Trademark Background Analysis Method Based on Human Cognition of Visual Psychology

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RESEARCH

Trademark Background Analysis Method based on Human Cognition of Visual Psychology

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Abstract

Trademark is a symbol that can be seen everywhere in life. In the case of effective use of trademark, people can quickly identify the organization, its image and reputation, so that the trademark owner can obtain resources for maintenance and development. However, there are unfair competitors in the market that would imitate similar trademarks to steal or damage the reputation and interests of the original trademark owners. Failure of preventing counterfeit trademarks from affecting the interests of others will make developers hard to develop novel technologies that contribute to the progress of the country and society due to insufficient or scarce resources. In the past research in this field, many studies have proposed protection methods for protecting trademark interests. These related studies have obtained excellent results in the search and analysis of trademarks. Nevertheless, some unfair competitors use the human cognition of visual psychology in the human vision system (HVS) to circumvent similar methods of trademark images to steal or damage the credit and interests of the original trademark owners. In order to deter unfair competitors or the abuse of such confusing trademarks, this article proposes a method for trademark background analysis. This article also proposes a method to generate a large amount of background trademark data. Then, we use that large amount of generated data for training neural networks that can analyze trademarks that are easily confused due to background. Eventually, we use the testing independent data for system verification. This experiment uses two common deep learning network architecture for testing. The experimental results show that the proposed system can achieve a true positive rate (TPR) over 98% in the face of this confusing trademark plagiarism method. And the comparison result is better than existing methods. This result confirms that the system proposed in this article can prevent infringement problems that used background.

Keywords: trademark; human vision system (HVS); human cognition; visual psychology

Introduction

Totem has been used since ancient time to recognize countries, groups, and representative mark that represent individuals or organizations. Today, the totem represent the trademark of goods, services, organizations and companies [1]. These remarkable marks can be seen everywhere in society of human life. They are composed of abstract symbols, words, letters and numbers, or they are visible shapes, packaging, entities, colors and stereoscopic figures. In addition, these marks may also be sounds, smells, behaviors, or graphics with distinctive characteristics [2]. In general, trademark has three function [3]: (1). Indicate source or ownership; (2) Ensure goods or services have the same quality or characteristics; (3) Advertising. Through

[width = 4.75cm]fig01a.pdf [width = 5cm]fig01b.pdf

(a) (b)

Figure 1 Example tradenark. (a) Without background. (b) With background.

effective use of trademarks, people can identify the organization and its image and reputation quickly, so that trademark holders can obtain the resources to maintain and develop their organization.

However, there are unfair competitors in the market that will imitate similar trademarks with the intention of sharing resources or destroying the image and reputation of the original trademark. These counterfeit trademarks will confuse the customers of the organizations, and then damage the interests, image and reputation of the organizations due to their similarity. Assuming that no one prevents these unfair competitors, developmental business organizations will not be able to develop novel technologies that contribute to the progress of the country and society owing to insufficient or scarce resources. Therefore, in order to protect the quality, innovation and interests of trademark holders, many countries will allow trademark holders to register trademarks. The registered trademark will be protected by law in that country, and the law will be used to prevent damage caused by unfair competitors.

In recent year, some methods have extracted high-frequency shape features to find similar trademark through Euclidean distance [4, 5]. In addition to high-frequency shape features, there is also a method for searching and matching images by using the intuitive results of image binarization as features as in work [6]. In searching for similar shapes, work [7] regards high-frequency features as sketched images, and then uses the combination of grids as features to search for related images. Some works such as [8] and [9] used Tversky's similarity theory to search for the similarity between trademarks based on the semantic combination in trademarks. With the rise of deep learning today, some works utilized convolutional neural network (CNN) to recognize different types of trademarks from the past to the present [10], or classify trademarks by countries and region [11]. And these works have achieved excellent results in the search and analysis of trademarks.

The related works on image-based trademark recognition seems to be mature. Nevertheless, supposing the optical illusion [12] in visual psychology [13, 14] is ignored, the unfair competitors today also use this problem to indirectly steal or destroy the image and reputation that is accumulated by trademark holder. Such as news reports [15] and [16], the content pointed out that through the background of the trademark, unfair competitors use existing cognition to make consumers associate infringement trademark with the true one directly, thereby affecting the image and reputation of the trademark holder. Fig. is an example that likes as news reports, Fig.1(a) and Fig.1(b) show two example trademarks without and with same background. When people see Fig.1(a) through side vision, the brain only notices two text which one is white, the other is black. And when people see Fig.1(b) through peripheral vision, the brain only notices two combined symbols with a blue background and text. This case is enough to make some consumers intuitively believe that the two may be the same brand, so that unfair competitors

may circumvent similar trademark issues and steal the image and reputation from the trademark holders.

