Application of Deep Convolution Neural Network in Automatic Classification of Land Use

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Abstract. Automatic classification of land use has always been a topic of concern for remote sensing and land science. It plays an important role in the field of land survey and land management and is the basis for the country to carry out land use planning. In last few years, with more and more high resolution remote sensing platforms is becoming usable, it is possible to update and evaluate land use classification quickly with the advantage of huge volume of data and more frequent of the image data updating. At the same time, we are facing more and more challenges of the big data in practice. With the rapid development and achievements of deep learning in the field of image recognition, this paper introduces a deep convolutional neural network to classify and evaluate the existing land use information, and conduct experiments and demonstrations through the self-constructed convolutional neural network. The test results show that the method has a good effect in the determination of houses, factories, greenhouses, waters and woodlands. Due to the small number of samples and the inconspicuous features, the site is confused with other land features, resulting in lower classification accuracy. The method of this paper can realize the automatic classification of land use types and the evaluation of classification effects.[1]

1. Introduction

Land use type has complex natural and social attributes, making it a hot and difficult problem in the field of land resource management to meet the needs of users for effective classification of land use[2]. Nowadays, with the continuous development of sensor technology, the sources of remote sensing images are becoming more and more abundant, making the solution of the above problems possible[3].

Automatic classification of land use has always been one of the key directions of remote sensing image classification research. The essence lies in summarizing and summarizing various types of land types, so as to obtain the unique characteristics of the category image and other land types, and automatically match the predicted land class to verify the probability of belonging to a certain land class, thereby realizing automatic classification.

Automatic land use classification plays an important role in land surveys, annual change surveys, and natural resource surveys. It can standardize and simplify the workflow of image interpretation, reduce the difficulty of working for internal staff, and improve the production efficiency of image data. Especially with the extensive use of deep learning in the field of image recognition and the continuous development of algorithms in recent years, as well as the improvement and excellent performance of various mature algorithm frameworks, it shows that deep learning is portable in the field of remote sensing image recognition. Based on this point, this paper explores the application of deep learning in land use classification.
2. Introduction to data and research method

2.1. Research progress on current land use classification methods
The main methods of current land use classification include field investigation and automatic interpretation of images. This article focuses on automatic interpretation of images. The methods of image classification mainly include supervised classification, unsupervised classification, and semi-supervised classification. Among the commonly used classification algorithms, support vector machine (SVM) classification, decision tree (DT) classification, random forest (RF) classification, and semantic modeling based classification algorithms encounter many difficulties in dealing with practical engineering problems (such as high resolution). Remote sensing image classification), the theoretically optimal method is difficult to obtain satisfactory results in practice. These are all automatic classification algorithms for shallow structure models. They are characterized by the fact that the input signals are often processed using only a small number of linear or nonlinear methods, and it is often difficult to achieve satisfactory results for complex signals. [4]

Deep learning is a deep-rooted machine learning method. It is the latest development trend of artificial neural networks. By extracting more abstract features from the lower layer to the higher layer, the input data is formed into a network weight structure that best fits the required features. Accuracy. Hinton et al. use the deep learning model to classify the data, and conclude that the deep neural network structure can learn more abstract features than the existing methods, and has stronger classification ability and good generalization ability. Dang Yu et al. used the AlexNet convolutional neural network to classify and evaluate the surface coverings, and achieved good classification results [1]. Men Jilin et al. used multi-structured convolutional neural networks for classification verification of high-resolution image land use. The research indicates that deep learning has certain feasibility in land use classification. [5]

2.2. Image and experimental area introduction
The data sources used in this study include: aerial imagery collected by the surveying and mapping department from June to September 2017. The image is RGB full-color band with a resolution of 1 m. The supporting data includes the administrative division maps of various levels in Shanghai, which are used to determine the scope of research, the current situation of land use in Pudong New Area (field survey, visual interpretation of images, and information provided by relevant departments) as a comparison standard for classification and classification results.

The research area of this experiment is located in the southern part of Chuansha New Town, which is a typical suburban area. There are a total of 496 land use maps, and the land use types are divided into six categories: buildings, farmland, greenhouses, woodland, waters and construction sites.

2.3. Make samples
This experiment uses land parcels from other regions as sample set. The features selection is done by the GIS masking tool. According to the purpose of classification, the samples are divided into waters, farm land, greenhouses, construction sites, buildings and forests. The feature sample selection shows in table 1.

| Features          | Number | Factory | Building | Farmland | Waters | construction | Greenhouse | Forest |
|-------------------|--------|---------|----------|----------|--------|--------------|------------|--------|
|                   |        | 101     | 107      | 183      | 80     | 60           | 106        | 50     |

2.4. Introduction of the experimental environment
The experiment uses the Tensorflow open source framework and CUDA-GPU acceleration scheme under the Ubuntu operating system, and the NVIDIA GeForce 1080Ti (11 G memory) used for the graphics card for GPU acceleration. The other main hardware is Intel Xeon E5-2620 eight-core processor, 64G memory, PCI -E X8 interface, 120 G solid state drive, etc.
2.5. Introduction of experimental methods
This experiment uses a multi-layer convolutional neural network built by itself, which is divided into six layers, which are two-layer convolution, two-layer pooling, and two full-connection layers. The first convolutional layer uses 96 convolution kernels (3*3*3) to filter the 96*96*3 image with a single sliding step. After being processed by the convolutional layer, the data is subjected to ReLu activation and normalization transformation, and then pooled, and passed as an output to the next layer.

