Land Cover Classification Based on Sentinel-2 Satellite Imagery Using Convolutional Neural Network Model: A Case Study in Semarang Area, Indonesia

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Land Cover Classification Based on Sentinel-2 Satellite Imagery Using Convolutional Neural Network Model: A Case Study in Semarang Area, Indonesia

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Abstract Regional land use planning and monitoring remain an issue in many developing countries. Efficient solution for both tasks depended on remote sensing technology to capture and analyze remotely sensed data of the region of interest. Although a plethora of methods for land cover classification have been reported, the problem remained a challenging task in computer vision field. The advent of deep learning method in the past decade has been very instrumental to develop a robust method for land cover classification using satellite imagery as input. The objective of this paper was to present empiric results on using CNN as a land cover classifier model using Sentinel-2 spatial satellite imagery. Prior to model training, the input image representation was extracted using eCognition to produce texture, brightness, shape, and vegetation index. Land cover labeling followed the Land Cover Class in Medium Resolution Optical Imagery Interpretation document provided by Indonesian National Standardization Agency. The training of CNN model achieved 0.98 mean training accuracy and 0.98 mean testing accuracy. As comparison, the same data and same feature were trained with another model: Gradient Boosting Model (GBM). The results revealed that the training accuracy and testing accuracy with GBMs were 0.98 and 0.95 respectively. CNN model showed small improvement of the accuracy to classify land cover with the image feature (NDVI, Brightness, GLCM homogeneity and Rectangular fit).

Keywords CNN · Land cover classification · Satellite imagery

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1 Introduction

Regional land use planning and monitoring remain an issue in many developing countries such as Indonesia. In the past two decades, both tasks largely depended on remote sensing technology to capture and analyze remotely sensed data of the region of interest. Remote sensing is a technology to obtain and analyze information over the earth. This technology facilitates faster data acquisition and wider data coverage compared with conventional technology or field observations [1]. The development of remote sensing technology was followed by the development of digital image analysis. Wide access to satellite imagery in the past ten years has attracted wide interest of researchers from various research domains into remote sensing imagery analytics, such as land cover classification, due to its wide potential applications [1].

Land use classification is a prominent computer vision problem that has gained wide research interest for many years. The challenge in addressing this task is how to duplicate human abilities in image understanding, thus the computer could recognize an object like a human. The advent of deep learning [2] in the past decade coupled with wide availability of satellite imagery and GPU computer server have regained research interest on satellite image analysis. These studies resulted in a plethora of proposed models available in literature. Many of the previous studies have reported a great result of deep learning model for satellite image analysis. One of the models that have been widely adopted is convolutional neural network (CNN) which is designed to imitate the image recognition system on human visual cortex [2]. To achieve such objective, the CNN model was designed as a hierarchy of convolutional and pooling layers and a fully connected layer (FCL) [3]. The hierarchical structure of CNN makes it possible for the model to learn hierarchical feature of the input data. In remote sensing image analysis, another critical factor for CNN performance is satellite image features.

The feature of satellite imagery can be divided broadly into two feature categories that represent: low-level objects and high-level objects. In the past decade, many research works mainly focused on classifying individual pixels or objects by identifying low-level local image features [4], such as color histogram [5]. Although having been widely used for satellite imagery classification, low-level local image features only represent object's local features such as color, shape, and texture. Consequently, the classifier can merely classify low-level objects, e.g. road, and soil [6]. On the other hand, land cover imagery requires to recognize multiple and more complex objects such as settlement, forest, water body and bare land. For that purpose, the feature of land cover imagery, therefore, should represent a wide range of objects. This requirement brought about the need of a method to extract various features automatically from a satellite image. The study by [2] claimed the strength of deep learning model was its ability to learn hierarchical feature from input data. Convolutional neural network (CNN) model is one of the deep learning models which is capable to perform such ability.

Despite many studies have proposed CNN model for land cover classification, to the best of our knowledge, little have been said on the use of spectral satellite image as input. Therefore, the objective of this study is to build a CNN model as land cover classifier using Sentinel-2 satellite imagery as input.

