Using Neural Network in the

Classification of Forest Types

From A Remote Sensing Data Set

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Abstract. Classification plays an important role in remote sensing study. This article will utilize a neural network method in the classification of forest types. This neural network method is mainly based on a previous research paper. Additionally, an evolutionary algorithm method is used in this neural network. After classifying the forest types of the data set, the study will make a comparison between this result and another result with the same data set for forest types classification. In conclusion, the neural network classification method in this case study has a satisfactory performance. The enhancement method adapted from the reference as well as the evolutionary algorithm method can slightly improve the quality of neural network while the technique of threshold modification is not suitable for this case study.

Keywords: Remote sensing, Image classification, Neural network, Histogram enhancement, Evolutionary algorithm

1 Introduction

1.1 Background

Nowadays, remote sensing data is one of the most indispensable tools in geography study. By surveying the earth surface using sensors, such as IKONOS, QuickBird and OrbView, on their platforms that usually are the remote sensing satellites, such as SPOT and LANDSAT, it dramatically declines the workload and time consuming in ground survey especially in the large areas, becomes an ideal information source to detect the variation on the ground automatically, and is widely used in various kinds of studies like biodiversity, deforestation impact, food security, desertification monitoring, nature conservation and other application fields [1]. For the investigation and application in those fields, the remote sensing images are frequently used in the classification of landscape types. Therefore, it is a necessity to figure out the image classification methods for remote sensing. At present, many remote sensing image classification methods are invented and applied in the researches.

Neural network is a rather common technique for classification for all kinds of data sets. Especially in the field of remote sensing study, neural network is a principal method of image classification, such as the hyperspectral image classification [2]. Generally speaking, when we want to implement the neural network method for image classification in a study, the main progress will be as follow: dividing the data set into 2 parts, the usage of the first part is training the neural network while the usage of another is testing the neural network has been trained previously. If the testing output of the neural network is of high accuracy, we could consider it as an effective neural network for image classification in this case. Then we can use this trained neural network in the whole image for classification in this case study.

1.2 Research Materials

This study aims at classifying the forest types in a remote sensing data set. In the study, the data this study picked for forest types classification is a multispectral Advanced Spaceborne Thermal Emission and Reflection Radiometer

(ASTER) satellite imagery, which has been divided into 2 parts (training.csv and testing.csv), has over 500 instances in total and 27 attributes. The data set digitized for four land cover classes: ‘Sugi’, ‘Hinoki’, ‘mixed broadleaf’ and ‘other’ that were named as ‘s’, ‘h’, ‘d’, ‘o’ in the data set respectively. Its output, the forest type map, will be useful for ecosystem study. The site of the data set is http://archive.ics.uci.edu/ml/datasets/Forest+type+mapping, provided by a previous study that utilized this data set for classification before [3]. Because this data set has adequate instances and attributes and has been implemented in a research paper that doing the forest types classification, which means this data set is suitable for the neural network classification as well as the comparison between results from a different paper, additionally the accurate image classification is significant for the local economy and ecology [3], we can consider it as a suitable data set for this study.

The neural network method this study adopted is based on a previous study, whose aim was also classifying the forest types using geographical data [4]. In that paper the forest was merely digitized for 2 classes: dry sclerophyll forest and the non-dry one. Before the classification the data have been preprocessed with a cumulative histogram enhancement technique. Then the original data set that had been classified into 5 classes, were classified into 2 classes, the dry sclerophyll forest and the non-dry one, since that study only wished to distinguish these 2 classes. The article used 3 different methods: maximum likelihood, decision tree and neural network method for the sake of making comparisons between these 3 classifications, however, the neural network one is the only one this study needs to concentrate on because it is stated that those 3 methods have little distinction in compare with the accuracy and this paper will just implement the neural network method for classification. To improve the output, the paper showed a simple technique of modifying the threshold in accordance with the results on the validation test set in the neural network method.

After the classification, this study will make comparisons between the study that had also adopted the same data set, but the method differed from the neural network classification [3]. The paper this study will compare with used geographically weighted variables in the Support vector machines (SVMs), a non-parametric classification algorithm to classify the image. By calculating the accuracy, it was showed that the utilizing of geographically weighted variables could improve the results of classification. In this study there will be comparisons and their analysis between these classification methods.

