International Journal on Emerging Technologies **12**(1): 122-128(2021)

ISSN No. (Print): 0975-8364
ISSN No. (Online): 2249-3255

Current Status of Classification Method for Mapping Application: A Review

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(Received 01 October 2020, Revised 28 December 2020, Accepted 27 January 2021)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: Image classification is the main process of remote sensing application. It is a process of assigning feature classes to pixels. For example, land use and land cover (LULC) dataset classifies images of urban, agricultures, water bodies, and others. Basically, this process includes the labelling of images into one of the predefined categories. Classification terms include image sensor, image pre-processing, object localisation or detection, segmentation process, feature extraction, and feature classification. Many classification techniques have emerged in which their feature classification is more uniquely different from the common classification purpose. Among the common classification algorithms are support vector machine (SVM), relevance vector machine (RVM), minimum spanning forest, fuzzy rules, global regularisation, nearest neighbour classifier, random forest, conditional random fields, and others. The challenge of the study is to find optimum classifier algorithm which achieve highest overall accuracy and kappa coefficient. The band combination/ significant spectral also significantly can help in better classification. From this paper, it can guide a newcomer to identify a good classifier algorithm for their classification study. Finding of study conclude an optimum classifier algorithm depending on the classification purpose and the way of classification process designed.

Keywords: Classification; Mapping; Algorithm, Object, data.

Abbreviations: kNN, K-Nerest Neighbour; RG, Random Forest; SVM, Support Vector Machine; CNN, Convolutional Neural Network; CRF, Conditional Random Field; LULC, Land Use Land Cover; PCA, Principal Component Analysis; MV, Measured Value; ESI, Ellipse Similarity Index; EFD, Elliptic Fourier Descriptors; CCS, Chain Code Subtraction; FCN, Fully Convolutional Network; UAV, Unmanned Aerial Vehicle; nDSM, normalised Digital Surface Model; PC, parallelepiped classification; MDC, minimum distance classification; MaDC, Mahalanobis distance classification; MLC, maximum likelihood classification; SAM, spectral angle mapper; SID, spectral information divergence;

I. INTRODUCTION

Remote sensing is an acquisition of information about study feature without making a contact to the feature. This term applied to acquire an information on earth. Main process of acquisition is by classification technique. Generated classified image useful for many purposes. Basically, the main function of remote sensing is to produce a classification map. Some of the products that have been generated from the classification process include land use/land cover map [1,3, 8, 17, 22, 25], urban hydrological map [20], urban classification map [15] glacier facies mapping [11], crop map [23, 27], and oil palm [24]. The most popular output from the classification process is land use/land cover map. The paper looked into the algorithms of classification that were mostly used and the products of classification map that have been produced. In conclusion, the study will conclude an optimal classifier algorithm for difference use. Multiple classifier algorithms have been introduced, which would suit certain objectives of application. However, some classifier algorithm may need integration for better accuracy and some fusions of band from different spectral resolutions to compliment the classification effect [10]. A data is known as training sample before classification process takes place. Commonly, unsupervised classification is known as clustering, while supervised classification is a form of learning that is supervised through examples of past data. Some researchers distinguish a classification method by pixel based-techniques, sub-pixel based-techniques and object-based techniques [15, 24]. Thus, the supervised and unsupervised technique's is identified as one group as the characteristic of the classification techniques is assume pure and typically labelled as a single land cover type. While, for sub pixel-based techniques, each pixel is considered mixed, and the areal proportion of each class is estimated. Figure 1 show a general methodology of supervised classification work. The work starts with preprocessing data, feature extraction from image, developing a training data and classify the image. Each classification will be assessed by overall accuracy and Cohen's kappa. Table 1 shows a method of classification.

Generally, image classification approach includes pre-processing, feature extraction, selection of training data, detection and classification, classification output, post post-processing and accuracy assessment. Fig. 1 illustrates the standard classification approach.

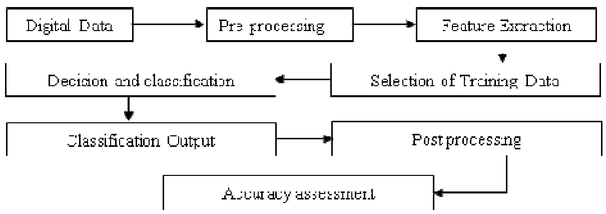

Fig. 1. Standard classification approach [10].

