING CNN

Pre-trained	**Fine-tune model-1**			**Fine-tune model-2**		
Data test	**AlexNet (%)**	**VGG1 (%)**	**VGG19 (%)**	**AlexNet (%)**	**VGG16 (%)**	**VGG19 (%)**
Test-1	90.53	92.11	92.63	92.11	91.58	**94.74**
Test-2	82.32	82.96	85.78	83.50	85.05	**87.10**
Test-3	69.50	71.87	**75.57**	70.98	72.59	72.99

TABLE II
RESULTS OF MULTI-CLASS CLASSIFICATION USING SUPPORT VECTOR MACHINE (SVM)

Pre-trained	**Fine-tune model-1**			**Fine-tune model-2**		
Data test	**AlexNet (%)**	**VGG16 (%)**	**VGG19 (%)**	**AlexNet (%)**	**VGG16 (%)**	**VGG19 (%)**
Test-1	83.68	**86.32**	80.53	83.68	85.79	82.11
Test-2	**76.34**	67.87	69.74	76.34	67.23	73.88
Test-3	64.41	66.19	65.64	62.17	66.67	**66.93**

The multi-class classification accuracy is obtained by summing the class results that comply with the ground truth. In this study ground truth is done manually. The results of multi-class classification depend on the predicted label that results from the classification step. The classifiers used in this study are SVM and CNN. The accuracy of the experiments that were carried out for each test data as in Table 1 and Table 2. Table 1 shows the classification results using the CNN Classifier with fine-tune model-1 and model-2 of pre-trained networks. Table 2. shows the accuracy of the classification results using SVM with fine-tune model-1 and fine-tune model-2 of pre-trained networks. In Table 1, the data test-1, the highest accuracy is 94.74% that obtained from the fine-tune model-2 on the VGG19 pre-trained network with the CNN classifier. In Table 2, the use of the SVM classifier gave the highest accuracy of 86.32% by using fine-tune model-1 on VGG16 pre-trained networks.

Data test-2 has a more complex background and larger dimensions than data test-1. The highest accuracy of test-2 data was 87.10%, that obtained from the VGG19 classifier with the fine-tune model-2 on the VGG19 pre-trained network, while the highest accuracy, using the SVM classifier is 76.34% using the fine-tune model-1 on the AlexNet pre-trained network. The images used in data test-3 have a more complex background and have larger image dimensions than data test-1 and data test-2. The highest accuracy of data test-3 is 75.57% obtained by using the VGG19 classifier with fine-tune model-1 on the VGG19 pre-trained network. The SVM classifier gave the highest accuracy of 66.93% obtained by using fine-tune model-2 on the VGG19 pre-trained network.

The CNN classifier's use gives better results than using the SVM classifier, either by using fine-tune model-1 or model-2. The accuracy comparison of the classification methods used can be seen in Fig. 6 and Fig. 7. By using the proposed CNN architecture model feature extraction, the oil palm plantation area can be recognized even better; these are 94.74% for data test-1 with the fine tuner model-2 on pre-trained VGG19, for data test-2 87.10% using fine tuner model-2 on pre-trained VGG19 and for data test-3 75.57% used fine-tuner model-1 on the same pre-trained as shown in Table 3.

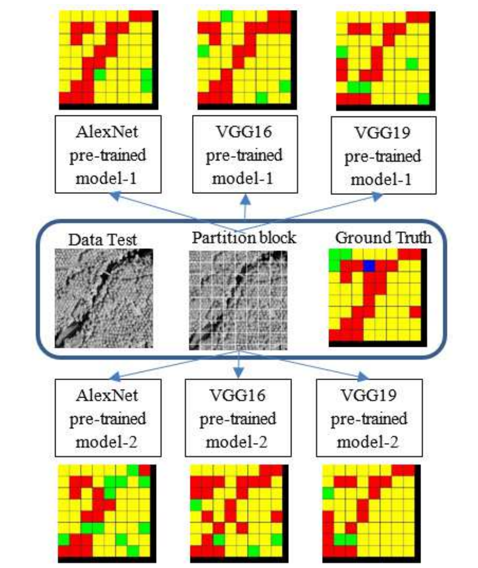

Fig. 6 Results of Multi-class Classification using SVM

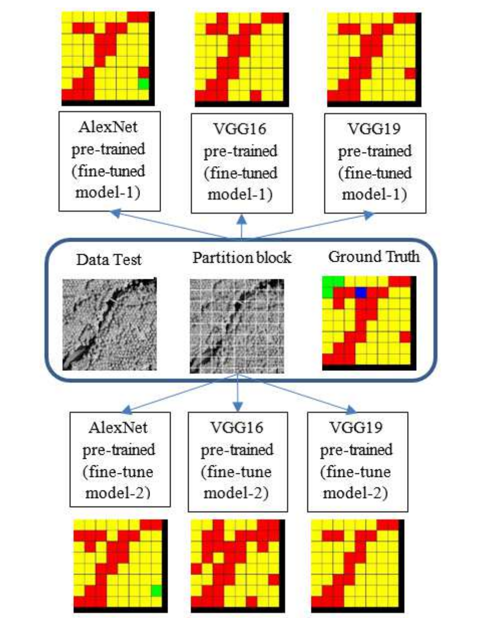

Fig. 7 Results of Multi-class Classification using CNN

TABLE III
CLASSIFICATION RESULTS OF THE PROPOSED METHOD

Classifier	Features Extraction	Data test-1 (%)	Data test-2 (%)	Data test-3 (%)
CNN	AlexNet model-1	90.53	82.32	69.50
	VGG16 model-1	92.11	82.96	71.87
	VGG19 model-1	92.63	85.78	**75.57**
CNN	AlexNet model-2	92.11	83.50	70.98
	VGG16 model-2	91.58	85.05	72.59
	VGG19 model-2	**94.74**	**87.10**	72.99
SVM	AlexNet model-1	83.68	76.34	64.41
	VGG16 model-1	86.32	67.87	66.19
	VGG19 model-1	80.53	69.74	65.64
SVM	AlexNet model-2	83.68	76.34	62.17
	VGG16 model-2	85.79	67.23	66.67
	VGG19 model-2	82.11	73.88	66.93

IV. CONCLUSION

CNN can recognize objects and provide good classification results for multi-class problems. Each layer on the CNN formed a feature map after the convolution layer. A simple form feature map was formed on the first layer. The further layers formed more complex feature maps. The use of SVM as a classifier provides stability during experiments, but accuracy with a CNN architecture gives higher results. In the overall test data used, pre-trained VGG19 types with the CNN classifier give the best results.

For data test-1, fine-tune model-1 gives an accuracy of 92.63%, while using the fine-tune model-2 gives the highest accuracy of 94.74%. For data test-2, fine-tune model-1 gives an accuracy of 85.78%, while using the fine-tune model-2 gives the highest accuracy of 87.10%. For data test-3, the use of fine-tune model-1 gives the highest accuracy of 75.57%, while using the fine-tune model-2 gives an accuracy of 72.99%.

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