In order to confirm the above narrative, optical illusion does cause confusion. This paper uses short-answer online questionnaires to survey respondents of different age groups on the Internet. In the third section, the statistical results of the survey are described to confirm that this method can indeed damage the reputation and image of the trademark.

In many countries and regions that have national laws to protect trademarks. However, because of differences in perception between people, the law has never provided clear standards for trademark review. This situation has caused many deliberate and unintentional infringement cases in applications for trademarks under national laws. In order to assist in the judgment of the similarity of the legal trademark graphics, we propose a trademark background similarity analysis system based on deep learning for trademark backgrounds that are prone to confusion on account of human existing cognition.

The contributions of this paper are as follow:

- Use statistical data and visual psychology to support the discussion that trademark background may cause confusion.
- Propose a trademark background analysis method based on visual psychology to assist existing systems. Make the system more able to protect the benefits of the original trademark, so that the trademark holder can obtain the resources needed for subsequent development.
- A method is proposed to combine the existing database to generate enough data to train and test the neural network, so that the neural network can assist this type of recognition work.
- Propose a trademark comparison method based on the human visual system, and compare the accuracy with the past methods to confirm that the method proposed in this article is indeed superior to the past methods.

The remainder of this paper is composed as described below. Section 2 presents four subsection. First subsection introduces HVS and optical illusion. The next subsection describes the pre-processing of data generation that is prone to confusion due to optical illusions. The third subsection explains the deep learning convolutional neural network we used in this paper. And the final subsection illustrates proposed trademark analyzed system based on background optical illusion. Section 3 displays the experimental results, discussion, contributions of proposed system. Section 4 is a summary of trademark research contributions and future work.

Method

Human Vision System (HVS) and Optical Illusion

Human Visual System (HVS) model is a biological and psychological process that is not fully understood in image, video, computer vision and expert system processing [13]. In the existing imaging technology, the technical application of HVS is mainly to use the restriction of the sensory organs or the inactivation caused by the long-term stimulation. Among them, the reaction of passivation is the optical illusion of "complementary color" and "persistence of vision" in terms of visual perception. Existing applications of HVS technology are quite diverse. Here are a few common examples:

[width = 4.5cm]fig02a.pdf [width = 4.45cm]fig02b.pdf

(a) (b)

Figure 2 The Exist Techniques of Using Optical Illusion. (a) JPEG Image Compressing. (b) Halftoning.

- JPEG image compression [13]: JPEG distortion compression technology compresses high-frequency details that HVS cannot recognize in detail, and achieves the effect of greatly reducing the amount of image data. The left side of Fig.2(a) shows the diagonal image, and the dashed frame is an enlarged image showing part of the diagonal.
- Halftone: This technology is used in existing printing technology. In view of the limitation of the number of robs in the human eye, its use produces an effect such as a low-pass filter [17], which makes the images and photos output on paper look like continuously adjusted images. Fig.2(b) is a comparison of continuous tone and halftone images.
- Video and animate: Since HVS produces a visual optical illusion, it can quickly play multiple images in a short time, so that the images have a continuous playback experience.

Regarding trademarks, when new trademarks and registered existing trademarks may confuse consumers due to optical illusions of existing cognition, the new trademarks may steal or damage the reputation of existing trademarks for consumers. The result may affect the interests of trademark holders.

Training and Testing Data Generation Pre-processing

Existing trademark search methods [4, 5, 6, 7, 8, 9, 10, 11] have achieved high accuracy in similar trademark search work. However, news reports [15][16] show that the confusion caused by optical illusion does affect the possibility of customers recognizing the wrong trademark and affecting the reputation and interests of trademark holders. As shown in Fig., when HVS receives graphics in the blink of an eye, the combination of two different symbols with the same background color can also cause confusion. These cases illustrate that when the commonly used background colors of trademarks are rooted in people mind deeply, unfair competitors may use this type of confusion to steal or harm the reputation and interests of trademark manufacturers.