No single form of algorithm for classification is appropriate for all datasets [30]. Therefore, a large toolkit of algorithm is developed for different tasks of features classification. Supervised classification is the technique mostly used for the classification of remote sensing image data. It is dependent on suitable algorithms and procedures to classify or label the pixels into a particular class of interest [25]. More specifically, supervised technique is used to arrange objects into different categories. The training data includes both the input and the desired results. The construction of proper training, validation, and data validation test is crucial. The supervised methods are usually fast and accurate [1]. Typically, they go through the step of training area selection, generating signature file, and classifying images. There are several options for classification, as shown in Table 1. Each option has different capabilities and advantages; however, it is best to test different methods in order to acquire good accuracy. Figure 2 shows an example of supervised and unsupervised classification work by Mohammady, Moradi, Zeinivand, and Temme (2015). Supervised classification has more procedure intact due to the need of classifier algorithm of a training sample comparing to unsupervised classification. Thus, it is easy to use unsupervised technique, however careful step needs to consider as the classification does not have sample classes count into. The user must have knowledge of the classified feature when the groupings of pixels with common characteristics produced by the computer have to be related to actual features on the ground [8].

Table 1: The variety of classification algorithm [13], [2].

Methods	Based	Algorithm	Description
Supervised	Probability-based (involves density-based function to classify instance)	Parametric: Decision Tree, Classification Tree, Minimal Distance Classifier, Bayesian, Multivariate Gaussian	Based on the statistical probability distribution of each class. Need to identify training sites in order to place them into classes whereby each pixel is classified with statistical analysis
		Non-parametric: K-nearest Neighbour, Kernel Density Estimation, Logistic Regression, Multilayer Perceptron, Artificial NN, Euclidean Distance, Neural Network, SVM, Fuzzy Classification, Random Forest, etc.	For unknown density function and used to estimate the probability density function. Unknown ground information. Pixel grouped with specific statistical criteria by similar spectral characteristic. Requires minimal amount of initial input from analyst. Clustering does not need training data
	Geometric-based	Fa classifier	
Unsupervised		ISODATA, Fuzzy C-Means, K-Means, etc.	
Object-oriented	Object based	OBIA	
Hybrid approaches	combination		System-aided artificial intelligence (AI)

Unsupervised technique includes the process in which the user identifies the number of classes to generate and which bands to use. Unsupervised classification is a form of clustering on pixel-based and each spectral class is created solely on numerical-based information derived from pixel values or indices. The algorithm is used to determine the natural, statistical grouping of the data. The spectral pixel is grouped from the similarity indices. The computer then clusters pixels into the number of classes set. Finally, the user identifies the land cover classes. Supervised classification algorithms such as Random Forest (RF), k-Nearest Neighbour (kNN), and Support Vector Machine (SVM) were reported as the foremost classifiers at producing high accuracies [18].

