Utilization of GIS Machine Learning for Mapping of Building Shapes in Tibang Village, Banda Aceh City, Aceh, Indonesia

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Abstract—**Tibang is one of the villages in Banda Aceh which is located in a high tsunami-hazard zone. Today, many initial aid houses in the area have grown larger than the original, and new housing complex has begun to emerge. Therefore, it is necessary to find an efficient method to map the buildings in the village, so that an up-to-date buildings map of the village can be prepared quickly. Machine learning GIS is the use of machine learning algorithms in processing and analyzing spatially-based GIS data. This study aimed at applying the Support Vector Machines (SVM) method of GIS Machine learning for classifying buildings in a very-high-resolution image of Tibang Village, SVM has been used with Object-Based Image analysis (OBIA) to classify UAV-based images for various Land-Use / Land Cover (LULC) applications. The stages in classifying buildings using SVM are starting with processing high-resolution data from UAV photos to create an ortho-mosaic image. The image was then segmented using OBIA techniques and then was classified using the SVM method. The result of the SVM classification was 230 house objects identified in the village of Tibang, Syiah Kuala District with the number of training data samples used for the building class being 29 with various variations of the shape of the building objects identified in the UAV images.**

Keywords—SVM, UAV, GIS, Machine learning

I. Introduction

Unmanned Aerial Vehicles (UAV) are used widely to acquire aerial photos because of various reasons. The price of a UAV unit is not very expensive and the operational cost of a UAV for mapping is much lower than that of an airplane. Thus, UAVs can provide aerial photos with a very high temporal resolution because it is very feasible to acquire aerial photos of an area daily or even more frequently using a UAV. Furthermore, a UAV can acquire cloud-free very-high-resolution aerial photos because it flies at low altitudes [1].

Although UAV aerial photos are very detailed, the automatic classification of images produced from very-high-resolution UAV photos is challenging. Since detailed aerial photos are made up of very fine pixel sizes (usually 10 cm or less), there is a large number of pixels which are needed to be classified [2]. The image classification process becomes more complicated because there is a high variability of spectral values among pixels of the same object. For example, roofs have different colors. Furthermore, pixels of different objects may have similar spectral values [3]. For example, roads made up of paving blocks have similar colors to concrete roofs. Most UAV images are produced from aerial photos acquired by ordinary cameras which can only capture three spectral bands in the visible light range, namely Blue, Green, and Red. This limits the possibility to differentiate objects based on the spectral values of their pixels.

An alternative approach for classifying images is offered by the object-based image analysis (OBIA) technique. Instead of classifying an image based on the value of an individual pixel, this technique carries out classification based on the properties of groups of neighboring pixels called segments using. In addition to spectral information, this technique also considers other information about the segments, such as forms and textures. [4]. It is common now to use machine learning (ML) methods to train computers to classify the segmented UAV images based on the segment information.

ML consists of a set of inductive models that identify patterns and/or minimize prediction errors of complex regression functions which associate outputs with some basic factors through an iterative learning strategy from training data [5]. In many disciplinary subjects and application domains where spatial characteristics are crucial, such as land use and land cover classification, machine learning (ML) is a strong and successful technique [6]. The use of machine learning in processing and analyzing geospatial data is called GIS machine learning.

Support Vector Machines (SVM), one of the most cutting-edge machine learning algorithms, are becoming frequently used in several remote sensing-related research due to their dependable and robust classification and regression findings [7]. SVM has been used with OBIA to classify UAV-based images for various Land-Use / Land Cover (LULC) applications [3].

This study aimed to apply the SVM method of GIS Machine learning for classifying buildings in a very-high-resolution image of Tibang Village, Syiah Kuala sub-district, Banda Aceh city, Aceh, Indonesia. Tibang is one of the villages in Banda Aceh which are located in a high tsunami-hazard zone according to the revised spatial planning of Banda Aceh City [8]. Today, many initial aid houses in the area have grown larger than the original 36-m2 footprint [9], and new housing complex has begun to emerge. Therefore, it is necessary to find an efficient method to map the buildings in the village, so that an up-to-date buildings map of the village can be prepared quickly

II. Research Method

The stages in classifying buildings using machine learning GIS using the SVM method start with processing high-resolution data acquired using an Unmanned Aerial Vehicle (UAV), which will be used as data for analyzing machine learning GIS using the SVM method. The step was then followed by the analysis process using the SVM method on the processed image. The flow diagram of the process stages in classifying buildings by utilizing machine learning GIS with the SVM method can be seen in Figure 1.

