ANALYSIS OF DATA OF ELECTRIC ENERGY METERING MANAGEMENT SYSTEM BY CNN ALGORITHM OF MECHATRONICS

Nan An, Huafei Wang, Jiahao Gao, Dan Wang, Bo Zhang
1Tangshan Power Supply Company, State Grid Jibei Electric Power Co., Ltd., Tangshan, Hebei, 063000, China

Abstract - With the development of science and technology, electromechanical integration and the Convolutional Neural Network (CNN) have developed rapidly. At present, one of the more widely used fields is the electric energy metering management system. Data analysis is one of the focuses of research in this field. Therefore, this paper introduces CNN algorithm and explains the advantages and disadvantages of the CNN algorithm in previous studies and the direction of optimization. Secondly, the target detection algorithm and data analysis are described, and the application of the target detection algorithm to image information processing and information analysis in the current research is introduced. Additionally, two methods are proposed for optimizing the CNN algorithm, and the optimization model is re-optimized by introducing the migration model. Finally, comparative experiments are conducted to verify the effectiveness and rationality of this model. The experimental results show that the detection rate of the two optimization methods is higher than that of the traditional model. The detection rate of CNN based on Region Proposal Network (RPN) is higher than that based on Region of Interest (ROI) pooling. Simulation experiments are carried out in different power metering management systems in the second experiment. The RPN-CNN model was introduced into the migration model. In system 1, the maximum difference between the detection rate and the traditional model is 0.2. In system 2, the maximum difference in detection rate is 0.12, which verifies the effectiveness of this model. Additionally, the stability of the RPN-CNN is better than that of the traditional model in the slope comparison of the curve, which proves the feasibility of the model. Therefore, this paper has certain reference significance for the data analysis of the power metering management system.

Keywords: Mechatronics; CNN algorithm; Electric energy metering management system; Data analysis; Migration model.

1. Introduction

Convolutional Neural Network (CNN) can abstract local features of images on different scales by using the operation of multiple convolution layers and has strong network expression ability and mathematical mapping characteristics. The Deep Neural Network (DNN) can better solve the over-fitting problem caused by a small amount of data or too many feature points [1]. Then, with the deepening of image research of CNN, target recognition has made more improvements. However, the deepening of the network level has introduced more features, leading to dependence on data and increased computing resources. Additionally, how to migrate the trained network features to unknown areas is worth applying. Therefore, the research on CNN's feature transfer and network adjustment is very significant. At present, the electric energy metering management system is mainly used to carry out accurate strategies for the consumed electric energy, which is an important link in the power production, marketing, and safe operation of the power grid [2].

In optimizing the CNN model, Wang et al. (2020) used a genetic algorithm to optimize the enhanced topological neural evolution method. An improved, enhanced topological neural evolution algorithm is proposed. This algorithm is based on the enhanced topological neural network method. It is optimized using the genetic algorithm to make the network more stable and efficient. Additionally, the coding mode is redesigned. The CNN model is optimized by using the redesigned coding mode and crossover and mutation operations in the genetic algorithm, and the experiment is carried out on image classification. The experimental results show that this method has a good effect on image classification [3]. Rhanoui et al. (2019) analyzed CNN algorithm structure information using underlying virtual machine translation tools. Then, with the help of algorithm structure information, a polyhedron model is constructed to describe the software features of the CNN algorithm. Finally, combined with the reconfigurable structure's hardware characteristics, the CNN algorithm's feature vector under the reconfigurable structure is constructed. The domain-
specific efficient compilation optimization method for reconfigurable structures has been proposed, which provides a new channel for exploring the compiler system's efficient and automatic conjecture parallel technology. Additionally, this also provides a new idea for improving the parallel performance of computing and data-intensive applications under the reconfigurable structure [4]. In terms of data analysis, Sun et al. (2020) used the K-nearest neighbor model and random forest model in the machine learning model and CNN and recurrent neural network in the deep learning model to explore the classification effect of each model. The above models are built on the original time series data, continuous image data, and their combined data. The results of the models on six data sets in the time series archives are comprehensively compared. The test results show that the dual-channel CNN model can achieve the best classification effect in most cases [5]. Alhichri et al. (2021) introduced a content caching architecture to intelligently enhance the edge environment to hot cache content. The description of the caching decision by reinforcement learning gets a series of data related to user satisfaction. The state and action spaces are large, fixed target network, and experience playback are introduced into the depth neural network approximator to estimate the maximum value. The data is analyzed in this way [6].