2 Literature Review

2.1 Convolutional Neural Network Model

Convolutional Neural Network (CNN) is a term referring to a neural network model which has been specifically used to process grid-structured data i.e. two-dimensional image. Convolutional Neural Network (CNN) is a development of multilayer perceptron (MLP) designed to process two-dimensional data in the image form [1]. Following [2], as a deep learning model, CNN architecture can be built with various deep structure. Despite its structure depth, the mapping process of input to output in a CNN model follows several stages. Each stage produces a data representation called feature maps. The structure wise of each stage consists of three layers, namely convolution, layer activation function, and pooling layer [1]. The Convolutional Neural Network architecture network is showed in Fig. 1.

In general, the first stage in the CNN architecture is the convolution stage uses a kernel of a certain size. The number of kernels used depends on the number of features produced. The second stage is the activation function; this function usually uses the ReLU activation function (Linear Unit Rectifier). Subsequently after passing the activation function, the process goes through the pooling process. This process is repeated several times until a sufficient feature map is obtained to proceed to the fully connected neural network [2].

The effective way to classify high resolution images by combining deep features and image objects has gained wide research interest. For example, a study reported by Zhao et al. [7] proposed a method utilizing deep CNN framework to automatically extract robust and discriminative features for the classification of complex urban

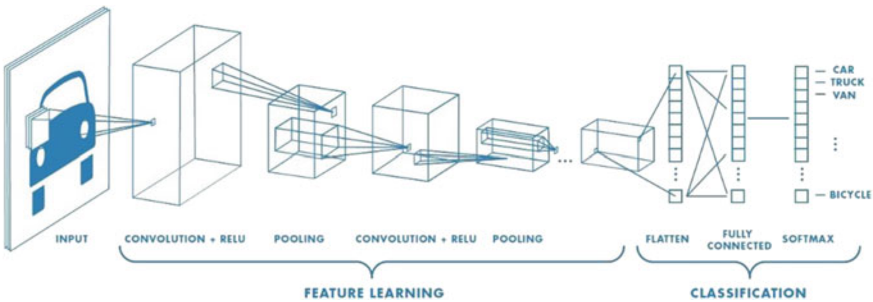


Fig. 1 A typical CNN achitecture. *Source* [2]

objects (such as building roofs and cars). However, the study has no access to the contextual information at the global level.

Kussul et al. [8] presented the use of CNN to reach the target accuracy of 85% for major crops (wheat, maize, sunflower, soybeans, and sugar beet). This study became a foundation for further operational use of remote sensing data within Sentinel-2 imagery.

Zhu and Newsam [9] demonstrated that land use classification is possible using high-level image features extracted using CNNs from geo-located ground-level images. The framework showing that high-level, semantic image features extracted using pre-trained CNN models generalize well to related problems.

Yang et al. [10] investigated the use of different encoder-decoder structures of CNN based on SegNet for the pixel-wise classification of land cover based on aerial images and derived data. The experiments have shown that an ensemble of CNN having different architectures and using different input data achieves the best performance with an overall accuracy of almost 86% for eight land cover classes (building (build.), sealed area (seal.), bare soil (soil), grass, tree, water, car, etc.). Kampffmeyer and Jenssen [11] proposed revision of a convolutional neural network architecture for urban remote sensing image segmentation trained on data modalities which are not all available at test time.

Suzuki et al. [12] proposed a Convolutional Neural Network (CNN) which mimics professional interpreters' manual techniques. With the proposed CNN, K. Suzuki shows that the multi-modal CNN works robustly and gets more than 80% user's accuracy. A novel Deep Learning architecture to leverage PAN and MS imagery for land cover classification has been proposed by [13]. The proposed method, MultiResoLCC, consists of a two-branch end-to-end network which extracts features from each source at their native resolution and lately combines them to perform land cover classification at the higher-resolution single-band panchromatic PAN resolution.

2.2 Convolutional Layer

Convolution layer is a layer in CNN architecture that performs a convolution operation on the output of the previous layer. This layer is the main process underlying the CNN architecture network. Convolution operations are operations on two functions of real value arguments. This operation applies the output function as a feature map from the input image. This input and output can be seen as two value arguments [2]. Convolutional operation can be seen in Eq. 1.

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a). \tag{1}$$

where: s(t) = function as a result of convolution operation; x = input; w = weight (kernel). The function s(t) provides a single output in the form of a map feature. The first argument is the input (x) and the second argument (w) is the kernel or filter. When input as a two-dimensional image, it can be said t as a pixel and replace it with i and j.