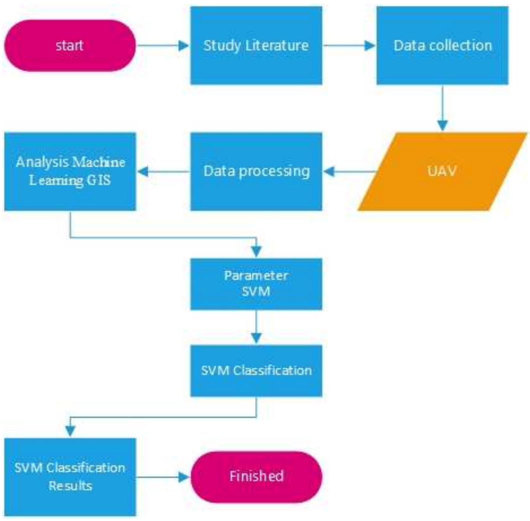

Figure 1. Research Workflow

A. Acquisition and Processing of UAV Data

The aerial photos of Tibang village in Syiah Kuala Sub-district, Banda Aceh City were acquired by using a DJI Phantom 4 Pro UAV. The flying altitude of the UAV was set to produce photos with 10 cm spatial resolution. After aerial photos of the whole study area were completed, they were processed to produce a mosaic image. The process started with the alignment of aerial photos by identifying the points in each photo and matching the same point in two or more photos. Next, the photos were merged into a single unit based on the similarity of coordinates and similarity to the object. The single image produced by this process is called a mosaic image. The last step was ortho-rectifying the mosaic image mosaic to produce an upright aerial photo image that has a geographical reference in accordance with the actual coordinates.

B. Processing using the SVM method

The SVM classification process looks for the optimal hyperplane that divides the input data into two groups. The essence of the process of learning in the SVM method training is to determine this hyperplane [10]. The learning process is illustrated in Figure 2. In the figure, the red squares represent patterns belonging to class +1, whereas the yellow circles represent patterns that are members of a class –1. A line (hyperplane) that divides the two classes must be found to carry out the classification process. Figure 2(a) displays a number of different separating lines (discrimination boundaries). The optimal dividing hyperplane between the two classes may be identified by measuring the hyperplane margin and determining the maximum point. The margin measures the distance between the hyperplane and the nearest pattern in each class. The nearest pattern is called a support vector. In Figure 2(b), the thick solid line represents the optimum hyperplane since it is placed directly in the middle of the two classes, whereas the red and yellow points in the black circle are support vectors [11].

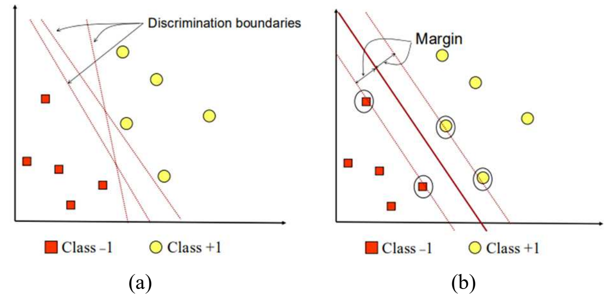

Figure 2. SVM tries to find the best hyperplane to separate two classes of –1 and +1 [10]

According to [11] the available data are symbolized as $\vec{x_i} \in \Re^d$, while each label is symbolized as $y_i \in \{-1,+1\}$ for $i = 1,2,\ldots,l$, where l is the number of data. It is assumed that both classes –1 and +1 can be segregated perfectly by a d-dimensional hyperplane, which is defined as

$$\vec{w}\cdot\vec{x} + b = 0 \qquad (1)$$

The pattern $\vec{x_i}$ which includes in the class –1 (negative sample) can be formulated as patterns that satisfy inequality (2)

$$\vec{w}\cdot\vec{x} + b \leq -1 \qquad (2)$$

whereas pattern $\vec{x_i}$ which is included in class +1 (positive samples)

$$\vec{w}\cdot\vec{x} + b \geq +1 \qquad (3)$$

The workflow for classifying the very-high-resolution UAV image is illustrated in Figure 3. In general, the workflow combined OBIA approach with SVM to classify objects in the ortho-mosaicked image. The first step was image segmentation which creates image segments by grouping nearby pixels based on the similarity of their pixel values by using a mean-shift algorithm [12]. The next step was creating a training set based on the image segments. The training set was created for 5 classes into which the image would be classified, namely building class, road class, vacant land class, river/pond class, and vegetation class. The SVM classification stage was conducted in two steps, namely training the machine (computer) using the SVM method and classifying image pixels based on the training. The objective of the training was to find hyperplanes that separate pixels in the training set into predefined classes according to predetermined parameters, such as pixel values, count of pixels, compactness, and rectangularity. The classification step was to apply the hyperplanes to divide all pixels in the image into predefined classes so that a classified image was produced. All procedures were executed using ArcGIS Pro with Image Analyst extension.