This paper optimizes the convolution neural network, improves the detection rate of the system by introducing the target detection algorithm and migration model, and conducts comparative experiments to verify the effectiveness and rationality of the optimization model. The innovation is introducing a migration model, which improves the analysis of underlying features and the detection rate.

2. Optimize the CNN Algorithm Model in the Power Metering Management System

2.1 Convolutional Neural Network

CNN is a feedforward neural network. The "convolution" operation - matrix multiplication is used in CNN to complete the full connection of image data. Convolution is the most important way for CNN to achieve feature extraction and classification. The typical structure of a convolution neural network usually includes input, convolution, pooling, full connection, and output layers [7]. Its structure diagram is shown in Figure 1:

![Figure 1: Schematic diagram of CNN structure](image)

Figure 1, the convolution layer transforms low-level features into high-level ones through multiple convolution cores. The pooling layer realizes the dimensionality reduction of features, removes redundant information from the convolved features, and retains advanced features that are effective for recognition. The full connection layer completes the classification task by comparing the advanced
features. For a certain layer in the CNN, the output of its upper layer is the input of that layer. Here, the input and output are called feature vectors.

The feature vector can be the data of one channel or the combination of multiple channels [8].

The essence of convolution is to extract the features of different image frequency bands. A filter matrix is used to perform the inner convolution operation on different data windows in the image. The structure diagram of the convolution core is shown in Figure 2:

![Figure 2: Structure diagram (a) original image; (b) convolutional kernel; (c) target image](image)

In Figure 2, the convolution kernel is called the image sharpening filter, which can enhance the edge effect. There are also convolution kernels with other effects, such as edge detection convolution kernels, gradient detection convolution kernels, Sobel operator convolution kernels, concave-convex convolution kernels, etc. CNN’s do not need to use hand-designed convolution kernels due to their property of backpropagation updating convolution kernels. The neural network can better make the features converge through the convolution kernel learned, which is the power of CNN [9].

The pooling layer is used to aggregate the features of different image positions. The 4×4 image is divided into four 2×2 regions, and the maximum value among them is taken for each region. A 2×2 image matrix is obtained.

This process is called maximization pooling. The pooling layer does not participate in the training of the convolutional network. Its design purpose is to effectively reduce the number of parameters and reduce the computation of the network’s characteristic parameters and network model while ensuring feature extraction. In a CNN model, the pooling layer is regularly placed behind the convolution layer, and the characteristic parameters are processed [10]. After the pooling operation, the depth of image features remains unchanged. The characteristics of maximum pooling are shown in Figure 3:

![Figure 3: Maximize pooling (a) Original feature map; (b) Target feature map](image)

The most common pooling methods are average and maximum. There are other pooling methods: overlapping, empty pyramid, etc. However, in recent years, the deep learning network mostly adopts maximum pooling to maintain the efficiency of feature extraction [11]. After the convolution core pooling operation, CNN needs to integrate advanced features to obtain higher logical classification and
differentiated local information through the integration network. In CNN, the neural network between adjacent layers corresponds to the relationship between input and output. Besides, the parameter relationship between weight and bias, there is a certain functional relationship between them. This function is the activation function.

The activation function changes the relationship between input and output and can replace the linear relationship with a relationship that approximates any function, making CNN more expressive.

In calculating the model, the selection of the algorithm is also the key point. The gradient descent method is commonly used, which is a common method for solving unconstrained optimization problems. In-depth learning, in order to make the feature parameters better fit the image features and minimize the loss function, the gradient descent method is used to calculate the weight parameters and offset parameters [12]. The gradient descent method is an iterative method that needs to solve the iterative vector of each step, as shown in Eq. (1):

$$E(w_{t+1}) = E(w_t + \eta \nu) \approx E(w_t) + \nabla E(w_t) \eta \nu$$  (1)

In Eq. (1), \(w\) is the weight parameter, and \(E\) is the first-order Taylor expansion. \(\eta\) is the step length. \(\nu\) is the position. \(w_t\) is the parameter before update. \(w_{t+1}\) is the updated parameter. In the process of gradient descent, the step size value affects convergence speed. Ideally, the larger step is taken when the extreme value is far away, and the smaller step is taken when approaching the extreme value. By setting the step, the convergence speed is accelerated. The update is shown in Eq. (2):

$$w_{t+1} \approx w_t + \frac{1}{N} \sum_{n=1}^{N} \theta(-y_n w^T \xi_n) (y_n - x_n)$$  (2)

