Image Steganalysis Method Based On Improved Smote And Focal Loss Algorithm

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Abstract

Aiming at the performance degradation of steganalysis model caused by unbalanced sample data set training, a model design method based on improved SMOTE algorithm and Focal loss algorithm is proposed. The improved SMOTE algorithm is used to synthesize new samples to balance the data set. At the same time, the Focal loss algorithm is introduced to pay more attention to the difficult samples and optimize the training process of the model. In the simulation test of the model on BOSSbase1.01 data set, under the training of the unbalanced sample set, the detection rate is significantly higher than the similar Zhu-Net method, and the average detection rate is increased by 0.9%, up to 1.9%. This proves the effectiveness of this method and improves the accuracy of model detection.

Key words: *Image steganalysis; Unbalanced sample; Oversampling; SMOTE algorithm; Focal loss algorithm.*

1. Introduction

In recent years, steganography, which hides information transmission behavior, has attracted more and more attention. It realizes the security of information by hiding the existence of information transmission behavior. It has been widely used in the field of digital multimedia security protection and secure communication [19]. However, with the development and promotion of steganography technology, while providing guarantee for people's communication security, it is also used by criminals to obtain personal interests or even applied to attacks. For example, in the "omnipotent cult" incident in 2011, the use of steganography for secret communication endangers social security [2]. Because of this, steganalysis, as a countermeasure technology against steganalysis algorithm, has gradually attracted the attention of the government and scientific research institutions. Steganalysis can extract and analyze some features of the carrier to determine whether there is hidden additional information in the carrier, and then intercept the suspicious target. The development of steganalysis is of great significance to prevent the disclosure of confidential information, combat criminal activities and maintain Internet Security [22].

With the development of steganalysis technology, steganalysis technology has gradually transformed from the analysis stage using empirical design features to classification using deep learning, and the detection rate of steganalysis has also been improved to a certain extent. In the research of deep learning, a widely concerned problem is the imbalance of samples [23], which also exists in the image steganalysis model designed by deep learning. In previous studies, some specific statistical features are generally extracted by neural network to distinguish steganographic images from normal images [15][16][17][20][21]. Although these algorithms can accurately classify steganographic images, most algorithms assume that the training data set can obey the ideal sample distribution, that is, there is no significant difference between the proportion of steganographic images and normal images in the sample [3]. However, in real samples, normal images are far more than steganographic images. When these steganalysis models are trained with unbalanced samples, the model is easy to be controlled by most classes of samples, thus greatly reducing the performance of the model [8].

In practical application, the false negative and false positive probabilities of most models are basically the same, but misclassifying a steganographic image is more expensive than misclassifying a normal image, because misclassifying the steganographic image will lead to the transmission of secret information to each other, resulting in great loss [10], so we should pay more attention to the

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characteristic information of the steganographic image with less samples.

Aiming at the problem of sample imbalance in steganalysis, this paper improves smote oversampling algorithm then proposes an oversampling method for unbalanced samples of gray image. This method is used to oversample relatively few steganographic image samples, so as to improve the class distribution of samples. At the same time, the influence of sample imbalance is reduced by modifying the traditional cross entropy. Based on the focal loss algorithm [12] proposed by he Kaiming's team, the training process of convolutional neural network is optimized, a steganalysis algorithm based on cost sensitive convolutional neural network is proposed, which pays attention to the differences between categories and within categories at the same time, and the F-1 value is introduced as the performance index of steganalysis sample imbalance, so as to make the evaluation standard more reasonable.

2. Theoretical basis

2.1. SMOTE algorithm

In recent years, the research on unbalanced data classification has attracted extensive attention. There are many ways to deal with unbalanced samples. He et al.[6] divided these different methods into the following four categories: sampling method, cost sensitive learning method, kernel based method and active learning method. Among them, the only method that can change the distribution of sample categories is the sampling method. The most famous is smote [1] algorithm. The basic idea of smote is to analyze relatively few samples and synthesize new samples according to relatively few samples to add to the data set. The principle of this method is as follows:

(1) In a small sample S_{min}, for each sample $x_i \in S_{min}$, look for k neighbors of the surrounding minority samples based on Euclidean distance.

(2) The k near neighbors are written as $y_1, y_2, \cdots, y_k$, from which a sample y_i is arbitrarily selected.

(3) The synthesized new sample S_i is obtained by interpolation between x_i and y_i, as shown in formula (1):

$$s_i = x_i + rand\ (0,1) \times (y_i - x_i) \qquad (1)$$

where rand(0,1) is a random number between [0,1].

