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Electric Theft Detection Method based on WGAN and WDNN

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Abstract

The majority of electricity theft detection methods focus on the application of shallow machine learning models, these shallow-architecture classifiers have weak generalization ability, resulting in poor detection accuracy. At the same time, the inherent imbalance of electricity theft detection data also affect the performance of electricity theft detection methods. This paper establishes a electricity theft detection model based on Wasserstein-Generative Adversarial Network (WGAN) and Wide and Deep Convolutional Neural Network (WDNN),which can combine the learning ability of WDNN and the data augmentation ability of WGAN. Firstly, through the confrontation training of the WGAN generator and discriminator, a synthetic electricity theft sample with a similar distribution to the real one is generated. Secondly, Wide Neural Network (WNN) and Deep Neural Network (DNN) are combined to enhance the recognition and memory of related features. This model is tested on actual data provided by a power company, and compared with multiple detection models, verifying it has better accuracy and effectiveness.

Keywords

Electricity Theft Detection; Data Imbalance; Generative Adversarial Network; Wide and Deep Convolutional Neural Networks.

1. Introduction

Electricity theft will not only damage the economic interests of the power industry, but also cause the load of the distribution network to be greater than the expected load in actual operation, bringing potential risks to the power grid [1,2]. Therefore, it is of great significance to study how to improve the detection effect of electricity stealing [3,4]. The application of advanced electricity stealing detection methods can further conduct more accurate positioning and more detailed behavior analysis of abnormal power users. Data-driven electricity stealing detection methods show broad application prospects [5]. Currently, machine learning algorithms such as decision tree [6], artificial neural network [7], support vector machine [8], and XGBoost [9] are widely used in electricity theft detection.

Data-driven electricity theft detection suffers from severe class imbalance problem [10]. In practice, the number of normal users in the electricity theft data is much larger than the number of abnormal users, and the imbalance of the data will affect the performance of the electricity theft detection method [11-13]. Reference [11] proposes a real-valued deep belief network-based detection method for user-side electricity stealing behavior. The model uses factor analysis to reduce data dimensionality, and uses random undersampling and lasso algorithm to deal with the problem of data imbalance. Reference [12] proposes a power stealing detection method based on random oversampling and undersampling technology, which randomly undersamples and oversamples normal users and power stealing users, respectively, to solve

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the problem of class imbalance in power stealing data. Reference [13] proposed to use an improved Wasserstein generative adversarial network model for oversampling of electricity stealing load sequences, increasing the number of minority samples to reduce the imbalance of electricity stealing data.

Most of the existing research on electricity stealing detection methods focus on the application of shallow machine learning techniques. Shallow techniques include support vector machines and other shallow neural networks based on handcrafted features. These shallow machine learning methods cannot handle high-dimensional data and cannot extract deep features, which will affect the detection accuracy. With the rise of deep learning concepts, various types of deep neural network models have also been introduced into electricity stealing data analysis [14-16]. Reference [14] proposed a method of electricity stealing detection based on deep bidirectional recurrent neural network, combining deep recurrent neural network and bidirectional recurrent neural network, and learning electricity representation through carefully designed recurrent neural network, so as to capture electricity stealing data. Deep information. Reference [15] proposed a method for electricity stealing detection based on ensemble deep convolutional neural networks, using random bagging technique in the first layer of the model to deal with imbalanced data. Reference [16] proposed an electricity stealing detection method based on the WDNN model, which combined wide neural network and deep neural network to process electricity stealing detection data.

The WDNN model is a deep learning model proposed by Google in 2016 [17]. This model combines the advantages of wide neural network and deep neural network, and can use both artificially selected features and deep features learned by the network to improve the performance of neural networks. Model classification accuracy. In the literature [16], the WDNN model is used to synthesize the memory ability of the shallow model and the generalization ability of the deep model, the wide neural network is used to learn the global features of the one-dimensional electricity consumption data, and the deep neural network is based on the two-dimensional electricity consumption data. Identify the aperiodicity of electricity theft data and the periodicity of normal electricity consumption.