2 Method

2.1 Data Set

The study area was a forested area in Ibaraki Prefecture, Japan where the tree species are mostly Sugi, or Japanese Cedar, and Hinoki, or Japanese Cypress that had been classified as ‘Sugi’ and ‘Hinoki’. Other land cover types are natural forest has deciduous broadleaf of many sorts and non-forest area such as roads, buildings and agriculture, which were classified as ‘mixed broadleaf’ and ‘other’ [3].

The data set that used in the study, ASTER satellite imagery with a 15 m spatial resolution, comes from 3 different days in order to acquire enough spectral discrimination for distinguish. The 26 September image was further georectified to prevent some classification errors. Since forest types classification merely needs spectral information, this paper only adopts 9 bands in the study which contain spectral information in the green (0.52–0.60 μm), red (0.63–0.69 μm) and near-infrared (NIR) (0.76–0.86 μm) bands [3].

Apart from the 9 bands of initial remote sensing data, there are 18 features that represent the distinction between the predicted spectral values and the actual spectral values of Sugi class and Hinoki class in the 9 bands. The reason why the study must use these 18 new variables is the classification considers 18 geographically weighted similarity variables may strengthen its validity. The inverse distance weighting (IDW) interpolation technique was used to calculate these 18 new variables [3].

Therefore, 27 variables are used in the classification of forest types. The data set downloaded from the UCI Machine Learning Repository located at http://archive.ics.uci.edu/ml/datasets/Forest+type+mapping is being divided into 2 parts, the training data which has nearly 200 instances and the testing data which has over 300 instances. Both have 27 columns (features), first of which is the type of the instance and others are variables that have been mentioned above.

2.2 Preprocessing

This study will load the 2 data sets respectively. In neural network the forest types will be the output and all the other variables are input so the 'training.csv' and the 'testing.csv' are encoded as follow. Both the 'training.csv' and the 'testing.csv' are divided into 2 sections. The first section of them is the first column that represents the category of forest types. The other is all the variables for classification.

Before using the data set for classification, the input data will be preprocessed as follow for a better classification accuracy.

First, the 2 data sets, training and testing, should be combined into one. The reason for this is this study will implement an enhancement technique in the preprocessing part, which requires all the data must be enhanced equally. In this procedure 'training.csv' and 'testing.csv' are combined into 'forest.csv'.

Second, the 9 variables from the second column to the tenth column that contain 9 bands of the original spectral data in the green, red and NIR will undergo an enhancement. The paper that this study refers to has used a cumulative histogram enhancement technique, which is the reason to implement an enhancement technique as well in this article [4]. In remote sensing study, the image enhancement techniques can destripe and increase the quality of image classification, thus enlarge the applications [5]. In order to gain better result, this study utilizes an enhancement method that is mainly based on the cumulative histogram enhancement technique to adjust the variables that represent spectral information. The idea of the cumulative histogram enhancement technique is, redistributing the values in the image according to the probability distribution of their initial values, while only the 9 variables from the second column to the tenth column that contain 9 bands of the original spectral data and other columns do not contain image information. So, the variables contain spectral information will undergo such method based on the cumulative histogram enhancement. After the preprocessing, 9 variables from the second column to the tenth column are redistributed by the probability distribution.

Third, the first column which is the classes of the instances must be changed into numbers in the neural network classification. In Pytorch when we implement a neural network, the program can only cope with numbers not verify the characters while the original data set is digitized for 4 classes: 's', 'h', 'd', 'o'. This step 4 classes 's', 'h', 'd', 'o' will be rewritten into '0', '1', '2', '3' respectively.

2.3 Classification

The structure of the neural network will be designed in Pytorch after preprocessing the data set.

After testing by varying the hidden layers of the neural network, it is found that it almost makes no difference in the abilities of classification. So, the 3-layer neural network has a 26-node input layer, a single 16-node hidden layer and a single 4-node output layer. The input layer represents all the variables that this article has been introduced. And 4 outputs are 4 types of the forest.