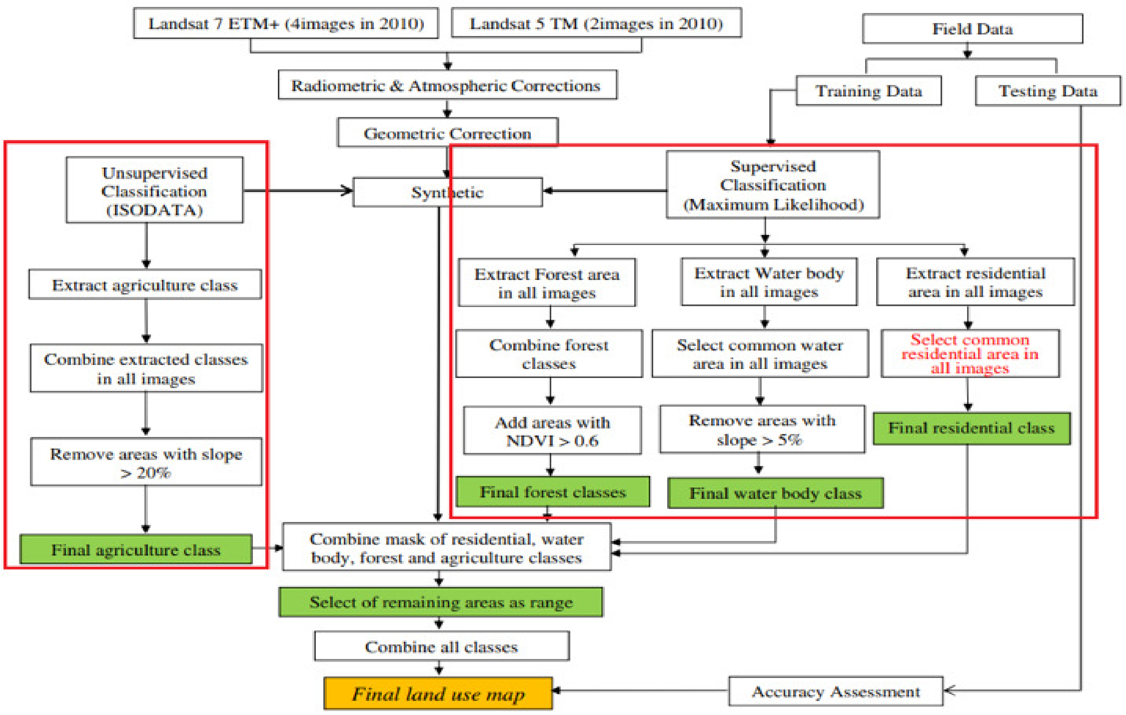

Fig. 2. An example of the process of supervised and unsupervised classifications adapted from [16].

II. SUPPORT VECTOR MACHINE (SVM)

Support vector machine is suited for extreme cases. It is a frontier that best segregates the two classes, which are hyperplane and hyperline. The SVM training algorithm assigns a new example into a few categories. It is a non-probability binary linear classifier. The concept of classification is a representation of the example of point in space mapping and distinguishes both samples evenly with a large margin distance among the data sets. SVM is widely used by remote sensing community for hyperspectral classification. SVM results were dependent on the data set used. Therefore, any implementation of classification by the SVM classifier is evaluated by comparing it with other classifiers in the same data set that have the same particular feature interest.

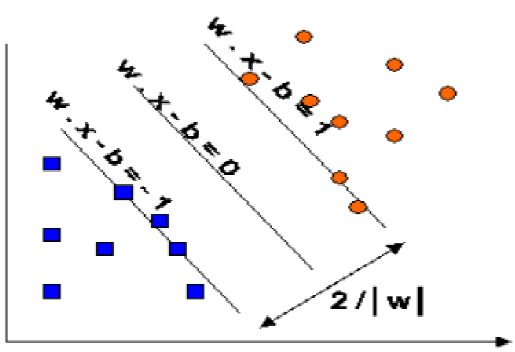

Fig. 3. Maximum margin hyperplanes for SVM, trained with samples from two classes [4].

Optimal hyperplane as separation of categories is defined as:

$$w*x+b=0 \quad (1)$$

Where, x is a point lying on the hyperplane, b is the scalar, and w is the p-dimensional vector. The vector w points perpendicular to the separating hyperplane. Offset parameter b, which is known as bias, allows the margin to increase. Meanwhile, parallel hyperplanes can be described by the following equation:

$$w.x + b = 1 \text{ and } w.x + b = -1. \quad (2)$$

For training pixel x, the distance from the hyperplane can be defined as:

$$f(x)=w*x+b \quad (3)$$

Where the distance from the hyperplane to the origin with Euclidean norm of w is defined as:

$$(|b|)/(||w||) \quad (4)$$

The main advantage of SVM is the ability to make good generalisations of high-dimensional data with few training samples [3]. Reference [6] used SVM as a benchmark of data accuracy to compare it with their suggestion of Convolutional Neural Network (CNN) for precise agriculture mapping. Meanwhile, Reference [7], [10] used SVM for tomb recognition and to improve image classification via fusion technique of panchromatic image with multispectral image. SVM is proven to have a better accuracy with outclass random forest by crop classification on single date Sentinel-2 Imagery US. Fodder achieved the lowest accuracy because there was an intermixing of pixels among Wheat and Fodder crops. The class specific accuracies of High-Density Forest attained the highest accuracy, whereas Fodder class reported the lowest accuracy [23]. Lastly, SVM was found as the ideal algorithm for oil palm mapping by [24]. A probe study had compared the method of phython algorithm classification (several libraries such as GDAL, Numpy, Scikit-Learn, and Matplotlib were imported into the Python script) with SVM.