3 Research Method

3.1 Study Area and Data

The test site for this study is Semarang area, Central Java, Indonesia. This area is selected for the following reasons: (1) Cloud covers of the observed area (2) Characteristics of geography and topography of Semarang area represent the land cover class analyzed in this study (3) It is one of the cities in Indonesia where the population growth and the development of the city has caused the increase of land requirement. Such reasons make regional land use planning and monitoring are crucial.

The Sentinel-2 satellite imagery was retrieved through web site with URL https://earthexplorer.usgs.gov/. The data was acquired on August 27, 2017, at 14:55:47 with the cloud cover in the observed area at 8.49%, Sun Zenith Angle Mean (average sun exposure in the observation area in vertical angle) = 29.93 and Sun Azimuth Angle Mean (average sun exposure in the observation area in horizontal angle) = 55.98. The image acquired was not in the rainy season, with high exposure of sun, dry and very low humidity.

The main land cover classes for this study were based on the Land Cover Classification of SNI 7645: 1: 2014 National Standardization Agency of Indonesia and National Standardization Agency of Indonesia for Land Cover Class in Medium Resolution Optical Imagery Interpretation consisting of: (1) primary dry forest, (2) secondary dry forest, (3) planting forest, (4) grassland, (5) settlement, (6) water body, and (7) bare land. These land cover classes were used in this study.

The Sentinel-2 is used for the following reasons: (1) This satellite image has 13 bands obtained from the MSI (Multispectral Imager) instrument, (2) Temporal resolution of Sentinel-2 is 10 days performed by one satellite and 5 days performed with two satellites that will make large amounts of observational data produced. This satellite has spatial resolution from 10 to 60 m. The satellite image is composed of the following bands: 4 (red), bands 3 (green), bands 2 (blue), bands 8 (Near-Infrared) and bands 11 (SWIR, Short-Wave Infrared). The band 4 is useful for identifying types of vegetation, soil and urban features; band 3 provides excellent contrast between clear and turbid (muddy) water; band 2 is useful for land and vegetation identification, forest type mapping, and to identify human-made features; while band 11 is useful for measuring soil moisture and vegetation, and it provides good contrast between

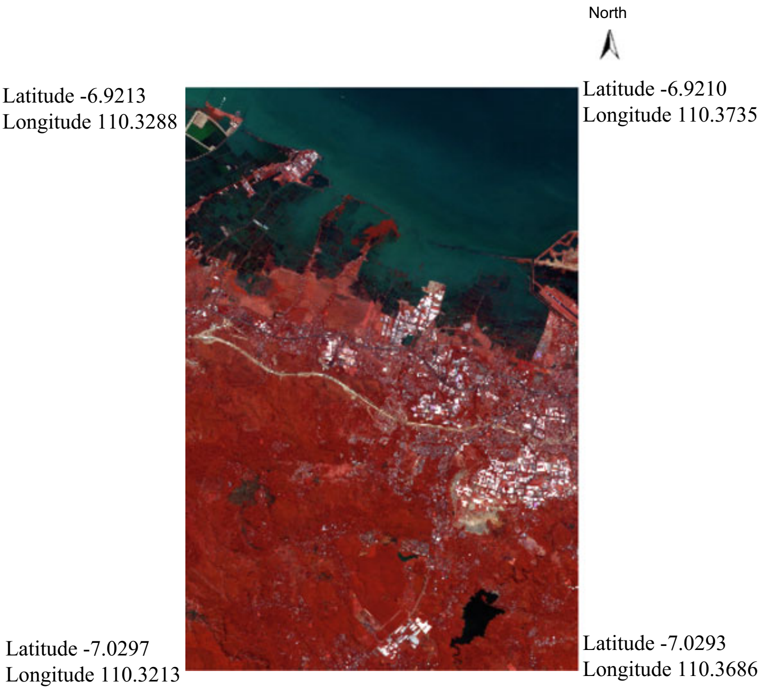


Fig. 2 False color image fusion result (band 4, 3, 2) of the Sentinel-2 satellite imagery for Semarang, Central Java, Indonesia

various types of vegetation. Figure 2 shows false color image fusion result (band 4, 3, 2) of the Sentinel-2 satellite for Semarang, Central Java Province, Indonesia.