Generative adversarial network [18] (generative adversarial network, GAN) is a generative model and an emerging method of data synthesis [19, 20]. The Wasserstein generative adversarial network model is an improvement on the generative adversarial network model, which has been applied to class imbalance problems.

In [13], the author proposed to use a generative adversarial network model for electricity stealing detection. The main idea is to augment the electricity stealing detection data through the WGAN model, thereby enhancing the electricity stealing detection data set. The WGAN model is trained against the generator and the discriminator, and the model training is completed when their mutual games reach the Nash equilibrium. Finally, the author uses convolutional neural network for feature extraction and classification. The experiment proves that this method can effectively solve the imbalance problem in the original electricity stealing data. However, in this method, the model is designed as a shallow network, which is prone to over-generalization, which will affect the accuracy of electricity theft detection.

This paper proposes a deep learning electricity stealing detection model based on WGAN-WDNN, and conducts electricity stealing detection experiments on this basis. The model can have both the learning ability of deep neural network and the data generation ability of generative adversarial network model, so it can better solve the problems of data imbalance and model over-generalization in the process of electricity stealing detection. Finally, the experimental test is carried out on the real data provided by a power company, and the simulation results fully prove the accuracy and practicability of the method proposed in this paper.

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2. Methodology

2.1. Generative Adversarial Networks

The generative adversarial network model consists of a generator and a discriminator. The generator generates new samples by learning the potential distribution of the original data samples; the discriminator is used to determine whether its input belongs to the real sample or the sample generated by the generator. The overall training process of GAN is a game problem. The objective function of the training process is as follows:

$$\min_G \max_D E_{\boldsymbol{x}\sim P_r}[D(\boldsymbol{x})] - E_{\boldsymbol{z}\sim P_z}[D(G(\boldsymbol{z})] \tag{1}$$

The training of GANs involves the adversarial training of the generator and the discriminator, but the training process is unstable and is likely to suffer from mode collapse problems. In order to solve the training defects of traditional GAN, WGAN chooses the Wasserstein distance to replace the JS distance of traditional GAN, and uses the Wasserstein distance to measure the gap between the generator's generated samples and the distribution of real samples, so that it is easier to obtain high-quality generated electricity stealing samples. The optimization function is:

$$\max_{w\in W} E_{x\sim P_r}[f_w(x)] - E_{z\sim P_{(z)}}[f_w(g_\theta(z)] \tag{2}$$

2.2. Width-deep Neural Networks

In 2016, Google proposed a wide-deep neural network model (WDNN) for the APP recommendation service of the Google store. The improvement of this WDNN model is: the model includes two parts: Wide module and Deep module. On this basis, a Wide model (linear model) is jointly trained, and the two models make classification decisions on the data at the same time.

The Deep model has good generalization ability. It can not only integrate some hidden feature attributes, but also discover or associate some feature combinations that have rarely appeared before, which greatly reduces the complexity of feature engineering. In the DNN network model, the input layer is each feature of the input data, and each hidden layer node is composed of an activation function. In order to overcome the problems of gradient disappearance, the default function of the DNN model is rectified linear unit Relu, and the function is defined as:

$$\mathrm{g(z)} = \max\{0, \mathrm{z}\} \tag{3}$$

The output layer of the multi-classification model is mostly a Softmax function in the form:

$$\mathrm{f}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_i)} \tag{4}$$

The overall function expression of the DNN model is:

$$\mathrm{f(x; W, c, w, b)} = w^T \max(0, W^T x + c) + b \tag{5}$$

The algorithm construction of the DNN model is mainly composed of the above functions. Function 3 defines the Relu function. The Relu function is the activation function of the hidden layer node and is used for nonlinear fitting of features. Connection and full connection; function 4 defines the Softmax function, which is a multi-classification function used to build the output layer of the deep learning model; function 5 is the mathematical representation of the feature after a hidden layer, that is, the output of the previous layer is After the Relu function performs nonlinear changes, it is passed to the next layer. The increase in the depth of the model is the multi-level nesting of the expression.

