DEEP LEARNING MODEL CONSTRUCTION OF URBAN PLANNING IMAGE DATA PROCESSING AND HEALTH INTELLIGENCE SYSTEM

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Abstract. In order to study the deep learning model of urban planning image data processing and health intelligent system, based on existing remote sensing image change detection methods, the author introduces and proposes the use of deep belief networks in deep learning to classify high-resolution remote sensing images and analyze urban expansion change detection. Compared with traditional methods, deep learning has the highest overall accuracy and Kappa coefficient. Deep learning has the highest producer accuracy and relatively low misjudgment rate, making it the most suitable for studying the trend of urban built-up areas. By calculating the information entropy of the image to predict the number of hidden layer nodes, the time for deep learning is greatly reduced. Under the same experimental conditions, the training time for each image can be shortened by 12 525 seconds has improved classification efficiency and made a significant contribution to research on urban expansion applications. Finally, the improved deep belief network was applied to classify and detect changes in the three phase remote sensing images of Beijing, and the urban expansion trend and characteristics of Beijing were analyzed. Provide technical reference and inspiration for urban planning and land use protection.

Key words: Deep learning, Deep belief network, Remote sensing images, Urban planning, Image data processing

1. Introduction. In the evaluation process of urban master planning methods, how to use practical and feasible evaluation methods to accurately and efficiently evaluate a large number of planning schemes is a practical problem faced by every urban planner [1]. As one of the deep machine learning methods, deep learning technology can extract features within samples and transform them. It has the outstanding advantage of strong learning ability and is widely used in fields such as image classification, object recognition, and object evaluation.

The commonly used deep learning techniques include automatic encoding, sparse encoding, deep belief networks, etc. These deep learning techniques utilize layer by layer feature transformation to transform meta spatial features into another space, facilitating feature classification and evaluation. Urban planning is a comprehensive work that not only considers the construction of tangible entities such as urban space, but also considers multiple aspects such as economy, society, environment, culture, etc. Throughout history, the formulation of urban planning has relied heavily on qualitative analysis and empirical judgment. Planners often fail to provide objective explanations for phenomena, and the scientific nature of the planning discipline has long been questioned, one important reason for this is the non collectability or non quantifiability of data. Nowadays, the emergence of intelligent planning has brought immeasurable vitality and change to the development of urban planning discipline.

Intelligent planning and design, with the assistance of computers, is particularly effective in saving manpower and computational costs, and the calculation and analysis results can also ensure absolute objectivity.

Remote sensing change detection is a technology that quantitatively analyzes the characteristics and information of land surface changes based on remote sensing images obtained at different times in the same region. It has become an important direction in current remote sensing image processing and analysis, and is widely used in many fields such as land use, vegetation cover, urban planning, crop growth monitoring, and disaster assessment and prediction.

At present, the change detection methods for remote sensing images mainly include algebraic operations, image classification, feature description, and other methods. In the field of urban expansion, due to the need to determine how urban land is transformed from other land uses, the research in this direction adopts the

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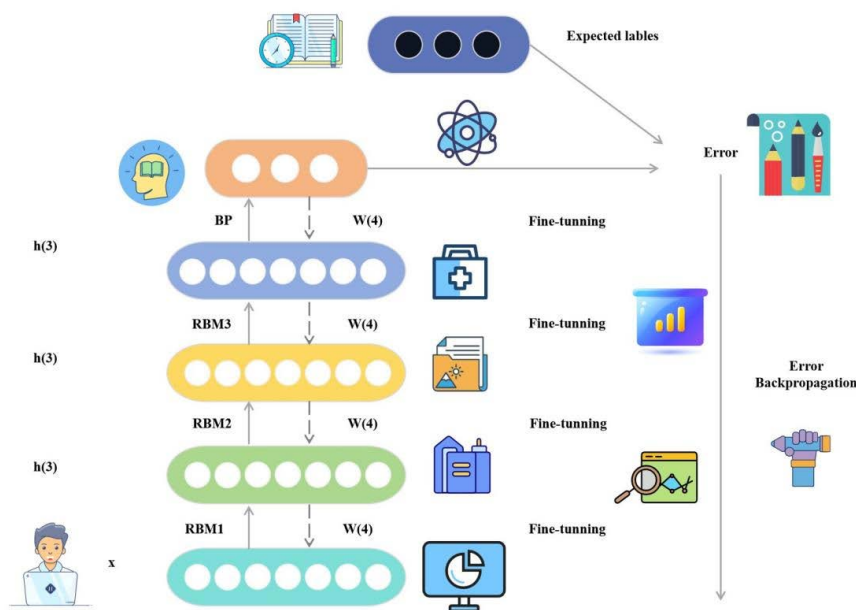
Fig. 2.1: DBN schematic diagram

method of image classification and change detection, which is more intuitive.