3.2 Land Cover Classes

The main land cover classes for this study were based on the Land Cover Classification of SNI 7645: 1: 2014 National Standardization Agency of Indonesia and National Standardization Agency of Indonesia for Land Cover Class in Medium Resolution Optical Imagery Interpretation. The Land Cover Classification of SNI 7645: 1: 2014 National Standardization Agency of Indonesia was compiled based on the UNFAO (Food and Agriculture Organization of the United Nations) land cover classification system and ISO 19144-1—Geographic Information—Classification Systems—Part 1: Classification System Structure ISO 19144-1. Following [14], definition of each land cover classes and its image features in this study can be summarized in Table 1 as follows.

Table 1 Land covers definition of each land cover class

Land cover class	Definition	Image features
Primary dry forest	The primary dry forest is characterized by the presence of dark green objects (in bands 8, 4, 3), tends to dark and coarse texture with clustered tree canopy. There are no logged marks	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape
Secondary dry forest	The primary dry forest is characterized by the presence of dark green objects (in bands 8, 4, 3), tends to dark and coarse texture with clustered tree canopy. There are logged marks	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape
Planting forest	Green (on the bands 8, 4, 3). Neatly arranged and have a certain pattern	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape
Grassland	Characterized by thin lines of very fine textured vegetation in moss green (on the bands 8, 4, 3)	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape
Settlement	Characterized by a group of dense building patterns in urban settlements and sparse building pattern in rural settlement. The road network looks solid	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape
Water body	Objects are indicated by the existence of light blue area, whitish blue or black (on bands 8, 4, 3) covering a fairly wide area	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape
Bare land	Objects (in bands 8, 4, 3) are characterized by pink to dark red area sometimes brown, depending on the content of the soil material, and white when the material is composed by lime	1. Color (band 8, 4, 3) 2. Hue 3. Texture 4. Shape

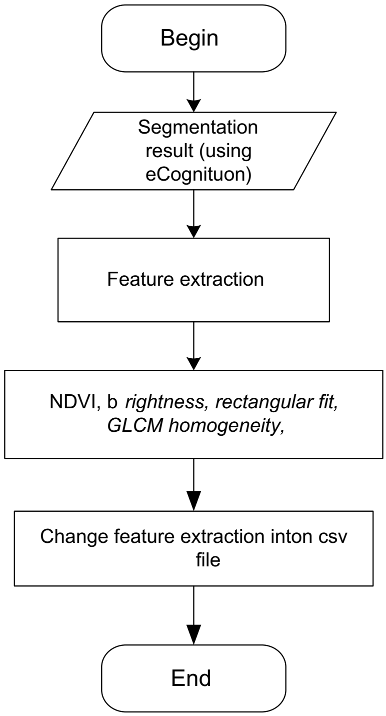
Source [14]

3.3 Feature Extraction

In this study, feature extraction of satellite image was implemented using eCognition software in several steps (see Fig. 3). First, eCognition implemented polygon-based segmentation to divide image into a number of segments/objects based on pixel similarity. This process was implemented by means of fuzzy logic that allowed the integration of a broad spectrum of different object features, such as spectral values, shape, and texture [15]. In this study, multi-resolution segmentation technique was applied to sequentially combine pixels with similar values into an object.

Next, image features were extracted from each segment to represent the associated land cover class. The extracted features are namely: Color, Hue, Texture, and Shape. Finally, each of the extracted features were transformed using eCognition to produce another set of features namely: NDVI (Normalized Difference Vegetation Index), Brightness, GLCM (the Gray-Level Co-occurrence Matrix) homogeneity, and Rectangular fit. Among the extracted features, NDVI (Normalized Difference Vegetation Index) is widely used as vegetation index due to its simplicity but effective for quantifying green vegetation. The NDVI value is calculated using the following equation [16].

Fig. 3 Feature extraction process



$$NDVI = \frac{(B08 - B04)}{(B08 + B04)} \tag{2}$$

3.4 The Classification Process with CNN Model

The process of land cover classification can be represented by Fig. 4. In general, the process comprises of the following main steps: loading data from hard disk, data splitting into training and testing dataset, training CNN model, and evaluating model performance.