The data set has to be combined in the process of enhancement. However, when it comes to the classification section they are taken apart as they were in the initial situation. That is, the first 200 instances are used to be trained in the training set until the error has reached its minimum and the rest of them will be used in the testing set. After testing the neural network, the output will be a confusion matrix.

It is demonstrated in the paper that this study refers to has used a technique that can increase the quality of the neural network classification by modifying the threshold, which has been proved to be effective in that paper [4]. However, this technique may not be useful in this study. The reason is in the paper that this study refers to, the neural network has only 1 output due to its requirement is distinguishing the dry sclerophyll forest and the non-dry one. In that case, increasing the output accuracy by modifying the threshold is an easy operation since there is only a single node output layer. Nevertheless, this study has 4 output layers that makes the improvement of neural network by modifying the threshold an inaccessible task. It becomes extraordinary hard to improve the quality of neural network has a single 4-node output layer by adjusting the threshold. Thus, this study will not implement the technique of changing threshold that has used in the reference.

Besides the previous neural network method, this neural network will ultilize an evolutionary algorithm (EA) method to improve its performance. We all know that the neural network is constituted by neurons. If we want to introduce an EA method in it, we could image that some of these neurons are randomly strengthened, weakened or pruned. After the modification of some neurons, the neural network will be selected by its performance. We will create several different neural networks at first, let them undergo a series of selection, reproduction and mutation. After several generations of evolution, we will eventually gain the neural network which has the best performance.

The basic idea of an evolutionary algorithm that used in this case is: create the first generation of the neurons in this neural network, let them become 'parents' of the neurons to produce the next generation of the neurons, each generation of the neurons will have a probability to undergo a mutation, all the neural networks will be under a selection and the selected ones will become the new ‘parents’ in the next generation to generate new ‘offsprings’ that will iterate the process above.

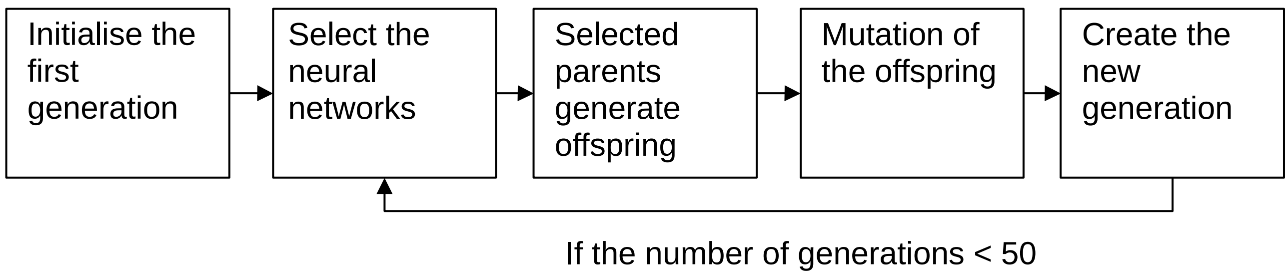

Fig. 1. This is an introduction of the process to iterate of the EA method in this case study.

Now, EA technique in this case study will be detailedly elaborated. The population of each generation of the ‘parents’ (neurons) will be 100. During the creation of the first generation of neural networks, some of them will purn their neurons randomly, by which those neural networks of the first generation will be already pruning and make a difference on their offsprings. Then the implement of the EA begins. The first step of the iteration is the evaluation and selection of the neural networks. In this study we evaluate these neural networks by its classification accuracy. After that the select ones will be stored. In the next step, the selected parents will generate their offsprings according to the genertic rules. Finally, the parents and their offsprings will become the new generation that repeats this iteration. It will create 50 generations of neural networks in this case study.

As for the evaluation, the neural network will generate a confusion matrix for testing, including its overall accuracy and the Kappa coefficient. The reason why picking these to evaluate the neural network is the research paper that this study will compare with adopt the confusion matrix for testing, its overall accuracy and the Kappa coefficient to evaluate its image classification methods as well. The evaluation that is convenient for comparison and discussion will be calculate in Pytorch.