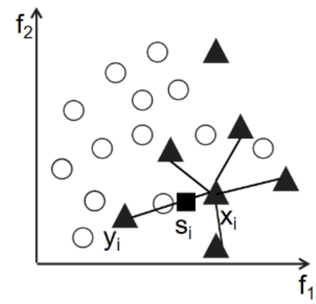


Figure 1: SMOTE example

Smote synthesizes new samples by interpolation between two nearest neighbor minority classes, expands the sample space of minority classes, balances the unbalanced samples, and is more conducive to the training of classifiers. However, as shown in Figure 1, there are many class samples around the new samples produced by smote. The new samples are easy to overlap or very close to these most class samples, which is easy to mislead the classifier and reduce the classification effect.

2.2. Improved smote algorithm for steganographic image

Gray image is a common carrier of steganography technology. If smote algorithm is used to oversample the steganographic gray image, the same weight is used for the gray value in the sample in the sampling, while in the steganographic image sample, the steganographic information is concentrated near the image contour, as shown in Figure 2. In order to enhance the background diversity of new samples in the data set, an image non contour region enhancement smote algorithm with variable weight is designed in this paper.

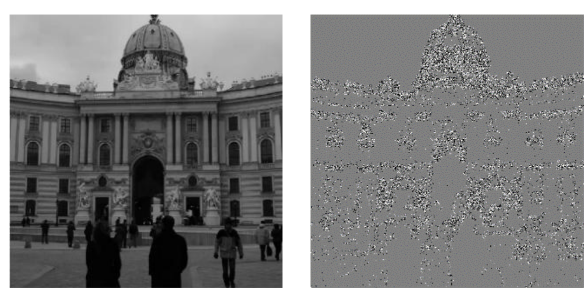


Figure 2: From left to right are the original image and the residual image between the original image and the dense image

The image non contour region enhancement smote algorithm with variable weight is based on the smote algorithm. When the adjacent pictures are superimposed and combined into a new picture, the complexity of the irrelevant information of the newly synthesized image is increased by increasing the weight of the image non contour region. The whole algorithm process is as follows:

(1) The input image is ($M \times N$) gray image, expand

the gray value of the image into a one-dimensional array, and the length of the array is ($M \times N$);

(2) For each array x in relatively few steganographic image samples, the Euclidean distance is calculated to calculate the k nearest neighbors in the array, assuming that the nth nearest neighbor is x_n;

(3) Any element a in the array and each adjacent element b_i in the image graph, When bi - $a \geq 40$ exists, set the weight of contour area $\omega_A = rand\ (0,1)$, , set the weight of non contour area in other cases $\omega_B = 2 \times \omega_A$. Obtain new samples through the algorithm formula, as shown in formula (2):

$$x_{\text{new}} = \begin{cases} x + \omega_A \times (x_n - x), & if\ bi - a \geq 40 \\ x + \omega_B \times (x_n - x), & \text{otherwise} \end{cases} \quad (2)$$

(4) Expand the obtained new array according to the gray value, and then restore it to an image.

2.3. Focal loss algorithm

The traditional approach to sample imbalance often only takes into account the imbalance in the number of samples in different categories, and there are many shortcomings in the processing method. For example, the oversampling synthesis of new samples used previously changes the sample distribution. However, because the newly synthesized samples can not be classified as a standard steganographic image, the emphasis on each sample is different. The loss of difficult samples has a greater impact on the total loss than that of simple samples. Therefore, this paper optimizes the training process of CNN by using the method of Focal loss proposed by He et al (He 2009).

Focal loss mainly improves the model through the loss level, the cross entropy loss function of the second classification is shown in formula (3):

$$CE(p, y) = \begin{cases} -\log(p) & \text{if } y = 1 \\ -\log(1 - p) & \text{otherwise} \end{cases} \quad (3)$$

where y represents the label of the sample, with two values of +1 and -1, respectively representing positive and negative samples; The value range of p is 0 to 1, which represents the probability that the model predicts that the sample is a positive class. In order to facilitate the next writing of cross entropy, definition p is shown in (4):

$$p_t = \begin{cases} p & \text{if } y = 1 \\ 1 - p & \text{otherwise} \end{cases} \quad (4)$$

Then cross entropy can be written as $CE(p, y) = CE(p_t) = -\log(p_t)$.