The main layer of a CNN architecture used in this study has the following formats: Conv1D (filters = 10, kernel_size = 2, activation = 'relu', input_shape = (1, 4), padding = 'same')) whose parameters and its meaning are:

1. filters = 10 is an output dimension (number of output filter in a convolutional).
2. kernel_size = 2 is the length of convolutional window.
3. activation = 'relu', activation function for Rectified Linear Unit (relu). ReLu does not activate negative input.
4. input_shape = (1, 4) is the shape of input vector.
5. padding = 'same' produces padding input, therefore output has the same length with the original input.
6. Epochs = 5000 is the number of times the entire dataset is passed through a neural network [1].

k-Fold Cross-validation (k is a constant) is a method to evaluate performance of a classifier model by first splitting the input dataset randomly into k partition. This method works in the following steps. First, the dataset is randomly split into k partitions. Second, for each unique partition, allocate the partition as a testing dataset and the remaining partitions as training dataset. The training dataset is used to fit or testing the model followed by evaluation using the testing dataset. This process is repeated k-times until each partition is used as testing dataset and the remaining

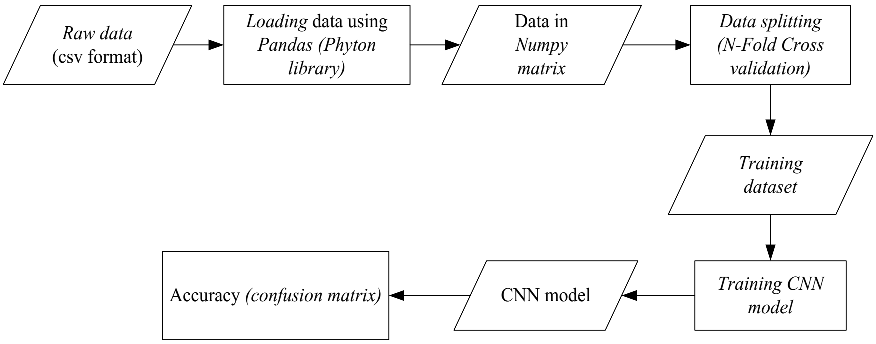


Fig. 4 Training process of the land cover classification model

partition as training dataset. Compute the average performance metrics as model performance measure [16, 17].

This study used supervised approach. Creating training samples from input image is a semi-automatic process. First, each segment/object resulted from segmentation process is represented by features (NDVI, Brightness, GLCM homogeneity and Rectangular fit). Next, compare each individual segment with the standard object in the Indonesia Thematic Map published by the Ministry of Forest and Environment 2017 for the study location to obtain a theme/class for each segment [18]. Final result of this process is a labeled dataset for training a classifier.

4 Research Result and Discussion

Image segmentation process using eCognition produced 2,072 segments/objects. For each segment as input, eCognition further produced features that represent each segment. Next, a semi-supervised process used to set out label for each segment. Finally, the overall labeled dataset was used to train classifier model supervisedly using Root Mean Square Error (RMSE) as objective function. In this study, K-Fold cross-validation is used to measure performance of two models namely: boosted tree gradient and Convolutional Neural Network (CNN) models. Model performance was measured using training, testing accuracy, producer accuracy and user accuracy.

Producer's accuracy is metric that measures accuracy of the map maker's (producer) view. The value can be interpreted as how often the real features in the field are correctly displayed on the classification map or probability of the certain land cover can be classified correctly. Producer accuracy was computed from the amount of reference data classified accurately and divided by the total number of reference data for a class. On the other hand, user accuracy is a metric that measures accuracy from the user's view, instead of mapmaker accuracy. The value of user accuracy (reliability) measures the proportion of the class on the map was actually present in the field. User accuracy was computed by taking the total number of correct classifications for a particular class divided by the total value of predictive data for a class. Table 2 shows user's and producer's accuracy of the model training.

The result of model performance evaluation of the training process was summarized in a confusion matrix (see Fig. 5). As can be seen in Fig. 5, the training accuracy is 0.984 in which it measures proportion of the training data classified by the trained model correctly.