3 Results and Discussion

After taking apart the ‘forest.csv’ into 2 parts and the first 200 rows are used in the training section, the rest of the data is used as the data set in the testing section for checking the accuracy of this neural network method and comparing with a relevant research paper.

Table 1 is the error matrix (including overall accuracy and Kappa coefficient) for the neural network classification without cumulative histogram enhancement or EA method.

Table 2 is the error matrix (including overall accuracy and Kappa coefficient) for the SVM classification which comes from the research paper to compare with [3].

Table 3 is the error matrix (including overall accuracy and Kappa coefficient) for the neural network classification that has implemented cumulative histogram enhancement and EA techniques.

Table 1. Confusion matrix and overall accuracy for a simple neural network classification.

Reference data	S	H	D	O	Total	PA (%)
The neural network classification without the implementation of techniques						
S	125	9	2	0	136	92
H	10	28	0	0	38	74
D	28	1	73	3	105	70
O	5	0	7	34	47	72
Total	168	38	82	37	325	
UA (%)	74	74	89	92		
Its overall accuracy is 80.0 %						
Its Kappa coefficient is 0.702						

Note: S, Sugi; H, Hinoki; D, mixed deciduous broadleaf; O, other; PA, producer's accuracy; UA, user's accuracy.

Table 2. Confusion matrices and overall accuracy for the SVM classifications.

Reference data	S	H	D	O	Total	PA (%)
(a) SVM classification with geographically weighted similarity measures						
S	122	11	3	0	136	90
H	4	34	0	0	38	89
D	7	3	88	7	105	84
O	1	0	10	35	46	76
Total	134	48	101	42	325	
UA (%)	91	71	87	83		
Its overall accuracy is 85.9 %						
Its Kappa coefficient is 0.795						
(b) SVM classification without geographically weighted similarity measures						
S	122	12	2	0	136	90
H	8	30	0	0	38	79
D	11	3	82	9	105	78
O	1	0	12	33	46	72
Total	142	45	96	42	325	
UA (%)	86	67	85	79		
Its overall accuracy is 82.2 %						
Its Kappa coefficient is 0.740						

Note: S, Sugi; H, Hinoki; D, mixed deciduous broadleaf; O, other; PA, producer's accuracy; UA, user's accuracy.

Table 3. Confusion matrices and overall accuracy for neural network classifications.

Reference data	S	H	D	O	Total	PA (%)
(a) the NN classification with cumulative histogram enhancement, without the EA method						
S	117	9	10	0	136	86
H	10	28	0	0	38	74
D	7	0	87	11	105	83
O	1	0	8	37	46	80
Total	135	37	105	48	325	
UA (%)	87	76	83	77		
Its overall accuracy is 82.8 %						
Its Kappa coefficient is 0.749						
(b) the NN classification with cumulative histogram enhancement and EA method						
S	122	12	2	0	136	90
H	8	30	0	0	38	79
D	11	3	82	9	105	78
O	1	0	12	33	46	72
Total	142	45	96	42	325	

UA (%)	86	67	85	79

Its overall accuracy is 84.9 %
Its Kappa coefficient is 0.780

Note: S, Sugi; H, Hinoki; D, mixed deciduous broadleaf; O, other; PA, producer's accuracy; UA, user's accuracy.

It can be seen in the tables that the overall accuracy and Kappa coefficient are all high enough to be confirmed that those methods are all effective methods for forest types classification in this case. The neural network classification method without any techniques carried out the worst performance, while other neural network classification methods performed better than the SVM classification without geographically weighted similarity measures since they have a slightly higher overall accuracy and Kappa coefficient. Among these methods the SVM classification with geographically weighted similarity measures has the best performance which means it is the most effective method for the forest types classification in this study.

It can be concluded that in this case the neural network classification method is almost the same quality as the SVM classification. Using the geographically weighted similarity measures will improve the SVM classification. As for neural network classification techniques in this study, both cumulative histogram enhancement and EA are able to improve its accuracy.

The reason why SVM classification with geographically weighted similarity measures has a little more accuracy may be in the comparing paper its SVM has adopted a radial basis function (RBF) kernel for classification. The SVM–RBF classifier can improve the classification method due to the increase of the separability between classes [3].