Focal loss deals with the imbalance of the number of samples in different categories by modifying the cross entropy loss weight of samples in different categories. The specific idea is to assign a weight factor to the positive and negative categories respectively α And $1- \alpha$. The value of α ranges from 0 to 1. It can be set as a value inversely proportional to the number of positive and negative samples, or it can be adjusted as a super parameter through cross validation. The adjusted cross entropy loss is as follows:

$$\text{CE}(p_t) = -\alpha_t \log(p_t) \quad (5)$$

Although the loss corrected by a can cope with the impact of the imbalance of the number of samples, it still can not deal with the training problem of difficult and easy samples. Although the loss of most samples has been greatly reduced, there are still a large number of easy samples in most samples, and the addition of the loss of these samples will dominate the gradient of back propagation, thus affecting the training effect. So also to correct the loss of difficult and easy samples, Focal loss adds an adjustment factor $(1 - p_t)^\gamma$ to adjust the loss of difficult and easy samples, where the focus parameter γ non-negative, and the loser of the adjustment factor is added as follows:

$$\text{CE}(p_t) = -(1 - p_t)^\gamma \log(p_t) \quad (6)$$

$(1 - p_t)$ represents the difference between the probability predicted by the model and the real value, which ranges from 0 to 1. If the model predicts the sample more accurately, the number will be closer to 0, and the loss of the sample will be reduced more. For example, when γ= 2, if the prediction probability p_t is 0.9, which is 100 times smaller than the previous loss. If the prediction probability is p_t is 0.97, it will be 1000 times, so as to reduce the impact of loss of simple samples on total loss. Finally, the weight factor α and the adjustment factor $(1 - p_t)^\gamma$ are added, and the final form of focal loss is shown in Equation (7):

$$\text{FL}(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t) \quad (7)$$

In this paper, Focal loss is used to replace the cross entropy function in steganalysis neural network, which ensures the attention to minority samples and difficult samples in identifying unbalanced samples, and optimizes the training process of convolution neural network for steganalysis.

3. Design of steganalysis model for unbalanced samples

In this paper, Zhu-net for steganalysis proposed by Zhu et al. [24] is used as the basic network. In order to solve the problem that the accuracy decreases due to sample imbalance, an improved smote algorithm for steganographic images is added before the input of the neural network, and the cross entropy function in the network is modified to improve the accuracy of steganalysis under the condition of sample imbalance. The flow of the model is shown in Figure 3, and each part is introduced as follows, Steps (2) - (5) are consistent with the Zhu-Net structure:

(1) According to the unbalanced characteristics of steganalysis samples, firstly, the unbalanced samples are oversampled by using the improved smote algorithm for steganographic images proposed in this paper to balance the number of steganographic images and normal images, and then the balanced image samples are sent to the input as a data set.

(2) The embedding operation of steganography can be regarded as adding a small amplitude noise signal to the original image. Therefore, residual processing is a necessary step before network feature extraction. After the data set is processed, it passes through the first preprocessing layer. We use a set of high pass filters (30 basic high pass filters of SRM), including twenty-five 3×3 filter cores and five 5×5 filter cores are combined to filter out the unimportant information in the image, which is more conducive to feature extraction.

(3) The next part is the separable convolution block, whose structural channels increase the correlation between them, reduce the storage space and enhance the expression ability of the model. In order to make better use of the residual information of the original image and the steganographic image, as shown in Fig. 3, this part includes the second layer and the third layer, and two different depth separable convolution modules are used, including 1×1 point convolution and 3×3 depth convolution, in which the number of groups is 30. First, execute 3×3 depth convolution to extract spatial correlation, and then perform in the depth separable convolution module 1×1 point by point convolution to extract the residual channel correlation and obtain the spatial residual characteristics and channel residual characteristics.

(4) The following part is the basic block for feature extraction, including layers 4 to 7. Each layer of the module contains four steps: convolution, batch normalization (BN), non-linear activation and pooling. The convolution operation uses a small convolution kernel (e.g 3×3) to reduce the number of parameters and extract local features effectively. The advantage of using BN layer is that it effectively prevents gradient disappearance / explosion and over fitting in deep neural network, and allows relatively large learning rate to accelerate convergence. The non-linear activation function uses the classical ReLU as the activation function to prevent the gradient from disappearing or exploding, generate sparse features, accelerate network convergence, etc. The application of ReLU to neurons can make them selectively respond to the useful signals in the input, so as to produce more effective features. The average pooling down-samples feature maps to better extract image features, reduce the size of the feature map and expand the receptive field. In addition, the average pooling also improves the generalization ability of the network.