Image classification based methods can provide the types of surface changes and reduce the impact of external factors such as lighting and atmosphere on detection accuracy. However, in practical operations, a large number of learning samples need to be obtained, and the training time is relatively long. Therefore, how to obtain learning samples and reduce the training time of classification is an urgent problem that needs to be solved in the field of urban expansion.

The author takes urban expansion as an example and introduces a classification method of deep learning. After image classification, multi temporal change detection is performed. The accuracy index is compared with existing change detection methods, and information entropy is used to improve the efficiency of deep learning, achieving fast, efficient, and accurate change detection [2].

2. Methods. The deep learning method utilizes Deep Belief Network (DBN) for data classification and has made breakthrough progress. Subsequently, various research and engineering fields have adopted deep learning methods for application experiments [3]. In recent years, deep learning methods have also been continuously applied in the classification and recognition fields of videos, images, speech, etc. The essence of deep learning is a multi-level neural network, which improves the accuracy of results by extracting features from each layer to form final features suitable for classification.

Deep learning is applied in the field of remote sensing, utilizing deep belief network models for road target recognition in airborne images. But so far, there is still a lot of research space to apply this method to the classification of remote sensing images in large regions.

A deep belief network is composed of a multi-layer unsupervised Restricted Boltzmann Machine (RBM) network and a layer of supervised Backpropagation (BP) network, as shown in Figure 2.1 [4]. The experimental process of DBN includes two steps. Firstly, the input data is pre trained, and the output of the lower layer Boltzmann machine is used as the input of the higher layer, which is trained layer by layer.

In the fine-tuning stage, supervised learning is used to train the neural network layers, and the obtained errors are passed down to fine tune the weights of the deep belief network. The pre training stage actually initializes the weights of the neural network, thereby avoiding the drawbacks of local optima caused by random initialization.

Unlike traditional neural networks and shallow learning, deep learning methods generally have multiple layers, ranging from 4-7 layers to more than 10 layers. Moreover, through layer by layer feature extraction, they make classification and prediction results more accurate. However, the difficulty of using deep learning methods for classification lies in determining the depth of the network and the number of hidden layer nodes. Therefore, how to improve computational efficiency is an urgent problem that needs to be solved.

3. Experiments and Analysis.

3.1. Research Area and Data Sources . The author chose City A as the research area. The remote sensing image data used in the study includes LandsatTM and ETM+data with imaging times in 2009, 2015, and 2022, as well as auxiliary data such as A city topographic map, A city center administrative area map, and A city yearbook statistical data.

3.2. Land use classification standards and training sample selection. Appropriate classification standards and the number of training samples are the basis for accurate classification. Generally, a hierarchical classification system is adopted. The national standard GB/T21010-2007 "Classification of Land Use Status" stipulates that land use is divided into three categories: agricultural land, unused land, and construction land, each of which is further divided into several primary and secondary categories. Based on the research purpose and in combination with the provisions of national standards, the author categorizes land use consolidation into 5 categories [5]. Farmland, forests, and grasslands can also be merged into vegetation. A sufficient number of training samples and their representativeness are key to image classification. The selection method of training samples will affect the accuracy of classification, such as using pixel method, polygon method, etc. The mixed pixels in medium and low resolution remote sensing images contain complex information. Considering the complexity of land use in the study area, high-resolution remote sensing images should be selected for training sample selection.

The author used high spatial resolution images as training samples, randomly selected a training area with a sample size of 200, of which 100 samples were used for training the model and 100 samples were used for detecting model accuracy, each sample contains 10 pixels, accumulating 1000 pixels. For each class of samples, 213 are selected for unsupervised training, and the remaining 1/3 is used for fine-tuning in the network. As the author is studying the changes in the built-up areas of Beijing, it is advisable to select as many construction land as possible when selecting training samples to improve the classification accuracy of construction land.

3.3. Parameter Setting and Experimental Process . The restricted Boltzmann machine used in DBN only allows connections between hidden layer neurons and visible neurons, and there is no connection between two visible neurons or between two hidden layer neurons. In RBM, the energy equation is shown in Equation 3.1:

$$Energy(v, h) = h'Wv + b'v + c'h \tag{3.1}$$

In the formula, W represents the weight matrix of the neuron connections between the hidden layer and the visible layer, and b and c are the bias vectors on the visible and hidden neurons, respectively. When training Boltzmann machines, we input to the network through visible layer neurons, with the goal of updating and adjusting weights and biases, so that when training data is used as input, the configuration energy is minimized. Training RBM first inputs training vectors to the visible layer, and then compares and disperses them by alternately sampling hidden layer units and visible layer units. When using RBM, we do not need to calculate the joint probability and it is easy to sample. After only one Gibbs sampling iteration, we can reset (update) the weights and biases of RBM, as shown in Equation 3.2:

$$\begin{cases} W_{kj} = W_{kj} - \alpha(<v_{k0}h_{j0}> - <v_{k1}h_{j1}>) \\ b_k = b_k - (<v_{k0}> - <v_{k1}>) \\ c_j = c_j - (<h_{j0}> - <h_{j1}>) \end{cases} \tag{3.2}$$