As can be seen in Figs. 5 and 6, the training accuracy and testing accuracy of CNN model were 0.984 and 0.98, respectively. Producer accuracy showing how often the real features in the field were correctly displayed on the calcified map or probability of land cover was classified correctly. Whilst, user accuracy showed how often the class on the map will actually be present in the field (reliability). As can be seen in Tables 2 and 3, the model achieved high training and testing user accuracy and producer accuracy. It can be concluded that the trained model achieved

Table 2 User and producer accuracy of CNN training

Land cover class	Producer accuracy	User accuracy
Primary dry forest	153/157 = 0.975	153/153 = 1
Secondary dry forest	147/150 = 0.980	147/152 = 0.9671
Planting forest	147/150 = 0.980	147/150 = 0.980
Grassland	245/251 = 0.9761	245/252 = 0.972
Settlement	165/165 = 1	165/165 = 1
Water body	224/233 = 0.9614	224/230 = 0.974
Bare land	446/446 = 1	446/450 = 0.991

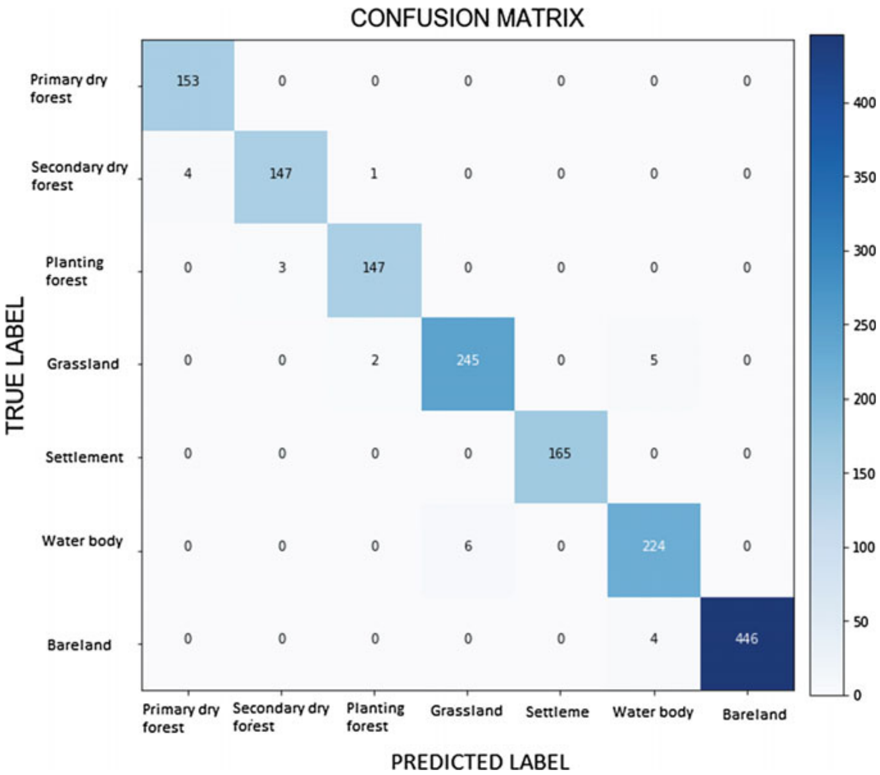


Fig. 5 Confusion matrix from CNN training

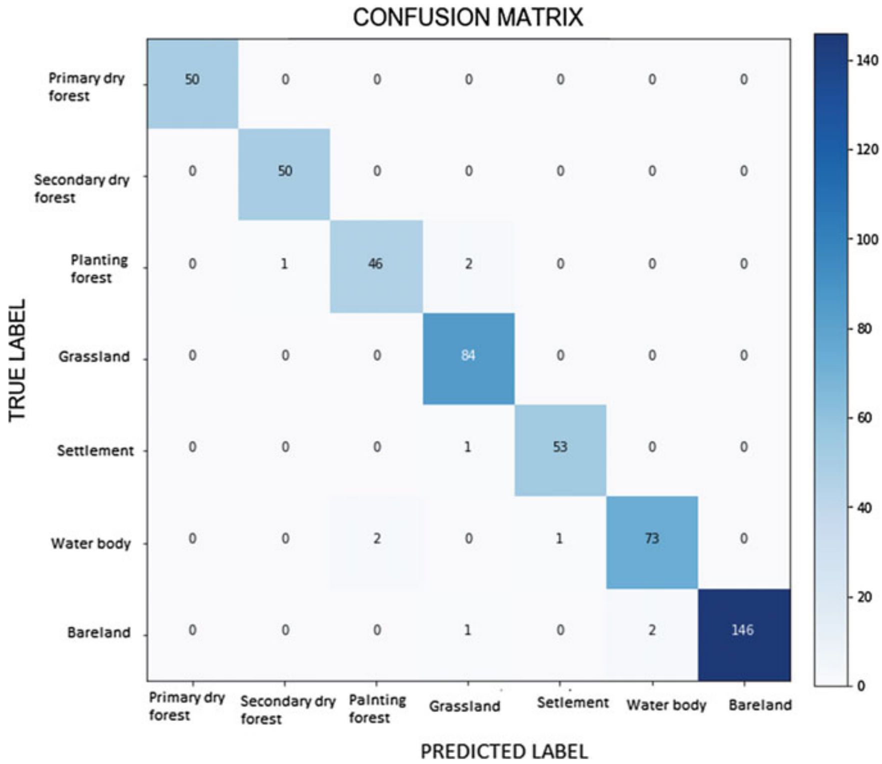


Fig. 6 Confusion matrix from CNN testing

Table 3 User's and producer's accuracy of model testing