In order to protect the reputation and interests of trademarks, this paper proposes a trademark recognition system based on background optical illusion analysis. This system can assist trademark holders prevent the possibility of unfair competitors applying optical illusion to steal their interests. In general, in order to recognize objects in different environments, the training data is fixed with the same objects in different environments in deep neural network training. This operation makes the deep neural network extract the features of the object from a variety of environments, so as to retain the most significant features of the object. Since the recognition goal of this paper is opposite to the past. Therefore, we introduce the pre-processing of the training and test data generated by combining the existing trademark database and background data set below.

[width = 9cm]fig03.pdf

Figure 3 The Block Diagram of Pre-processing

In the proposed pre-processing operation, the database and background data set are first normalized to the same size. Next, the main trademark graphics is extracted by region growing [13] from trademark image data. The operation of region growth must meet the conditions from Eq (1) to (5).

$$\bigcup_{n=1}^{N} S_n = S \tag{1}$$

$$S_n \text{ is a connected region}, n = 1, 2, ..., N \tag{2}$$

$$R_n \cap R_m = \emptyset \text{ for all } n \text{ and } m, n \neq m \tag{3}$$

$$P(S_n) = \text{TRUE for } n = 1, 2, ..., N \tag{4}$$

$$P(R_n \cap R_m) = \text{FALSE for} n \neq m \tag{5}$$

Where S is the area representing the entire image, N is the process of dividing the image S into n sub-areas, P is logical predicate, and $\emptyset$ is empty set. After completing the extraction of the trademark graphic, the graphic is overlaid on the corresponding position of the background data set to form the data for training and testing the neural network. Fig.3 indicates the operation block diagram of pre-processing.

The Model of Deep Learning Convolution Neural Network

This section introduces deep learning convolutional neural networks based on the recommended system requirements. Convolutional neural network includes input layers, convolutional layer, pooling layer, fully-connected layer, classification layer, and inception. The following describes the functions of each layer of the convolutional neural network:

- Input layers:
  Input layer is the pre-processing before the data is input to the neural network training, which contains two processing. One is to normalize the image size and value, and the other is to distinguish training and verification data based on a set ratio. In normalization process, the value is normalized from digital data (8-bits) to float value (0-1). And image size is normalized by architecture requirement, such as AlexNet is 227×227 pixels [18][19] and GoogleNet is 224×224 pixels [20]. In distinguishing data ratio setting, general training and verification data are 80% and 20%, separately.
- Convolutional layer:
  Convolutional layer is a processing layer for extracting image features, and each layer has its corresponding kernel size and stride. These extracted features are called neurons in the neural network. The extracted neurons are

active by an activation function layer, and the commonly used activation function layer is rectified linear units (ReLU) [21].

- Pooling layer:
  Pooling layer is subsample processing layer, and its main purpose is to prevent overfitting and reduce the amount of calculation. The most common pooling layer method is max-pooling method [22], this method keeps the largest value in the kernel size as result. In addition, some networks use other pooling methods for processing, such as GoogleNet pool5 layer uses average-pooling method [20].
- Fully-connected layer:
  Fully-connected layer is a processing layer that connects related neurons. This layer connects neurons according to the dependency between neurons. During processing, this layer uses dropout technique to reduce overfitting and ReLU activation function layer to activate connected neurons.
- Classification layer:
  The purpose of the Classification layer is to output the processing results of a fully-connected neural network, Softmax and cross entropy function. In test of this paper, the number of neurons in the output layer is 11. After the neurons are output, the final recognition result is generated by the processing method of cross-entropy loss regression. Among them, the Softmax function of cross-entropy loss regression is shown in formula (6) [23], k and l are the indexes of category c.

$$\text{Softmax} = \frac{e^{c_k}}{\sum_l e^{c_l}} \tag{6}$$

- Inception:
  Inception is the processing layer for deep network processing to avoid vanishing gradient problems [20]. It usually consists of multiple convolution layers of different kernel sizes and a max pooling layer.