In the formula, α is the learning rate, v_0 is sampled from the training sample, h_0 is sampled from $P(h|v_0)$, v_1 is sampled from $P(v|h_0)$, and h_1 is sampled from $P(h|v_1)$. We repeat this update operation on several
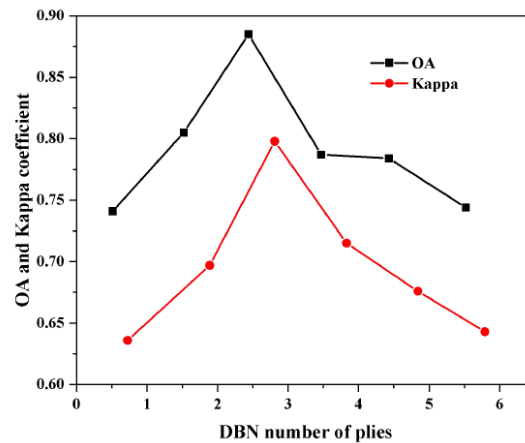
Fig. 3.1: Classification accuracy of different DBN layers

samples of the training data, and then iteratively train each next layer by using the activity of the hidden units in the previous layer as input data/visible units for the first layer.

For each pixel to be classified on an image, it is necessary to consider a region that includes its surrounding neighboring pixels. Assuming the neighborhood window size is winsize, it can be expanded into a one-dimensional vector with a wins-sizewinsize dimension. For DBN, the input data consists of three processed Pauli parameters, namely the diagonal elements of the correlation matrix (0.5 | HH+VV12, 0.5 | HH-VVI2, and 2 | HV12), which can be assembled into a data vector for the first phase, therefore, for the data of period m, the dimension of the input vector is winsize×winsize×3×m. Calculate the spectral and texture feature vectors of the three bands synthesized by pseudocolor separately, and combine the three feature vectors into one feature vector as the input. The input dimension is 147. The experimental parameters are set as follows: The learning rate   is initially set to 0.01, W is all random numbers from a normal distribution, and the hidden layer bias is initialized to 0. Due to the fact that the number of input and output nodes in the experiment is 147 and 5 (to be classified), the hidden layer nodes of the Boltzmann machine are set to take values of 5 to 147, respectively, when the error is minimized, it is the number of nodes in the first hidden layer, and so on for the remaining hidden layer nodes. The depth of the deep belief network is set to 1-6 layers, and the misclassification error, omission error, producer accuracy, user accuracy, overall accuracy, and Kappa coefficient are calculated to evaluate the classification accuracy. The results show that the highest accuracy is achieved when the network depth is 3, as shown in Figure 3.1 [6].

The experimental method is to preprocess remote sensing images; Based on the analysis of existing data and the establishment of interpretation criteria, the main land types in Beijing are extracted using computer classification methods; For smaller land classes, set an area threshold for neighboring merging; Extract boundaries of various land uses after merging, and correct incorrect boundaries through visual interpretation; Overlay the classification results of each image for later analysis and evaluation.

3.4. Classification Results and Analysis. The experiment focuses on the detection of changes after classification, using the ISODATA method in unsupervised classification, the maximum likelihood classifier in supervised classification, and deep learning methods to classify and analyze remote sensing images. The accuracy of the three methods is evaluated using measurement indicators such as classification accuracy, overall accuracy, and Kappa coefficient. The results are shown in Tables 3.1 to 3.4 [7,8].

The results showed that the overall accuracy and Kappa coefficient of deep learning were the highest, followed by the maximum likelihood classifier, and ISODATA was the worst. Deep learning has the highest producer accuracy and Kappa coefficient, with a relatively low misjudgment rate, and is most suitable for studying the trend of changes in built-up areas. The possible reason is that deep belief networks avoid ran-

Table 3.1: Precision Evaluation of ISODATA Classification Results

Category of features	Misclassification error	Omission error	Producer's accuracy	User Accuracy
land used for building	56.09	15.87	84.15	46.93
Forest and grassland	21.82	71.54	28.48	78.2
Water bodies	5.13	0.00	100.00	94.89
Naked ground	86.86	76.2	23.82	13.16
cultivated land	67.02	15.93	84.09	32.99

