Electric Power Equipment Image Recognition Based on Deep Forest Learning Model with Few Samples

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Abstract: Power system equipment have many characteristics, such as many kinds, single color, similar appearance and complex environment of transmission and substation. These characteristics make it difficult for traditional image recognition technology to achieve good recognition results. If there are few training data samples, the performance of in-depth learning recognition declines sharply. To solve these problems, this paper designs an optimization and training recognition method based on the combination of generating confrontation network and deep forest. Firstly, the generated countermeasure network is used to expand the samples of power equipment, and then the active learning method is used to optimize the generated samples. Secondly, the traditional model-enhanced sample expansion method is used to expand the optimized samples twice. Finally, the robust network model is obtained by using the deep forest method to accurately identify the power equipment. Experiments show that this method has high recognition accuracy and is superior to many other algorithms.

1. Introduction

Generally, the identification of power equipment image adopts manual inspection and analysis, which is inefficient and subjective[1][2]. Artificial intelligence technologies represented by deep learning can effectively extract semantic features with high robustness and high standards for information and have excellent feature learning ability. However, deep learning requires a large number of data samples for training to build effective models, so its application field is limited. On the basis of random forest, the deep forest algorithm combines the fewsample recognition ability of random forest with the strong feature extraction ability provided by hierarchical design by referring to the algorithm idea of deep education background, and realizes the strong classification ability of fewsample data bar.

Aiming at the problem of typical power equipment identification under fewsample conditions, this paper designs a method based on the combination of generation antagonistic network and deep forest to optimize and train the identification model, so as to realize the intelligent identification of typical power equipment under limited sample conditions. Firstly generated against expanding network of electric power equipment samples, and then adopt the method of active learning of the generated samples is optimized, and the traditional model of enhanced sample extension method for the optimized secondary extended samples, and then based on the extended samples, deep forest method is robust network model for accurate identification of electrical equipment.
2. Generating high-quality sample data based on generating antagonistic network model

In the absence of reference sample data, this paper uses generator and decision-maker to form a generation counter network to generate high-quality samples. Generator fits real samples, and decision-maker classifies real samples and generated samples. The generated antagonism network is shown in figure 1:

![Fig. 1](image)

The principle of fewsample data expansion based on antagonistic generation network

Its specific process is as follows:

2.1. Generator and Network Design

The generator uses noise signal and real samples to generate sample data. The generator is a network containing convolution structure, as shown in formula (1):

$$\max_{E_{x \rightarrow p}} \left[ \log D(x) \right] + E_{x \rightarrow p} \left[ \log (1 - D(x)) \right]$$

Where, $r$ is random noise, $G$ converts this random noise into data type $x$, $D$ is a discriminant model, and for any input $x$, the output of $D(x)$ is a real number in the range 0-1. $P$ and $P_2$ respectively represent the distribution of real features and the distribution of generating features. The generator network design is shown in figure 2:

![Fig. 2](image)

4 Mixed Layer Structures

2.2. Discriminator and Network Design

The decision-maker is used to distinguish generated data from real data. Smoothing function is added into the decision-maker to prevent overfitting. With continuous game between generator and decision-maker, the training ends when the difference between generated data and real data is very small. In this paper, because of the use of multilayer convolution and normalization acceleration training[3][4], the features are few and no pooling layer acceleration training is required. The optimization process is realized by maximizing and minimizing objective functions, and the formula is shown in (2):

$$\min_g \max_D E_{x \rightarrow p} \left[ \log D(x) \right] + E_{x \rightarrow p} \left[ \log (1 - D(x)) \right]$$
3. Sample optimization based on active learning

Study methods by choiceReduce the size of training set and improve the efficiency of classification. The algorithm can be shown in formula (3).

\[ A = (C, L, S, Q, U) \]  

Where C is one or a group of classifiers, L is labeled training sample set, Q is query function, U is unlabeled sample set, and s is supervisor. The main learning algorithm first randomly selects the parts of unlabeled samples, and the supervisor labels them to establish the initial classifier model. S selects some unlabeled samples from U according to the standard of query function Q, and then adds them to training set 1, and trains the classifier again, iterating until the training stop standard is reached.In this paper, heuristic active learning algorithm based on posterior probability is adopted to generate sample optimization. This algorithm predicts the posterior concept size of acquired samples, and sorts candidate sample sets. Uncertain regions are identified by the posterior probability change and candidate sample classification status, and samples are selected to form the training set.