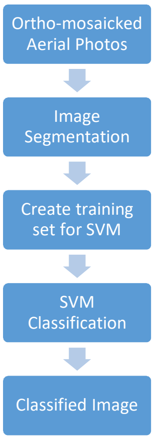

Figure 3 SVM method process

Figure 5. Preparing training sample data

III. Results and Discussion

The results of UAV data processing are upright images or orthorectified images that have been corrected by the coordinate system used and are in accordance with the actual coordinates of the earth. Figure 4 shows the results of UAV data processing.

Figure 4 shows the results of orthoimages of the research area with various variations of land cover ranging from vegetation, buildings, and non-vegetation. In each class of land cover type, there are also various variations in the shape and color of the object.

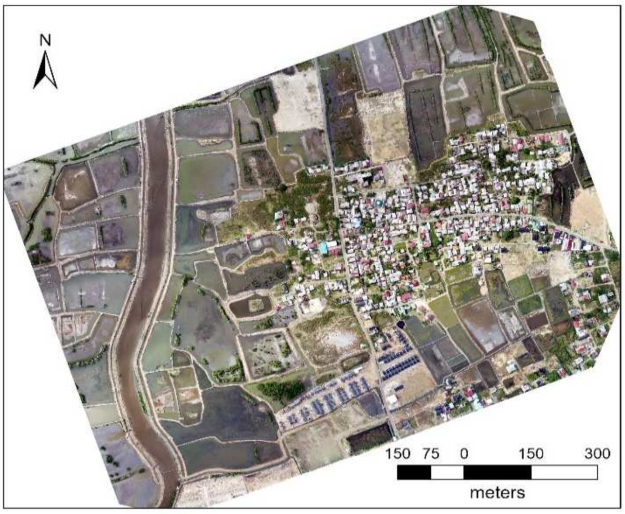

Figure 4. Aerial image produced from processing UAV photos.

Figure 5 shows the sampling of training data used in the learning process for the SVM method in classifying land cover. The training data sample was taken in each class from 6 predetermined classes, namely building class, road class, vacant land class, river class, pond class, and vegetation class. Table 1 shows the number of training data samples taken in each class.

Table 1 shows the variation in the number of samples taken for each class of data classification. At the training data sample stage, a training data sample was taken for each class. Each sample class is taken based on the appearance of objects in each class. Each class has several variations of samples taken in the same class. The more variations of objects in the same class, the more samples are taken. For the building class, vacant land class, pond class, and vegetation class, more samples were taken because there were more variations in each class based on the appearance of objects from aerial photo images. Less sampled roads and rivers are taken because the variations in each class were less or almost homogeneous in the appearance of objects in the image in each class.

TABLE I. SVM TRAINING SAMPLE DATA

No	Training Sample Data	
	Class Name	***Sample Counts***
1	Buildings	29
2	Road	10
3	Vacant land	49
4	River/Ponds	58
5	Vegetation	44

Figure 6 shows the results of the machine learning classification of the SVM method with object-based classification, while Table II shows the results of the SVM method in identifying objects based on predetermined classes and given training data samples. The classification results of object-based SVM machine learning methods show that the classification results for each class vary. Based on the five classes that have been classified, the river/ponds was the class with the most number of objects identified, which was 627. This class was followed by the vacant land class with 468 objects. The building class, road class, and vegetation class become the class with the fewer number of objects identified. The class which has the least number of objects was vegetation with 224 objects.

Figure 6. Image classification result of very-high-resolution UAV image of Tibang village

No	SVM Classification Results	
	Class Name	***Object Counts***
1	Building	230
2	Road	234
3	Vacant land	468
4	River/Ponds	627
5	Vegetation	224

TABLE II. SVM CLASSIFICATION RESULT

IV. CONCLUSION

The results of the classification carried out using object-based machine learning SVM methods in the village of Tibang, Syiah Kuala District, obtained several land cover classes, especially the building class which is the main focus of this research. The results of the classification of building classes in the village of Tibang, Syiah Kuala District, obtained 230 building objects. The number of training data samples used for the building class is 29 with various variations of the shape of the building object identified in the aerial photo image.

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