Table 3.2: Maximum likelihood classifier result accuracy evaluation Table

Category of features	Misclassification error	Omission error	Producer's accuracy	User Accuracy
land used for building	33.37	1.59	98.43	66.65
Forest and grassland	9.65	0	100.00	91.37
Water bodies	0.00	0.6	99.42	100.00
Naked ground	1. 68	37.46	62.56	98.34
cultivated land	0.56	1.89	98.13	99.46

Table 3.3: Precision Evaluation of Deep Learning Classification Results

Category of features	Misclassification error	Omission error	Producer's accuracy	User Accuracy
land used for building	11.99	9.72	90.3	88.03
Forest and grassland	25.2	12.29	87.73	74.82
Water bodies	21.63	25.01	75.01	78.39
Naked ground	18.8	0.00	100.00	81.22
cultivated land	1.41	21.65	78.37	98.61

Table 3.4: Overall accuracy and Kappa coefficient accuracy evaluation Table

classification method	Overall accuracy	kappa coefficient
ISODATA	54.3569	0.4499
Maximum likelihood classifier	87.5641	0.8934
Deep learning	93.4144	0.9141

domly assigning initial values to neural networks and better overcome the problem of local optima through pre training methods. Therefore, deep belief networks combine the advantages of unsupervised neural networks and supervised classification, which can improve classification accuracy and efficiency.

3.5. Determining the number of hidden layer nodes by calculating information entropy. Deep learning methods have high classification accuracy, but it is difficult to determine the number of hidden layer nodes and the number of hidden layer layers, which requires continuous attempts to determine [9,10]. While ensuring that the feature dimensions are maintained within a small range, it is also necessary to ensure that
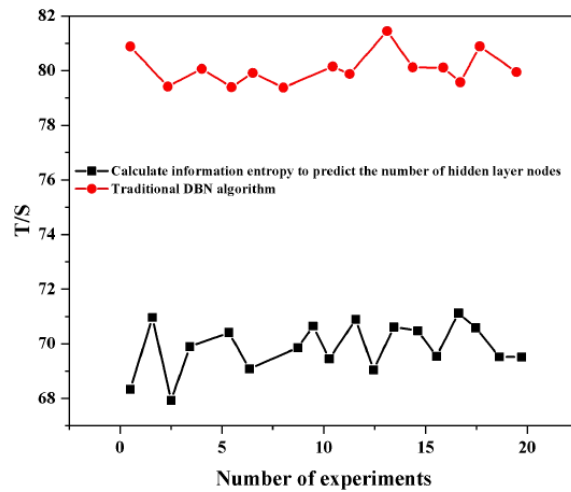
Fig. 3.2: Comparison of Calculation Time between Information Entropy Estimation of Hidden Layer Nodes and Traditional DBN Algorithm

there is sufficient classification information in the features. Therefore, we need to estimate the number of hidden layer nodes and the number of hidden layer layers to improve classification efficiency, save time and labor costs. During the calculation process, we found that for images with richer content, their information entropy increases, on the contrary, images with more uniform terrain types have relatively lower information entropy. Therefore, we attempt to apply information entropy to determine the number of hidden layer nodes used for classification, which greatly shortens the calculation time and improves classification efficiency. In order to verify the above proposed ideas, we conducted experiments using the following preset training parameters and compared the calculation time between traditional methods and estimation methods. The experiments were conducted more than 20 times. The running time results are shown in Figure 3.2.

The experiment compared the calculation of information entropy to estimate the number of hidden layer nodes and the training time of traditional DBN algorithms. When the maximum training period is set to 100, the method of calculating information entropy to estimate the number of hidden layer nodes has an average training time of 68.427 seconds, while the traditional DBN algorithm network training time is 80.952 seconds. Compared with traditional methods, the training time is shortened by 12.525 seconds, greatly reducing the training time and improving classification efficiency.

4. Conclusion. The author applied the DBN model in deep learning to conduct change detection research on City A and compared it with traditional classification methods. The experiment shows that deep learning has the highest producer accuracy, overall accuracy, and Kappa coefficient, with a relatively low misjudgment rate, and is most suitable for studying the trend of urban expansion and change. By calculating the information entropy of the image to predict the number of hidden layer nodes, the time of deep learning is greatly reduced. When the maximum training cycle is set to 100, the method of calculating the information entropy to predict the number of hidden layer nodes reduces the training time by 12.525 seconds compared to traditional methods, improving the efficiency of classification. The experiment proves that this method is suitable for the classification and change detection of urban expansion. Accurately characterizing the characteristics of urban expansion changes is of great significance for identifying its expansion regularity, further explaining the coordination between built-up area expansion and socio-economic development, analyzing the spatiotemporal evolution process, and predicting future evolution trends. On the basis of change detection, further analysis of the characteristics and mechanisms of urban expansion, analysis of influencing factors, and prediction of change trends can be carried out in the future.

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