Due to the limitation of the structure of the DNN model and the influence of the network characteristics, the DNN model cannot correlate the strong coupling between features and is not easy to deal with sparse features. Therefore, when the input data includes association and sparse data, the DNN model cannot accurately optimize the parameters of association features. So a Wide model is trained on the basis of the DNN deep learning model.

The Wide model is good at dealing with sparse features. It only needs fewer model parameters, and it can memorize the correlation between features by cross-producting the features, and is good at dealing with fixed combinations between features. The mathematical model of the Wide network is expressed as:

$$y = W^T + b \tag{6}$$

Among them, $X = (x_1, x_2, \dots, x_n)$,$W = (w_1, w_2, \dots, w_n)$, X is the feature vector, W is the network model parameter, b is the bias of the model, and y is the Wide network output.

The WDNN model is an integrated model that combines the Wide module and the Deep model. After merging the two models, it not only maintains the good generalization ability of the deep network, but also strengthens the model's recognition and memory of associated features.

2.3. Electricity Stealing Detection Method based on WGAN-WDNN

In [13], the author uses a generative adversarial network model for oversampling of electricity stealing load sequences, and generates synthetic samples with a similar distribution to the original electricity stealing samples through adversarial training between the WGAN generator and the discriminator. Finally, the convolutional neural network is used for feature extraction and classification. This method effectively solves the problem of data imbalance in the process of electricity stealing detection. However, the classification model has the problem of easy over-generalization, which will affect the accuracy of electricity stealing detection.

The WDNN model combines a wide neural network WNN and a deep neural network DNN. The WNN model is a linear model, and a cross-product transformation is added to the linear model to capture the co-occurrence between features. Combining the linear model with the neural network can give full play to the advantages of the memory feature of the linear model and the strong generalization ability of the neural network. After combining with the DNN model, the performance can be further improved on the basis of the existing better performance of the deep model, which can effectively solve the problem of over-generalization of the model.

In this paper, the WDNN network is used for feature extraction and classification. At the same time, the wide neural network WNN and the deep neural network DNN are combined. The DNN network uses a two-dimensional convolution layer to extract periodic features from the input two-dimensional electricity stealing detection data for accurate identification. Aperiodicity of electricity theft data and periodicity of normal electricity consumption. One-dimensional electricity stealing data is time series data, and the WNN model can accurately learn the global features of one-dimensional electricity stealing data. At the same time, combining the advantages of the WNN model and the DNN model, the two parts are weighted and summed to obtain the final output, which can effectively improve the accuracy of electricity theft detection.

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This model draws on the information extraction method of the WDNN model for input features, and changes the embedding layer used to convert the text input data of the recommendation system into vectors to a fully connected layer for information fusion of input data; at the same time, the WGAN module is added. , which is used for data enhancement of electricity stealing data. In addition, the activation function of the output layer of the WDNN model is changed to Relu, so that the model can handle the electricity stealing detection and classification problem. Finally, the generated data is combined with the original data into an augmented training set, which is trained using the WDNN network model on the augmented training set synthesized during the WGAN training process.

In order to solve the data imbalance problem in electricity stealing detection, this paper firstly uses WGAN for oversampling of electricity stealing load sequence. A few samples of electricity stealing are used as real samples in WGAN, and then synthetic samples with distribution similar to the original samples are generated. The generation model and the discriminant model of the WGAN model use the training method of cross confrontation. When the game between the generator and the discriminator reaches the Nash equilibrium, the Wasserstein distance between the original electricity stealing data distribution and the generated data distribution also approaches 0. At this time, the entire WGAN model training is complete. The synthetic electricity stealing data is used for the augmentation of the original training set, and the WDNN classification model is used to train on the augmented training set.