The first fully linked layer is stacked after the last convolution and pooling layer, and the number of signatures is reduced by half after the final pooling layer. The last full link layer output fuses the softmax result of the tag. There are 6 nodes in this layer, which correspond to 6 categories of farmland, forest land, water body, house, construction site and greenhouse. After being processed by the fully connected layer, the network accurately distinguishes the six land features and accurately classifies the imported house maps. As follows:

![Figure 1. CNN structure diagram](image)

2.6. Experimental process
According to the method described in 2.2, the sample characteristics are determined and the sample set is selected. The sample set is used as input to carry out model training. According to the training result, the convolution layer, the pooling layer and the fully connected layer are fine-tuned to obtain a suitable prediction network model. The experimental process shows in figure.2.

![Figure 2. Classification work flow diagram](image)

The parameters of the full connection layer were trained with the selected sample set. The parameters were set to a learning rate of 0.01, a batch size of 100, a weight attenuation rate of 0.002, and a training set of 687. Through the training loss value and the development trend of the verification loss value, the
degree of fine adjustment and over-fitting phenomenon are judged[6]. The figure.3 shows the loss and classification accuracy of the training set after each iteration.

![loss and accuracy curve diagram](image)

Figure 3. Loss and accuracy curve diagram

It shows that in 100 iterations, the loss rate drops rapidly but the accuracy does not change much. After 3000 trainings, the model's loss rate and accuracy tend to be stable, so the 3000th training model is selected as the prediction model.

3. Experimental analysis

The prediction data set is taken as input, and the training model derived from 2.6 is used as the prediction model for classification prediction. The classification result is compared with the land use status map to obtain the classification result confusion matrix. The result shows in table2:

| Predict category | Actual category | Factory | Building | Farmland | Waters | Construction | Greenhouse | Forest | Total | User Accuracy/\% |
|------------------|-----------------|---------|----------|----------|--------|--------------|------------|--------|-------|-----------------|
| Factory          |                 | 29      | 6        | 0        | 0      | 0            | 0          | 0      | 35    | 82.86           |
| Building         |                 | 2       | 90       | 2        | 0      | 6            | 4          | 0      | 104   | 86.54           |
| Farmland         |                 | 0       | 7        | 151      | 1      | 7            | 5          | 5      | 176   | 85.80           |
| Waters           |                 | 5       | 3        | 0        | 35     | 0            | 3          | 1      | 47    | 74.47           |
| Construction     |                 | 0       | 5        | 2        | 0      | 3            | 1          | 0      | 11    | 27.27           |
| Greenhouse       |                 | 2       | 10       | 2        | 0      | 2            | 89         | 0      | 105   | 84.76           |
| Forest           |                 | 0       | 0        | 2        | 0      | 0            | 2          | 14     | 18    | 77.78           |

| Total            |                 | 38      | 121      | 159      | 36     | 18           | 104        | 20     |       | 77.78           |
| Cartographic Accuracy/\% |      | 76.32   | 74.38    | 94.97    | 97.22  | 16.67        | 85.58      | 70.00  |       |                  |

Overall classification accuracy=82.86%  Kappa coefficient=0.7792

As the results shows the overall classification accuracy is 82.86%, Kappa coefficient is 77.92%, the consistency test results are highly consistent, and the classification results are highly reliable.

Among them, the classification accuracy of users in farmland, buildings, factories and greenhouses is higher than 80%, the classification accuracy of water and forest land is above 70%, and the classification accuracy of construction is low, which is 27.27%. The cartographic accuracy in farmland
and waters is high, about 90%; The classification accuracy of greenhouse is 85.58%; The cartographic precision of plant, building and forest land is above 70%, and the classification accuracy of construction site is low, which is 16.67%. This confusion matrix shows most of the construction lands are classified into buildings and farmland for the reason that the characteristics are overlapped among them, which leads to ambiguity of features. The number of prediction sets of the construction features is small, which is one of the reasons for the high misclassification rate. Among them, the comprehensive classification accuracy of farmland and water area is the highest, and the classification effect of greenhouses and buildings is better. Because forests' feature is close to farmland and greenhouse, there is also a certain degree of misclassification.

In summary, it is applicable for using the convolutional neural network of deep learning in land classification.

4. Conclusion
This paper mainly studies the application feasibility of deep learning convolutional neural network in land use classification, and takes the aerial image of a certain area in Shanghai as an example for experimental demonstration. The experimental results show that deep learning is applicable in land use classification.

In land use surveys, land use monitoring, and land change surveys, deep learning can also be used to automatically classify features. At the same time, the classification prediction model can be continuously improved, so that it can adapt to the classification of different seasons and different regions, and improve the prediction accuracy of classification. The current depth learning in the field of pattern recognition has reached 90% of the overall recognition accuracy of objects. Above, of course, the land use type has certain characteristics such as high complexity and homogenization, which makes the classification accuracy more challenging.

(1) Feature extraction automatically. The extraction of current features also requires manual intervention, which requires automatic segmentation of remotely sensed images, thereby reducing manual workload. Achieve complete automatic classification.

(2) The classification accuracy of subdivisions needs to be improved. At present, it is only possible to achieve higher classification accuracy between the first-level land types and the land types with obvious differences between the classes. How to improve the classification of features with small differences between classes needs to be discussed in the future.

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