SVM is introduced as a robust tool for classification and regression analysis. Based on empirical analysis, it uses statistical learning theory to find a regularised hypothesis that matches the available data smoothly without overfitting. It is used as hypertext and text categorization, image classification, handwritten identification character, and other science products. SVM is created as a robust machine for data mining purposes, especially classification, regression, and outlier detection. The formula uses statistical learning theory to search for a generalised hypothesis without overfitting. Without the need for a separate validation set during training, the parameters of SVM can be optimised using generalisation theory [12].

III. RANDOM FOREST (RF)

RF is a non-parametric algorithm, provide high classification accuracy. RF use ensemble method consists consist number of classifiers whose response are combined to get final classification. RF select random multi subset of decision/variables at each split. It has few benefits in remote sensing application such as to handle large data sets, can handle large input variables, it can estimate variables importance during classification procedure and complexity of RF computation is low compared to others. In context to remote sensing application, RF capable to run large datasets with various numbers of input variables. It's a robust to the noise as well as outliers. RF is simple computational as compare to other ensemble method (e.g boosting) [21].

Random forest (RF) was applied to map land use and land cover using Landsat 8 OLI [17]. Two (2) RF parameters of ntree (number of tree) and mtry (the number of variables used to split at each node) were tested and compared. The authors concluded that RF is a potential method to map LULC from the satellite image. Reference [20] investigated the potential of automatic supervised classification for urban hydrological applications. The method was to determine the coefficient of imperviousness, which is a major parameter for urban drainage models based on the supervised classification of aerial imagery and height data. The RF method was compared with conditional random field (CRF) for accuracy assessment whereby three variants of RF classifier and CRF were compared. The results of land cover classification showed no clear advantage of either classifier. Meanwhile, [14] combined principal components analysis (PCA), guided image filtering, and RF to classify Indian pine tree. The integrated method by RF produced high classification accuracy of more than 90%. RF had totally broken through the "curse of dimensionality" of hyperspectral data. RF was also tested along with four descriptors from the image of fruit, which are Measured Values (MVs), Ellipse Similarity Index (ESI), Elliptic Fourier Descriptors (EFDs), and Chain Code Subtraction (CCS) for the purpose of strawberry quality control identification [9]. It was proven to have a high ability to classify the fruit shape.

IV. OTHER CLASSIFIERS

Enderle *et al.,* [8] classified hyperspectral image using ISOMAP and RVM. It is a method that combines ISOMAP, RVM and spatial weight to reduce the dimensions of hyperspectral data and carry out classification. With ISOMAP, the dimension is reduced but the information is well remained at the same time, whereas with spatial weight, the result is improved. In general, this method can effectively enhance relevant vector machine model for the classification accuracy of hyperspectral data. Reference [1] proposed a framework of hyperspectral data classification. A pixel-based SVM algorithm is first used to classify the image. Then the marker-based MSF spectral-spatial algorithm is applied to improve the accuracy for classes with low accuracy. The proposed technique achieved 5% higher accuracy in comparison to the original MSF-based method [19]. Similar results can be seen in the study on classification accuracy via object-based method [11]. Both methods concluded that object-based has higher accuracy than pixel-based classification.