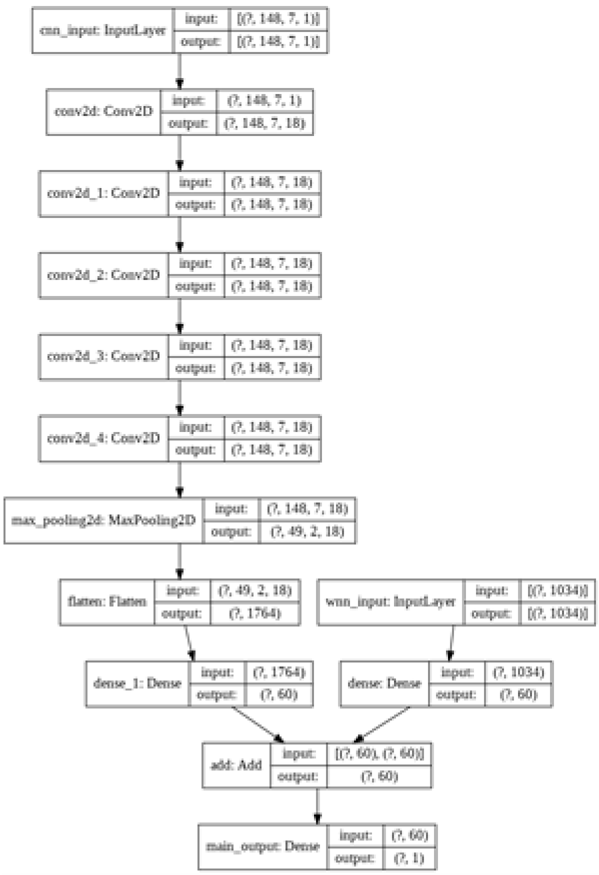

Figure 1. Network structure of WDNN model

After the electricity stealing detection data is enhanced, the WDNN model is built. This framework consists of the WNN model and the DNN model. The first layer is the input layer, whose input is the one-dimensional time series electricity stealing detection data and the two-dimensional electricity stealing detection data after data conversion. The one-dimensional electricity stealing detection data is input into the WNN network, and the two-dimensional

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electricity stealing detection data is input into the DNN network. In the last layer, the WDNN model combines the outputs of the WNN and DNN models. Because this article uses a functional API, the inputs to WNNs and CNNs can be defined as specific tensor dimensions, respectively. The network structure of the WDNN model is shown in Figure 1.

WNN networks are fully connected layers that learn global knowledge from one-dimensional electricity theft detection data. The electricity consumption of a customer is essentially one-dimensional time series data, and WNN memorizes the one-dimensional time series data.to learn common patterns of features. Convert the one-dimensional electricity consumption data to two-dimensional data according to the number of weeks, and the DNN model processes the electricity consumption in a two-dimensional manner volume data. The DNN model consists of multiple convolutional layers, pooling layers and fully connected layers. Flatten layers are used to "flatten" the input for the transition from convolutional to fully connected layers. The Add layer is a fully connected layer, which splices the weights of the WNN model and the DNN model, and is used as parameter training during network backpropagation. This paper uses Relu as the activation function, which can effectively prevent overfitting.

Finally, through data processing and feature engineering, the dataset is divided into three parts: training set, validation set and test set. The weight of each neuron of the WGAN-WDNN model is trained through the training set, and the model effect is continuously updated iteratively by evaluating the performance of the AUC and other evaluation indicators in the validation set, so as to obtain the optimal model. Finally, the optimal model obtained by training is used to make predictions and output the prediction results.