4. Recognition of few Samples Based on Deep Forest

Decision tree is the basic unit of deep forest. As a traditional machine learning method, decision tree requires far less data than in-depth learning. On small-scale samples, the generalization ability of model is stronger than in-depth learning method[5][6].

4.1. Multi-granularity feature extraction

Multi-granularity scanning forest is designed to extract more object features. Multi-granularity scanning uses windows of different sizes to slide values on data. For the same kind of data, each value has the same label. In the process of multi-granularity scanning, the number of forests and the number of layers of forests belong to two superparameters. Because the advantage of deep forest is insensitive to hyperparameters, the depth and breadth of hyperparametric forest are 2, and the categories are completely random forest and random forest, respectively[7].

4.2. Target recognition based on cascade forest

Cascade forest is an integrated forest structure designed for target classification. The first level of cascade forest receives the transformation features from multi-granularity scanning results as input. The input of each stage is the output of the former stage and the splicing of the original features. The number of forest layers continues to deepen until the model converges on the verification set. The average value of the characteristics obtained from the last stage of forest output is the final output of the model. In cascade forests, the species, number and depth of forests belong to super-parameters. Because of the insensitive Super-parameters of deep forests, two types of forests are adopted, the width is 4, the depth is 8, and the number of decision trees is 500. The final output of multi-granularity scanning is 1806 dimension, which passes through the first layer of forest with a width of 4. Twelve features are obtained. Similarly, 12 features are obtained in 1206 dimension and 606 dimension. These 12 features are combined with multi-granularity scanning (1818, 1218, 618) transformation features as input features of the next cascade forest. The stopping conditions of iterative optimization of cascade forests are determined by the verification set and forest depth. A reasonable set of validation sets can ensure that the model has a certain generalization ability while maximizing the accuracy of the model. The validation method is to select some or all layers, observe the output results of the selected layers, and verify the output gains of these layers. When the output gain is no longer increased, the training is stopped and the output of the current layer is used as the last layer of the model output.

4.3. The whole process of training recognition

Feature extraction from data with multi-granularity scanning structure. After 3 to 5 different sizes of sliding windows (granularity) are used to select features, there are enough differences in the transformation features. In the process of feature selection by sliding window, if the original feature is too long, the pooling layer can be used to sample the original feature. The transformation features obtained by multi-granularity scanning will be stored on disk for the use of subsequent cascade...
structures. The transformation features obtained by multi-granularity scanning will be used to extract the features of cascade forests. The first level of forest accepts the transformation features of different dimensions as input and outputs the probability of belonging to different categories. The next level of input is the combination of the former level's output and the transformation features obtained by multi-granularity scanning, so as to construct a multi-level forest and the output of the last level of forest. The average of probability results for each category will be the final output of the model.

5. Experiments and analysis

5.1. Construction of experimental data set

In order to verify the validity of this method, a set of power equipment image database is built in this paper. The data set consists of 804 pictures of different sizes, which are divided into five categories. The data categories are basically uniform. The five categories are insulators, transformers, circuit breakers, poles and iron towers[8][9], as shown in Figure 4. In order to test the recognition ability of the algorithm for similar power equipment, some categories of civil equipment are added to the database.