(5) The next part is the spatial pyramid pooling (SPP) [7] module, which is the eighth layer. SPP module has the function of fixed length for any size of input and output, and uses multi-level pooling to effectively detect the change of objects. Finally, since the input is of any size, SPP module can perform feature aggregation for images of any scale or size.

(6) The next is the fully connected layer, including the ninth layer and the tenth layer, which integrates the extracted features for learning. The last part is softmax, which classifies the images according to the characteristics. In this part, focal loss algorithm is used to replace the cross entropy function in the original network, and different weights are given to different samples, which makes the network pay more attention to relatively few samples and difficult samples.

By applying the focal loss algorithm modified neural network to steganalysis, the impact of the imbalance of the number of samples on the classification performance is reduced, and the learning performance of the network on steganographic images is enhanced. The training process of the modified model is mainly divided into three steps, as follows.

Step 1: input the number of samples as N and assign an initial weight of 1 / N to each sample;

Step 2: start training. After each iteration, test the training set, count the error rate and adjust the weight of each sample;

Step 3: repeat step 1 until all iterations are completed;

Step 4: end the training and save the model parameters.

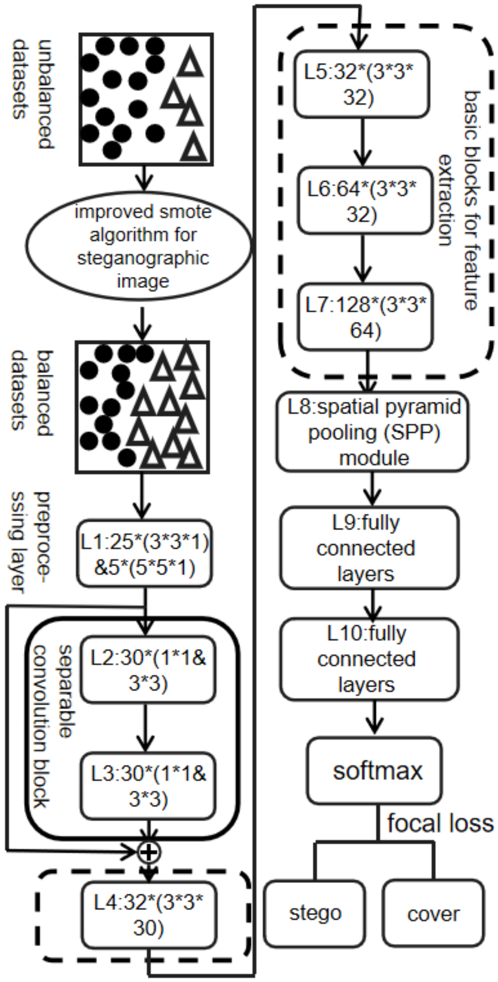


Figure 3: The overall flow chart of the algorithm in this paper

4. Simulation and test experiment

4.1. *Test data set and environment*

The test environment is a Windows 10 operating system, using a deep learning framework of pytorch 1.8.1, a programming language using Python 3.6.12, a graphics card of NVIDIA 3060 (12 GB), and a computing architecture of CUDA 11.1. The test dataset was based on BOSSbase1. 01, S-UNIWARD [18], WOW [11] and HILL [14] adaptive steganography algorithms were used for steganography, with embedding rates of 0.2 and 0.4 bpp (bits per pixel).

4.2. *Parameter setting*

In this paper, the neural network uses small batch random gradient descent (SGD) to train CNN network. The initial learning rate is set to 0.001, the momentum is 0.9, and the weight attenuation factor is 0.0003. Due to the limitation of GPU memory, the minimum batch size of training is 16 and the minimum batch size of testing is 30. The maximum number of iterations of the model is 500000. In order to better evaluate the performance of the network, we test it every 5000 times, a total of 100 times. The pictures in the test are all 512×512 normal pictures in BOSSbase 1.01 and scaled to a grayscale image in 256×256png format, and then steganographed.

4.3. *Evaluating indicator*

Steganalysis is a binary classification problem. There may be four situations after prediction, as shown in Table 1:

Table. 1 Confusion matrix of binary classification

	Positive	Negative
True	*TP*	*FN*
False	*FP*	*TN*

According to the confusion matrix in Table 1, we can calculate the desired evaluation index. The most commonly used steganalysis is the accuracy. Generally speaking, the higher the accuracy, the better the performance of the classifier. However, because the classifier is not sensitive to a few classes, when classifying unbalanced data, a few classes are judged as most classes to a large extent, resulting in a low recognition rate of minority samples. Therefore, the accuracy rate is not suitable for evaluating unbalanced problems [13]. This paper selects the index F-measure commonly used to evaluate unbalanced problems.