Land cover class	Producer accuracy	User accuracy
Primary dry forest	50/50 = 1	50/50 = 1
Secondary dry forest	50/51 = 0.980	50/50 = 1
Planting forest	46/48 = 0.958	46/49 = 0.939
Grassland	84/88 = 0.955	84/84 = 1
Settlement	53/54 = 0.981	53/54 = 0.981
Water body	73/75 = 0.973	73/76 = 0.961
Bare land	146/146 = 1	146/149 = 0.980

high performance for land cover classification task or achieved a high probability to classify land cover correctly.

The results of classification reveal high accuracy when it classified land cover using CNN with the image features (NDVI, Brightness, GLCM homogeneity and Rectangular fit). Furthermore, this study examines the method employed by another artificial method.

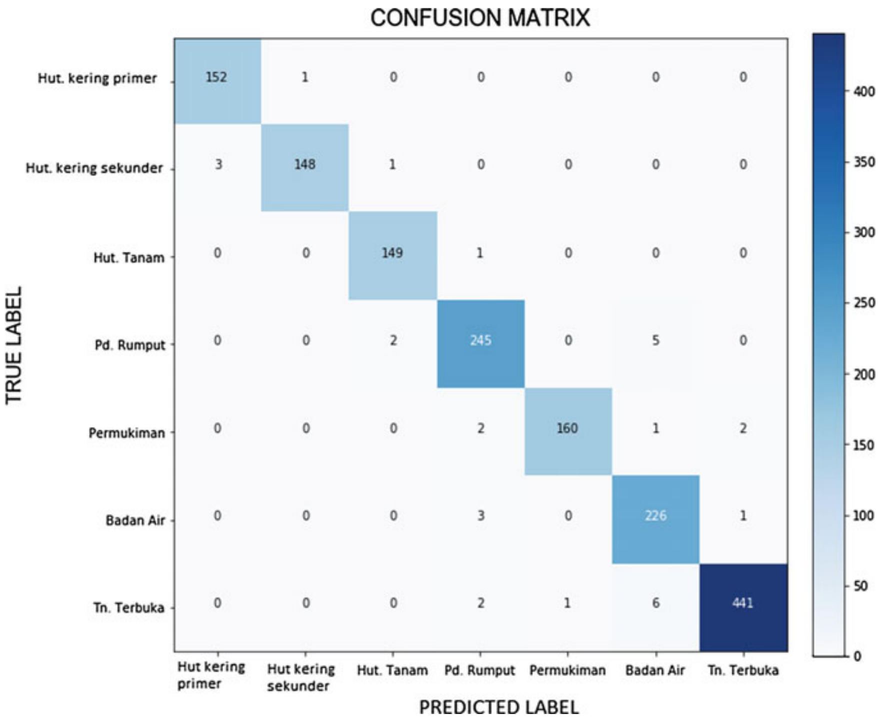


Fig. 7 Confusion matrix from GBM training

Gradient boosted tree model was used as a comparison model. The gradient boosting (GBMs) is a machine learning technique for classification problems. GBM is an extremely popular machine learning algorithm that has proven successful across many domains [19]. Figures 7 and 8 show the confusion matrix for GBM training and testing process. As can be seen in Figs. 7 and 8, the training accuracy and testing accuracy were 0.98 and 0.951, respectively.