3. Results and Discussion

3.1. Data Preprocessing

In this paper, the experimental graphics card is 1080ti, the running memory is 8G, the deep learning framework is TensorFlow and Keras, and the software environment is Windows 10 operating system. The experimental data comes from real scenarios, and the dataset is provided by [19], which records the daily electricity consumption of 42,372 power users in 1035 days (January 1, 2014 to October 31, 2016).

Since the experimental data comes from real scenarios, the electricity consumption of a large number of users in a long period of time is recorded, and there are some missing and incorrect information. For missing values, the interpolation method is used to process the missing data, and the specific operation is shown in the following formula (7). Among them, x_i represents the electricity consumption data of a certain day. If x_i is empty or a non-numeric character, this document represents it as Nan.

$$f(x_i)=\begin{cases}\frac{x_{i-1}+x_{i+1}}{2} & x_i\in \mathrm{NAN}, x_{i-1}, x_{i+1}\notin \mathrm{NAN}\\ 0 & x_i\in \mathrm{NAN}, x_{i-1}\ or\ x_{i+1}\notin \mathrm{NAN}\\ x_i & x_i\notin \mathrm{NAN}\end{cases} \tag{7}$$

For the wrong power consumption records in the power consumption load sequence, the 3σ principle is used to correct, and the correction method is as follows:

$$f(x_i)=\min\big(x_i, \mathrm{mean}(\boldsymbol{x})+3\mathrm{std}(\boldsymbol{x})\big) \tag{8}$$

Where x represents the electricity load sequence of a user, and$x_i$represents the electricity consumption in x.In order to ensure the stable training of the generative adversarial network

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model WGAN, the normalization operation is required for the electricity load sequence that completes the processing of missing values and outliers. The normalization method in this paper is as follows:

$$f(x_i) = \frac{x_i - \min(\boldsymbol{x})}{\max(\boldsymbol{x}) - \min(\boldsymbol{x})} \tag{9}$$

3.2. Evaluation Indicators

Considering the imbalance of the sample ratio between normal users and abnormal users in the electricity theft detection problem, it is unreasonable to use the accuracy rate as the evaluation index. This paper uses the confusion matrix shown in Table 1 to evaluate the model performance.

Table 1. Confusion matrix applied in electricity theft detection

User category	Detect abnormal users	Detect normal users
Actual abnormal user	TP	FN
Actual normal user	FP	TN

This paper divides all power users into 4 categories:T_P,F_P,T_N, andF_N. Based on the confusion matrix, a variety of evaluation indicators that are more suitable for the electricity theft detection problem can be generated. The detection rate T_{PR}, the false detection rate $F_{NR}$and $F_1$are selected as the evaluation of the detection results, which are defined as T_{PR}=$T_P/(T_P$+$F_N)$, F_{NR}=$F_P/(T_N$+FP), F_1=2$T_P/(2T_P$+ F_N+FP).

In addition, this paper selects AUC as the evaluation index. AUC is the area under the curve. When comparing different classification models, the RUC curve of each model can be drawn, and the area under the curve can be compared as an indicator of the pros and cons of the model. AUC is also a good evaluation index in the electricity stealing detection problem, which can reflect the comprehensive ability of the detection model to classify normal users and abnormal users, and is used to synthesize electricity stealing samples and evaluate the final detection results. The AUC calculation formula is as follows:

$$\text{AUC} = \frac{\sum_{i \in positiveClass} Rank_i - \frac{M(1+M)}{2}}{M \times N} \tag{10}$$

3.3. Comparison of Data Synthesis Methods

3.3.1. WAGN Network Structure Analysis

In the experiment, both the generation network and the discriminant network are four-layer fully connected neural networks. The generation network includes two hidden layers, each with 256 neurons, the activation function takes the Relu function, the number of neurons in the output layer is consistent with the dimension of the electricity stealing data, 1034, and the activation function selects sigmoid; the two hidden layers in the discriminant network The number of neurons in the layer is 256 and 128 respectively, and the activation function selects the LeakyRelu function.