F-measure [9] is a weighted harmonic average of accuracy and recall, which is used to maximize the evaluation of the performance of a single class. Therefore, it can be used to measure the classification performance of the classifier on a few class samples. It is defined as follows:

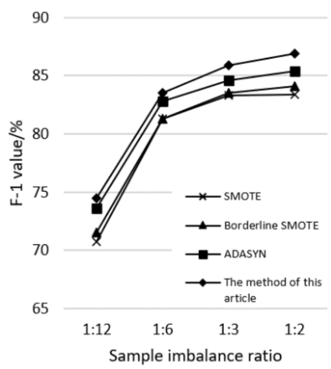
$$F-measure = \frac{(1+\beta^2)\times recall \times precision}{\beta^2 \times recall + precision} \tag{8}$$

where the accuracy rate $precision = \frac{TP}{TP+FP}$, the recall rate $recall = \frac{TP}{TP+FN}$, where the parameter β is usually 1, called F-1 value.

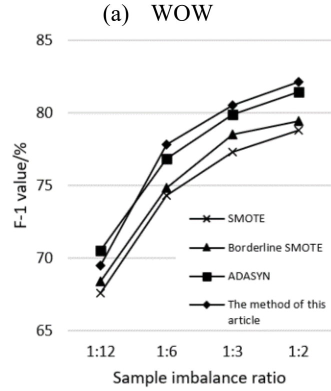
4.4. *Test result*

4.4.1. *Effectiveness test of improved smote algorithm*

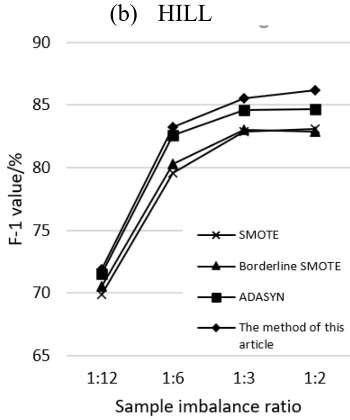
In the 10,000 images of the BOSSbase1.01 dataset, three adaptive steganography algorithms of WOW, HILL and S-UNIWARD were used for steganography, and the embedding rate was 0.4bpp. 6000 normal images and 6000 steganographic images are randomly selected, and an unbalanced sample set is formed using all normal images and partial steganographic images, and the remaining normal images and 4000 steganographic images each form a test set. The number of steganographic images is 3000, 2000, 1000, 500, respectively, and the ratio to normal images is 1:2, 1:3, 1:6 and 1:12. After the proposed algorithm is oversampled, the newly synthesized steganographic images and the original steganographic images form a training set. The SMOTE algorithm, the boundary SMOTE algorithm [4], the ADASYN algorithm[5] and the method proposed in this paper were compared and tested, and the Zhu-Net steganographic analysis network was used for classification, and the evaluation criteria used F-1 values that focus on the classification performance of minority samples, and the results of the comparative test were shown in Figure 4:



(a) WOW



(b) HILL



(c) S-UNIWARD

Figure 4: Comparison of experimental results of different oversampling methods under different steganography algorithms

From the test results of the figure below, Compared with other oversampling algorithms proposed in this paper, the improved SMOTE algorithm proposed in this paper has a significant improvement in the classification effect of balancing steganographic images and normal images. The oversampling algorithm proposed in this paper is to synthesize new samples by enhancing the complexity of irrelevant information in steganographic images, and pays more attention to preserving the steganographic information in steganographic images and improving the training effect of neural networks than other sampling methods.