![Fig. 3 Power equipment image expansion](image)

(a) insulators (b) transformers (c) circuit breakers (d) poles (e) iron towers

5.2. Setting of experimental parameters

In the experiment, the sliding windows of 8*8, 11*11 and 16*16 sizes were selected for the deep forest model, and the sliding window step was 2. The cascade forest model is selected as random forest and completely random forest. The number of decision trees in two types of forests is 1000 (the best value of the experiment), and the number of forests in each layer of cascade forests is 4. The output values of four forests in cascade forests will be sent to the next layer of cascade forests together with the output features in multi-granularity scanning. In such an iteration process, the stopping conditions are controlled by cross-validation. In cross validation, the training set is divided into five parts, four parts are used for training, and the remaining one is used for testing. When the classification results are not improved, the overlay layer is stopped. At the same time, because the input dimension of cascade forest is fixed during model training, all image training data are pre-processed, that is, the image is adjusted to (30, 30).
5.3. Analysis of experimental results

Table 1 shows the classification and recognition results of various types of power equipment. The recognition rate of this method is compared with that of other methods. The experimental results of the test data show that the average recognition accuracy of the deep forest recognition algorithm in five categories of the database is higher than that of the contrast algorithm, with a larger lead, and the average recognition accuracy of typical electric power equipment is higher than 78%.

| Identification Method | Insulators | Transformers | Circuit Breakers | Poles | Towers |
|-----------------------|------------|--------------|------------------|-------|--------|
| KNN                   | 0.3000     | 0.0385       | 0.2340           | 0.6000| 0.6060 |
| SVM                   | 0.3000     | 0.0385       | 0.4280           | 0.2000| 0.5455 |
| CNN                   | 0.2900     | 0.1500       | 0.3282           | 0.2356| 0.3455 |
| DF                    | 0.7840     | 0.7255       | 0.7655           | 0.8023| 0.8333 |

Table 2 shows the average recognition accuracy of different algorithms on test sets under different training sets. The test results show that the performance of KNN and SVM algorithms fluctuates smoothly and does not change with the size of training set. Comparatively, with the increase of training set, the recognition accuracy of convolutional neural network algorithm and the algorithm of this subject has been improved. The reason for this phenomenon is that CNN and deep forest algorithms contain feature extraction structure. When the training set increases, they can extract stronger and richer features, so they can continuously improve the recognition accuracy. However, KNN and SVM do not have such feature extraction structure, so their performance is basically unchanged. In the experiment, the deep forest has a great advantage over the contrast recognition algorithm in all kinds of training sets.

| Method | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| KNN    | 9.75% | 11.22% | 11.83% | 12.15% | 12.82% | 12.65% | 13.95% | 14.08% | 17.81% |
| SVM    | 21.58% | 24.64% | 26.51% | 28.83% | 27.59% | 28.47% | 28.09% | 28.83% | 30.22% |
| CNN    | 2.55% | 3.50% | 4.73% | 8.55% | 12.50% | 17.45% | 22.38% | 27.46% | 31.45% |
| DF     | 22.24% | 30.75% | 34.15% | 34.73% | 37.50% | 48.48% | 61.70% | 64.65% | 76.73% |

In the experiment, with the help of multi-granularity scanning structure, the feature selection by manual design is avoided in the deep forest, which makes the deep forest more practical and more suitable for the identification of few samples of typical electric power equipment. At the same time, the test data show that the deep forest model demonstrates its superiority in few sample data recognition, and the average recognition accuracy is higher than that of the contrast algorithm. Compared with other contrast algorithms, the deep forest model is undoubtedly the best model choice. It is noteworthy that the parameters of the algorithm involved in the comparison are basically adjusted to the best, while the deep forest has not adjusted the super parameters because of the hardware constraints. Even so, the deep forest still shows relatively good performance on few samples. When the hardware conditions permit, increasing the size of the image, increasing the number of sliding windows, and using more classifier types, the deep forest can show better results.

6. Summary

Aiming at the problem that the recognition of power equipment can not meet the detection requirements under the condition of few samples, this paper proposes a training and learning model which combines the countermeasure generation network and the deep forest learning model to realize the intelligent recognition of power equipment in images. Because of the multi-granularity scanning structure, the proposed method does not need manual feature selection. At the same time, experiments show that the average recognition accuracy of this method is better than general deep learning methods such as CNN and KNN. The method proposed in this paper realizes the construction of high-quality target recognition model by using artificial intelligence technology under the condition of
limited or even less training data, thus automatically recognizing typical electric power equipment in time and accurately, and provides effective technical support for the application of state detection of electric power equipment.

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