3.3.2. WDNN Network Structure Parameter Analysis

The WNN network consists of a densely connected hidden layer with 60 neurons. The multi-convolutional layer uses Relu as the activation function, and uses filters with the same receptive field size to perform convolution operations on the input two-dimensional data. This paper uses γ as a parameter that controls the number of filters in the convolutional layer. The value of γ is adjusted from 1 to 20 on the validation set, and the value of γ is selected to maximize the AUC value. Through experiments, the AUC increases with the increase of the γ value at the beginning, and when the γ exceeds a certain threshold, the AUC decreases. When γ=18, AUC takes the maximum value. So each convolutional layer consists of 18 filters that work independently, and when the input two-dimensional data passes through the filters, the convolution operation is performed.

3.3.3. Ablation Experiment

This paper uses the CNN model, the WDNN model and the GAN-CNN model to make predictions, and compares with the method proposed in this paper. The comparison is shown in Table 2.

Table 2. Comparison of test model effect

model	F1	Precision	Recall	AUC	Map
CNN	0.9453	0.9394	0.9513	0.7631	0.7740
WDNN	0.9462	0.9320	0.9563	0.8000	0.9023
GAN-CNN	0.9323	0.9490	0.9062	0.8132	0.8722
GAN-WDNN	0.9651	0.9420	0.9656	0.8211	0.9563

(1) To explore whether WGAN plays a substantial role, one group of experiments uses WGAN to generate augmented training sets for comparison, and the other group does not use WGAN and trains directly on the original training set after data processing. From the data in Table 4, it can be seen that on the CNN model, the AUC index of the model using WGAN for data augmentation has a small improvement, which indicates that the electricity stealing samples synthesized by WGAN have a high correlation with the real electricity stealing samples, which effectively improves the model's performance. Ability to predict.

(2) To explore whether the WDNN model plays a substantial role, one group of experiments uses the WGAN-WDNN model, as a comparison, the other group uses the WGAN-CNN model. The augmented training set generated by the generative adversarial network is trained on the convolutional neural network and the wide-deep neural network respectively. According to the data in Table 5, compared with the WGAN-CNN model, the AUC index of the WGAN-WDNN model is slightly improved. , which shows that the comprehensive effect of the WGAN model and the WDNN model is good, and it has both the characteristics of the WDNN model and the WGAN model, and can well express the electricity stealing detection data with time series characteristics.

(3) Explore whether the WGAN-WDNN model plays a substantial role. By comparing the effects of CNN and WGAN-WDNN models, the AUC index has a small improvement, which can effectively prove that combining generative adversarial networks and Width-deep neural networks, and training the WDNN classification model on the augmented training set synthesized by WGAN, can A higher predictive power of the overall model is obtained.

4. Conclusion

This paper proposes a method of electricity stealing detection based on generative adversarial network and wide-deep neural network. The WGAN model is used to generate samples that conform to the distribution of the original electricity stealing data to enhance the original data. DNN can accurately identify the aperiodicity of electricity theft data and the periodicity of normal electricity consumption based on the two-dimensional electricity theft detection data. Meanwhile, WNN can capture the global features of one-dimensional electricity stealing data. Experimental results show that the WGAN-WDNN model can achieve excellent performance in electricity theft detection. The approach is entirely data-driven and requires no elaborate modeling process. Based on the real data provided by a power distribution company, the experimental test is carried out, and the following conclusions are drawn.

(1) Through the adversarial training method, the distribution of real electricity stealing samples can be effectively approximated, and synthetic samples that conform to the fluctuation law of the original electricity stealing load sequence can be generated. This method can effectively solve the imbalance problem in the original data.

(2) In the WDNN model, the neural network is used as the depth model, and the linear model is used as the width model. The two parts are weighted and summed to obtain the final output. During the training process, the parameters of the WNN model and the DNN model are optimized at the same time, thereby improving the prediction ability of the overall model. Electricity theft in smart grids can be effectively detected.

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