4.4.2. Performance test of focal loss algorithm for steganalysis of unbalanced samples

To verify the effectiveness of the Focal loss algorithm, the test compares the model that did not replace the cross-entropy function with the focal loss algorithm with the model that has already been replaced. The steganographic analysis test was carried out on the dataset using the S-UNIWARD steganography algorithm and the embedding rate of 0.4bpp, the image selection of the dataset was consistent with the test in 3.4.1, and the sample imbalance ratio was set to 1:2, so the adjustment factor in the Focal loss algorithm α set according to the inverse scale of the sample, that is, 2/3, the focus parameter γ still use the default value 2, and the oversampling method proposed in this paper was used to balance the samples after training, the test results were shown in Table 2, and the detection accuracy curve was shown in Figure 5. From the test results, it can be concluded that the Focal loss algorithm can indeed improve the accuracy of steganalysis, because the Focal loss algorithm can overcome the impact of the imbalance in the number of steganographic samples and deal with the training problem of difficult samples in the sample. Focal loss by adding weight factor, weakening the negative sample in training loser, reducing the negative effect of steganographic sample number imbalance; adding adjustment factor significantly reduces the gradient of easy to divide samples in training backpropagation, and the loss weakening of difficult samples is small, which is equivalent to improving the attention to difficult samples in the training process, and the test results show that Focal loss can effectively optimize the training process of Steganalysis models and improve the accuracy of classification.

Table. 2 The accuracy of the improved steganalysis network model and the original steganalysis network model using Focal loss

Network structure	F-1 value/%
With Focal loss	88.12
Without Focal loss	86.23

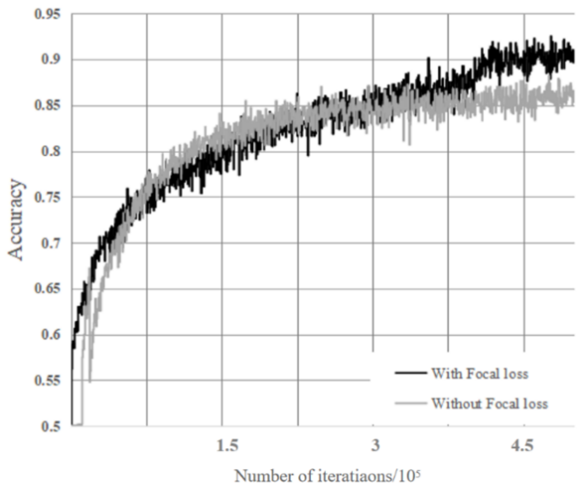


Figure 5: Comparison of detection accuracy

4.4.3. Model accuracy comparison test

The test compares the steganalysis accuracy of the scheme proposed in this paper with the classical network structure of Zhu-net in S-UNIWARD, WOW and HILL steganography algorithms, 0.2 and 0.4bpp embedding rates. The sample imbalance ratio is set to 1:6 and 1:2. Other test conditions are consistent with those in 3.4.1. The comparison results are shown in table 3.

Table.3 F-1 values detected by different steganalysis models

Steganog-raphy algorithm	Discrimi-nating networks	Imbalanced proportions 1:6		Imbalanced proportions 1:2	
		0.2bpp	0.4bpp	0.2bpp	0.4bpp
S-UNIWARD	Zhu-Net	76.2	83.9	78.6	86.2
	The method of this article	**77.2**	**85.7**	**79.1**	**88.1**
WOW	Zhu-Net	**71.3**	85.5	74.1	86.6
	The method of this article	71.0	**86.7**	**75.5**	**87.9**
HILL	Zhu-Net	**64.7**	75.8	**66.5**	81.3
	The method of this article	63.8	**77.2**	66.3	**81.9**

According to the test results, the F-1 value of the steganalysis scheme proposed in this paper is higher than that of Zhu-net when all the unbalanced ratios are 1:2 and most of them are 1:6, which also proves the effectiveness of the steganalysis model proposed in this paper for unbalanced steganalysis samples. However, the model has poor detection effect on some samples with an embedding rate of 0.2bpp. The reason is that when the picture is complex and the embedding rate is low, the number of difficult samples is too large and the difference from the normal image is small, ignoring the characteristics of individual easy samples, resulting in the loss of extracted information.

5. Conclusion

The imbalance of steganalysis samples brings challenges to image steganalysis based on deep learning. When these steganalysis models are trained with unbalanced samples, the model is easy to be controlled by most classes of samples, which affects the performance of the model. This paper proposes a design method of image steganalysis model based on improved smote algorithm and focal loss algorithm. By improving smote algorithm, this method synthesizes new samples by using the characteristics of steganographic gray-scale image to balance the sample data set. At the same time, focalloss algorithm is introduced into steganalysis model to optimize the training process of steganalysis model and realize the training of image steganalysis model by using unbalanced sample set. This method can effectively avoid the impact of sample imbalance on model performance, and improve the accuracy of model detection by paying more attention to difficult samples. The test results show that the improved smote algorithm has a good effect on steganography gray images. The accuracy of steganalysis of the proposed model in unbalanced samples is generally better than Zhu-net, but the detection accuracy of some unbalanced samples with low embedding rate needs to be further improved.

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