In Eq. (2), \(x_n\) and \(y_n\) are the parameter used to obtain the gradient. \(\theta\) is the minimum value of the loss function. \(N\) is the number of iterations. \(w_t^2\) is the variable parameter. The advantage of the random gradient descent method is that only one data is used for each parameter update, and it does not need to traverse all training sets. The random gradient descent method transforms one parameter at a time and completes a linear convergence under certain conditions. Because only one sample is used to update the gradient direction, the solution is not necessarily the optimal local solution, but the advantage of random gradient descent is more obvious.

### 2.2 Target Detection Algorithm and Data Analysis

Target detection is to accurately find the object’s position in the image scene in the given image and mark the category of the object. When used in the power metering management system, it is mainly used to visualize the electricity consumption or to label the power grid to ensure the safety of the power grid. The traditional detection algorithm follows the idea of "design manual features + classifier". It searches the area by designing the detection frame, scales, and slides in the image area through the rectangular window set by the computer. It uses the classifier to predict whether there is a target object in the area where the current sliding window is located [13]. The traditional detection algorithm is subject to manual features and cannot reflect the characteristics of the image well. In the target detection algorithm, the sliding window size is random due to the uncertainty of the candidate region, resulting in many redundant calculations. The experiment shows that the image features trained by convolution neural network perform better than the manually designed features in all aspects of detection. So, researchers have done a lot of in-depth research on applying convolution neural networks to image detection methods [14].

Regions with CNN (R-CNN) is a multi-category image classification algorithm. The detection of targets in the image is mainly divided into three steps. Firstly, the selective search algorithm is used to extract image information to obtain the preliminary target detection region, the second is to convolution each candidate region, and the last is Support Vector Machine (SVM) classification and candidate box regression [15]. After candidate frame regression and SVM classifier for target identification, the previously obtained target frame is used after translation and scaling to adjust. At this time, the target frame of each category obtained is not unique. Generally, the average value of the coordinate values of all target frames is taken as the final region recommendation. Although the R-CNN model has completed the target recognition and positioning task, it provides CNN ideas for target recognition and positioning. However, the Selective Search algorithm of this model extracts 2000 proposal regions for an image. Each region relates to 4096-dimensional neurons in the fully connected layer. If the experiment is trained on 1000 images, one feature parameter takes up 4 bytes in the computer system, and the file size of all feature parameters is at the TB level. In image recognition, it is very inefficient for the network to carry out many convolution calculations, which makes the training and detection occupy a lot of computer resources and consume a longer time [16]. In addition, the
proposed image of the region input by the R-CNN algorithm into the CNN network is to be translated and scaled, resulting in image distortion and feature distortion of network training. Finally, the features of R-CNN in SVM classification and border regression have not been updated by network learning and cannot achieve good results [17]. Therefore, the convolution neural network based on Region of Interest (ROI) pooling has been improved based on R-CNN. The specific process is shown in Figure 4:

Images of any size are input. Additionally, the Selective Search algorithm is used to select candidate regions, and the CNN algorithm is used to select the features of the target image. The candidate regions are mapped to the features of the last layer of CNN. After pooling, feature maps of fixed size are generated. Finally, Softmax and the frame regression classification probability and target detection frame are jointly trained. This optimization mode has some disadvantages for CNN, such as the inability to realize end-to-end real-time applications and training tests. Therefore, Region Proposal Networks (RPN) are also considered to optimize CNN. The specific structure is shown in Figure 5:

Figure 4: CNN flowchart based on ROI pooling

Figure 5: Structure diagram of optimized neural network (a) RPN network; (b) RPN network integrated into CNN
The improved method mainly uses the output of the last convolution layer as the input of the RPN network. This output can be an image of any size. Then, two convolution layers are used to complete the feature extraction. The result is used as the input of the border extraction. The output of the RPN is a group of target region recommendations and the detection score of whether the target region is the corresponding category of objects. ROI pooling needs to calculate the real area of a target in the proposed rectangle and image. If the intersection ratio of the two regions exceeds the set threshold upper limit value, the rectangular box will be used as a positive sample. Suppose the intersection ratio is less than the lower limit of the set threshold. In that case, the region of the rectangle is suggested to be added as a negative sample to the subsequent training. If the intersection ratio is between the upper and the lower limit, the suggestion in the rectangular box area will be removed so that it will not participate in the subsequent network training. In practical application, the upper and lower limit of the proposed intersection ratio in the RPN area can be adjusted according to the actual effect.