Convolutional neural network was proposed on the panchromatic image of GF-1 high resolution satellite of China. The classification uses various method including CNN but CNN show better results [6]. Reference [5] used the same classification method on high resolution image from Unmanned Aerial Vehicle (UAV). They used map information to label images for training samples before they were fed to a pre-trained fully convolutional networks (FCN) by removing relief displacement, adjusting building representation difference, and removing occlusion. Noise tolerant regression classifier and the standard multiclass logistic regression algorithm were used to automatically classify urban areas in Saudi Arabia. The accuracy improved if the height information in the form of nDSM values applied with the classification process [15]. Supervised maximum likelihood was used for land cover classification in Jodhpur City. The study created classified maps with five main land use and land cover from two different periods, i.e. 2018 and 1990, generated on a 1: 50,000 scale. Change detection was made possible by this technology in lesser time and with better accuracy [22]. Several supervised classification techniques were used to classify the regions of Uttarakhand, India. They were parallelepiped classification (PC), minimum distance classification (MDC), Mahalanobis distance classification (MaDC), maximum likelihood classification (MLC), spectral angle mapper (SAM), spectral information divergence (SID), and support vector machine (SVM). MDC was the best in terms of accuracy while MLC was the best in terms of kappa coefficient. Furthermore, both MLC and MDC classification techniques could provide good accuracy and kappa values. This is supported with suitable algorithms and procedures to classify or label the pixel into a particular class of interest with supervised classification. Reference [26] increased the classification accuracy by several decomposition levels with discrete wavelet transform and minimum distance classifier applied together. Hence, the previous studies on different classification algorithms can be describe in Table 2.

Table 2: Applied classifiers on previous studies.

Method	Algorithm	Features	Total
Hybrid	Isomap and RVM	Land Cover	1
	Minimum Spanning Forest and SVM		1
Object-based Method	Nearest Neighbour Classifier	Landform	1
		Glacier Facies	1
Supervised	CNN	Building	1
		Crop Classification	1
	Decision Tree		1
	Label Tolerant Classification Using Logistic Regression,	Urban Area	1
	Mahalanobis Distance	Land Cover	1
	Maximum Likelihood		3
	Minimum Distance		2
	Parallelepiped Classification		1
	Random Forest	Crop Classification	1
		Indian Pine Tree Distribution	1
		Land Cover	1
		Strawberry's Shape	1
	Random Forest and Conditional Random Field	Urban Hydrological ROW	1
	Spectral Angle Mapper	Land Cover	1
	Spectral Information Divergence		1
	SVM	Building	1
		Crop Classification	1
		Land Cover	2
		Oil Palm	1
		Tomb Recognition	1
		Total case study	28

V. CONCLUSION

Image classification in remote sensing is developing rapidly and many techniques are available in different software or designed by local programmers through the integration of programming software. Classification technique is subjectively chosen for its ability in certain feature classification or proposed by researchers to discover their capability. Many classifications of land use and land cover are available in research papers and the Internet. These researches need a stage of understanding of feature classification target, to make sure procedure carried out wisely. Some attentions need to be addressed before classification research is carried out. First, the researcher has to determine the requirement and propose the product derived. This is to ensure that the classification system is chosen wisely. Second, the evaluation of land use characteristic that needs to be detected can be extracted from the remote sensing data and needs to take count of the remote sensing system, such as characteristic of spectrum, spatial, temporal, and polarisation. Third, crosscheck from other data such as topographic map, committed land use, and aerial images or the field data acquired before verifying the classification product accurately. Fourth, no guideline of decide the classification method, only by understanding the process and referring to current study can help to a suitable method.

Finally, a few vegetation indexes can help in the classification process. The success of image classification in remote sensing depends on many factors, such as the availability of high-quality remote sensing images and ancillary data, the design of a proper classification procedure, and the analyst's skills and experiences.

VI. FUTURE SCOPE

The common approaches of classification can be categorised as supervised, unsupervised, object-based, and hybrid. Other small subcategories that are divided under supervised are probability- and geometric-based. Meanwhile, the subcategories of probability-based are divided into two small categories, namely parametric and non-parametric algorithms.

ACKNOWLEDGEMENTS

Faculty of Architecture, Planning, and Surveying Universiti Teknologi MARA (UiTM), Research Management Institute (RMi) and Ministry of Higher Education (MOHE) are greatly acknowledged for providing the fund GPK grant 600-RMC/GPK 5/3 (223/2020) to enable this research to be carried out. The authors would also like to thank the people who were directly or indirectly involved in this research.

Conflict of Interest: We have no conflict of interest based on this research

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How to cite this article: Abd Mukti, S.N. and Tahar, K.N. (2021). Current Status of Classification Method for Mapping Application: A Review. *International Journal of Emerging Technologies*, **12**(1): 122–128.