Nevertheless, all of these classification methods have little difference between each other, for which the data set in this study should be responsible. This study used a data set with merely 200 instances to train the neural network, which will result in a serious data insufficiency. Due to the inadequate training data, the classification methods are negatively influenced that they cannot gain a very high accuracy of classification. The techniques, cumulative histogram enhancement and EA, have little improvement to the performance of neural network classification. In addition, the neural network will inevitably become over-fitting because of this.

4 Conclusion and Future Work

4.1 Conclusion

In this case study, neural network classification is used to classify the forest types. The study derives the classifications for 4 types that are based on tree species: 'Sugi', 'Hinoki', 'mixed broadleaf' and 'other' that were named as 's', 'h', 'd', 'o' respectively in the data set. Based on a reference which making classification of forest type as well, the study test whether the techniques of cumulative histogram enhancement technique, modifying threshold and evolutionary algorithm are effective or not in this case study. The classification method is in comparison to a research that using the same data set but different classification methods.

In the preprocessing this study utilizes an enhancement method adapted from cumulative histogram enhancement technique adopted in the previous research [4]. In remote sensing study, enhancement techniques can increase the quality of image classification. The method has been proved to be effective after the control experiment with the one does not implement the enhancement technique.

The technique of modifying the threshold in accordance with the results on the validation test set is useful for keeping high accuracy and lessening the false [4]. However, this study of forest types classification is varied from 4 types, has 4 output layers. When the classification method is merely required to distinguish 1 supra-type, the technique of modifying the threshold will be effective because it make the adjustment of threshold so convenient that enable the results of classifications obtain a higher quality. If the classification method has the purpose of distinguishing from several types, this technique will not be suitable.

This study uses an evolutionary algorithm method to gain better result. In this case, the EA method has showed that it can improve the performance of the neural network after the control experiment with the one does not implement the EA technique.

However, some problems still remain in this study.

The most significant issue is the lack of sufficient examples in the data set. Not only does it cause the enhancement technique and EA cannot work well in the neural networks, but also lead to the over-fitting problem of the neural network classification. Especially the EA technique, it usually works better in a relatively larger data set. The inadequate training data restrict the classification methods to gain better results.

Because of the limitation of data set, the techniques are relatively simple in this study. The EA method implements in the neural networks can be more complicated to obtain a better classification result. And we can construct a more complex neural network structure for the EA technique.

4.2 Future Work

To obtain a better classification quality, these recommendations on neural network classification method are put forward as followed:

First and foremost, a larger and more complicated remote sensing data set is very essential for the image classification. A larger data set may guarantee the better performance of the neural network classification as well as the techniques that can improve the classification such as evolutionary algorithm. Other features can also be taken in account. For instance, we can also use the spectral information of the neighborhood of the training data. It is widely acknowledged that in the field of geography, the information in the space is continuous, the objects are linked and associated with each other. However, in this case study only the discrete training data were considered when training the neural network. In the remote sensing the spectral information of the neighborhood of the training data can be easily acquired to be used in the neural network classification method. Using larger and more complicated information is likely to improve the accuracy of image classification.

Second, spatial information can improve the accuracy of the remote sensing image classification as well. It is proved that the geographically weighted similarity measures calculated by IDW is an effective method in remote sensing image classification, which can be an example for the application of spatial information [3]. In the future, more spatial information can be used to contribute to the neural network.

Third, in this case the class ʻmixed broadleaf' and 'other' could be further subdivided. In the reality, various kinds of deciduous broadleaf are distinctive in the remote sensing data set, as well as different kinds of land cover like roads, buildings and agriculture. However, this study treats all the deciduous broadleaf except for Sugi and Hinoki as ʻmixed broadleaf', and all the other land except for forest as 'other', which will probably influence the results of neural network classification method negatively. The further study may classify those sorts of land cover with more subdivisions to improve the neural network.

Apart from these suggestions, the evolutionary algorithm implemented in the neural networks has the potential of being more complex to obtain better performance in image classification. With a much larger data instances and variables, the EA technique may make a bigger influence on the neural network classification and result in a better result.

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