2.3 Analysis Algorithm Improvement based on Transfer Learning

Transfer learning is using the knowledge learned from one environment to help the learning task in the new environment [18]. It mainly solves the over-fitting problem in the convolution network and improves the generalization ability and expansibility of the network. The convolution network can fit the training data well by using many convolutions of nuclear energy and even achieve a loss function of 0. However, this situation often leads to the unsatisfactory performance of the trained network structure in the test set. If some training data do not meet the requirements in the data set, the convolution network can completely fit these data through parameters. Then, the trained network can easily deviate from the actual results. On the other hand, the random gradient descent method is often used in the training and backpropagation of DNN. Too many neural network parameters will also lead to the problem of gradient disappearance or gradient explosion. By transferring some trained network parameters to another network, migration learning can quickly fit the training set, improve the convergence speed, and reduce the computational load.

According to the realization of technology and transfer learning methods, there are several methods. Firstly, in example-based transfer learning, sample transfer is to extract part of the data from task A and train it with other data suitable for task B. Secondly, similar neural networks are used to identify parameters in feature-based transfer learning. After that, the dataset is added to train the network for the desired recognition. Again, model-based transfer learning has many practical use cases. New assistive features can be added depending on experimental requirements. However, transfer learning generally saves development time and computing resources for learning, and can achieve the same or even better detection and analysis results. Finally, in correlation-based transfer learning, the relationships between things can be extrapolated to similar things. It can be applied in natural language processing and other machine learning fields with specific rules and can also be extended to machine understanding of more words [19].

There are many types of transfer learning. According to the source and target, transfer learning can be divided into inductive, direct, and unsupervised. According to the specific task method, transfer learning can also be divided into classification regression and cluster dimension reduction. How to properly select the types of transfer learning according to the target environment and data set is the focus of much research work in the academic field. Transfer learning is not mature in the practical application field, which is a big proposition. The conditions and nature of transfer learning have not yet formed a set of orthodox systems to lead the research direction, and more are groping in experiments. The goal of transfer learning is to improve the task effect of the target area, in which negative transfer is a problem many researchers face. How to effectively improve and avoid negative transfer needs to be weighed and evaluated. Inspired by migration learning, this chapter uses the existing network weights to initialize the network model and retrains the training set of the tasks to be classified. The strategy of using model transfer is used to achieve deep features suitable for the task to be classified. In the aspect of image information features, extracting feature expression from the pre-trained network structure can make the required network have good discrimination ability and generalization characteristics and improve the recognition ability.

In applying to the network structure, the main purpose is to reduce the number of parameters. The improved structure is shown in Figure 6:
Since the CNN based on RPN adopts two 4096-dimensional full connection layers after ROI pooling (7*7*512 pooling), resulting in more network parameters of the whole network, and network parameters occupy a large part of the entire algorithm space. Suppose the network parameters can be properly reduced. In that case, it can greatly save storage space and speed up the training of network parameters, so the convolutional layer adopts the Visual Geometry Group 16 (VGG-16) model. The convolution and pooling layers can be divided into five different blocks. Each block contains several convolution and pooling layers and is finally wrapped by three layers of full connectivity.

After determining the model, in order to get better classification results, different categories should be separated to minimize the distance within the category. Center Loss can increase the distance between classes and reduce the distance within classes. Based on Softmax Loss classification, Center Loss maintains a class center for each classification. During training, the experiment gradually reduces the distance between class members and the center and increases the distance between other class members and the center.

3. Experimental Environment and Dataset

The chosen environment for this paper is as follows: the processor model is Inter(R) Xeon(R) CPU E5-2620 v4 @ 2.10GHz, the graphics processing unit model is NVIDIA Titan Xp 12GB, the memory is 128GB, and the operating system is Ubuntu 16.04 LTS. In order to ensure the accuracy of the experiments, the parameters are uniformly set. In the experiment comparing the detection rates of CNN-optimized models and traditional models, the learning rate is set to 0.0002, the maximum iteration position is 2,000, and the overall sample minimum error is 0.001. In the experiment comparing detection rates of different types of recognizers, the learning rate is 0.02, the maximum iteration position is 1,000, and the overall sample minimum error is 0.01.