In compare to GBM model, CNN model showed small accuracy improvement to classify land cover with the image feature: NDVI, Brightness, GLCM homogeneity and Rectangular fit.

5 Conclusion

Regional land use planning and monitoring remain an issue in many developing countries such as Indonesia. Despite many proposed models have been reported from previous studies, the task remained a challenging problem. The advent of deep learning models and wide availability of satellite imagery in the past decade has

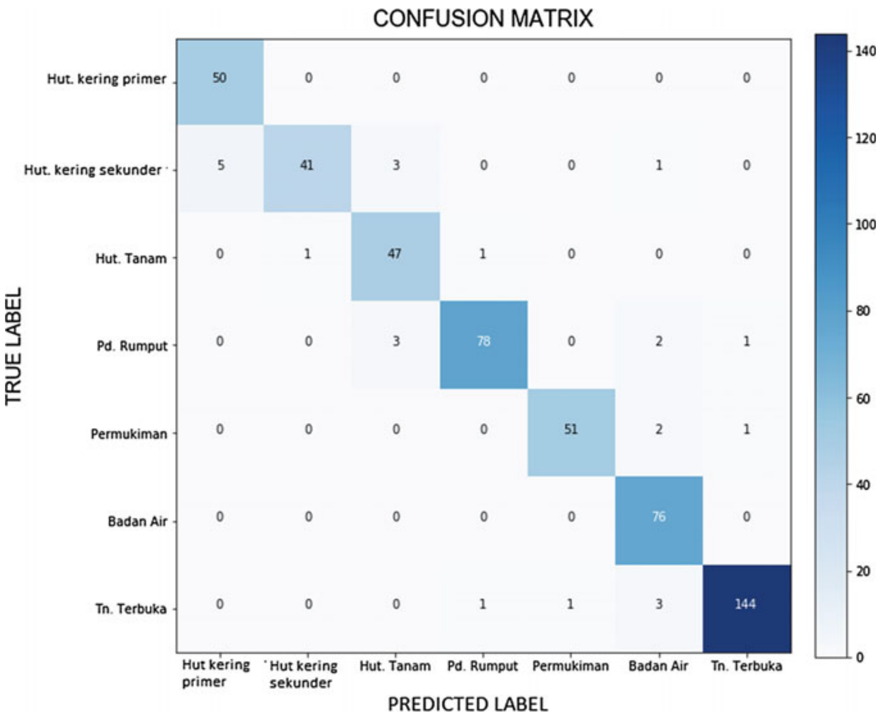


Fig. 8 Confusion matrix from GBM testing

motivated many researchers to adopt deep learning model to address land cover classification problem.

This study presented the results of land cover classification using Sentinel-2 satellite imagery as input, CNN model as the classifier, and Semarang area as the location for this study. The results showed that CNN model achieved high performance for classifying image objects dataset using 4 features namely: texture, brightness, shape, and vegetation index.

In this study, the input image was Sentinel-2 satellite imagery. eCognition was used as a tool to do the following tasks: (1) segmentation of input image into a number of polygon-based segments, (2) extract Color, Hue, Texture, and Shape as feature of each segment, and (3) transform the extracted features from each segment into NDVI, Brightness, GLCM homogeneity and Rectangular fit. A semi-supervised process was implemented to set the land cover class for each segment. Given a set of image segments represented by a set of features and a set of land cover classes associated by each segment, a deep learning model such as CNN can be trained supervisedly as land cover classifier. Hence, in principle, this method can be adopted to train land cover classification model at any location given availability of Sentinel-2 satellite imagery for the location of interest and availability of thematic map standard published by local government to determine land cover class for each segment.

The future research works will include exploration of the other deep learning models to address the problem and extracting more satellite imagery features from other area with suitable land cover classes that fit to the area of interest.

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