The chosen dataset for the experiment is the Canadian Institute for Advanced Research - 10 classes (CIFAR-10) dataset, widely used for image classification. It is favored by researchers for its diverse categories and high-quality images. The dataset comprises 60,000 32x32 pixel color images from 10 different categories, with each category containing 6,000 images.
These images are divided into a training set (50,000 images) and a test set (10,000 images). CIFAR-10 serves as a common benchmark dataset for testing and validating image classification algorithms. The dataset can be downloaded from the official website (https://www.cs.toronto.edu/~kriz/cifar.html). The software used to build the model in this paper is TensorFlow, an open-source machine learning framework that provides rich tools for creating and training neural network models. CNN models can be constructed and optimized using Python or other supported programming languages through TensorFlow.

4. Experimental Results of CNN Model Optimization for Data Analysis in Electric Energy Metering Management System

4.1 Comparative Experimental Results and Analysis of Detection Rate between CNN Optimized and Traditional Models

The Receiver Operating Characteristic Curve (ROC) of the results of the two optimization and traditional models is shown in Figure 7:

![Figure 7: ROC curve (a) Comparison between ROI model and traditional model; (b) Comparison between RPN model and traditional model](image)

In Figure 7, the convolution neural network based on RPN is superior to the convolution neural network based on ROI pooling, mainly because the convolution neural network based on RPN network uses more network layers. So, its performance is more advantageous. With the increase of the False Positive Per Image (FPPI) value, the detection rate of CNN based on RPN increases faster than that of CNN based on the ROI network. The result verifies the advantages of the RPN-CNN model.

4.2 Comparative Experimental Results of Detection Rates of Different Types of Recognizers

RPN-CNN and the traditional model compare the detection rate in two systems.

The experimental results are shown in Figure 8:

![Figure 8: Comparison of detection rates in different systems (a) Comparison with traditional system 1; (b) Comparison with traditional system 2](image)
In Figure 8, in System 1, the maximum difference in detection rate is 0.2. In System 2, the maximum difference in detection rate is 0.12. The detection rate of the RPN-CNN model is higher than that of the traditional model. In the slope comparison of curves, the stability of RPN-CNN is better than that of the traditional model. The feature migration of the RPN-CNN model makes the target detector obtain better underlying features and has more advantages in recognition effect. The network adjustment and the improvement of the loss function make the target detector more robust. It also shows the importance of network adjustment, underlying features, and loss function in model optimization.

5. Conclusions

Convolution neural network algorithm has been applied in various fields. The electric energy metering management system is a more widely used field. Image data processing and power information analysis are inseparable from convolution neural network algorithms. The convolution neural network algorithm is optimized to improve the data analysis ability of the power metering management system. Firstly, the structure and composition of the convolution neural network are introduced. The convolution layer is analyzed. Secondly, the object detection algorithm is illustrated. The current stage of the development of object detection algorithms and their shortcomings are described. CNN is optimized. Thirdly, transfer learning is introduced into the model. The adjustment of network parameters can increase the detection rate of the model. Finally, the effectiveness and feasibility of the model are verified through comparative experiments.

The experimental results show that the two optimization methods have improved the traditional model, and the detection rate is higher than the traditional model. The convolution neural network based on the RPN network is better than the convolution neural network based on ROI pooling. The second experiment is to introduce the migration model into the RPN-CNN and conduct simulation experiments in different power metering management systems. The maximum difference in detection rate in system 1 is 0.2, and the maximum difference in system 2 is 0.12, which verifies the model's reliability in this paper. By comparing the slope of the curve, the stability of the RPN-CNN model is better than that of the traditional model.

There are also many deficiencies in this paper. At present, the improvement of network recognition in deep learning depends on small convolution kernels instead of large ones. This method not only deepens the depth of the network but also improves the recognition rate of the network. The future research direction can be studied in improving the network width and the recognition rate of the network. On the other hand, most of the current experiments are implemented on the software framework of the computer. How to apply the model trained in the computer to the power metering management system is the main development direction at present. How to effectively reduce the characteristic parameters of the network and make the network more suitable for the power metering management system is the prospect.

References