Proposed Trademark Analyzed Method based on Visual Psychology

In this subsection, we introduce the trademark analysis system based on the background optical illusion. Fig.4 is the trademark-background (TM-BG) analysis neural network training block diagram of the proposed system, and Fig.5 is the system flowchart for recognizing the background similarity of trademarks. First, the neural network used to analyze the trademark background is obtained through the proposed neural network training. Training this neural network uses the trademark

[width = 9cm]fig04.pdf

Figure 4 The Block Diagram of Proposed CNN Training

[width = 9cm]fig05.pdf

Figure 5 The Flow Chart of Proposed Analyzed System

database and background data set, and generates training data that is easy to confuse HVS by the method described in subsection 2.2. Afterwards, the training data is input to CNN for neural network training, and the TM-BG analysis network is obtained. After obtaining TM-BG analysis network, target trademark is entered into proposed system. The system flow chart is shown in Fig.5. First, considering the impact of object distance on HVS, a variety of subsamples will be performed on the input image first. The various subsample images are normalized, and then the features of the original and subsample images are extracted by the classical feature method. When the Euclidean distance F_{dist} between the two image features is greater than twice the standard deviation 2σ, the trademark network analysis with confusing background proposed in this article is added. Finally, the analyzed result is output. The following describes the process of proposing the system in the form of steps:

$$F_{dist} = \sqrt{(\mathbb{N}(F(I_{tm})) - \mathbb{N}(F(I_{tm,a})))^2} \tag{7}$$

$$O = Net_{bg}(\mathbb{N}_{cnn}(I_{tm,a})) \tag{8}$$

1. Use the trademark database and background data set to generate easily confusing training data through the pre-processing described in subsection 2.2.
2. Employ the generated training data to obtain the TM-BG analysis network $Net_{bg}(\cdot)$ through CNN training to analyze the trademark background.
3. Enter target trademark image I_{tm}.
4. Obtain $I_{tm,a}$ by subsampling I_{tm}, where $a = \{0.5, 0.4, \ldots, 0.1\}$ is the side length magnification of the image subsample.
5. Regularize original and subsampled image.
6. Hire classical feature extraction method $F(\cdot)$ to extract the features of original and subsampled image.
7. As formula (7) to get Euclidean distance F_{dist}.
8. Inspect whether F_{dist} exceeds twice the standard deviation 2σ of the original image.
9. If the distance F_{dist} is not exceeded, the distance of the classical method is used as the similarity output result.
10. Otherwise, enter the trademark background analysis network that proposed in this article.
11. Normalize $I_{tm,a}$ according to the requirements of CNN.
12. Apply proposed TM-BG analysis network $Net_{bg}(\cdot)$ to analyze the target trademark as formula (8).
13. Output the result O to assist trademark legal judgement.

Experimental Result and Discussion

In this paper, the proposed system is implemented and tested through MATLAB 2019b on Intel(R) Core(TM) i7-4790HQ CPU 3.6GHz and NVidia TITAN X GPU. In system implementation, we employ Graphis public trademark database [24]. The database contains 5,906 JPEG trademark images. In these data, there are 5,450 images with a size of 670×670 pixels, 254 images with a size smaller than 670×670,

and 202 images with a size larger than 670×670 pixels. In this paper, 45 trademark photography images that are not suitable for testing have been filtered out in the database. Therefore, the total number of trademark images in the database used in this paper is 5,861. The trademark background data set is derived from the common trademark backgrounds of the Google image search engine. This paper uses 11 common trademark background combinations (including no background) for systematic testing experiments. In order to avoid the problem of overfitting, this paper used networks trained by ImageNet to perform transfer learning in network training to reduce the occurrence of this problem.

In order to confirm the hypothesis that the optical illusion of the trademark background does cause confusion, this paper uses short-answer online questionnaires to interview respondents aged 21 to 65. Where, the age ratio of respondents is 62.65% from 21 to 35, 25.3% from 36 to 50, and 12.05% from 51 to 65. The questionnaire uses the trademark background used in this paper and the revised graphics of the literature [14] as the interview questions. The results of the questionnaire survey show that an average of 77.51% of the respondents only rely on the trademark background provided by the questionnaire to answer the correct trademark. Where, the correct answer rate for each age is 85.26% from 21 to 35, 65.08% from 36 to 50, and 70% from 51 to 65. In addition, for the revised literature [15] graphics, 87.95% of the respondents believe that this similar background will cause confusion in trademark recognition. And 95.89% of the respondents who thought it would be confused could directly answer the original trademark that was imitated. The age ratio of respondents who believe that trademark confusion is caused is 88.56% from 21 to 35, 90.48% from 36 to 50, and 100% from 51 to 65. Since then, the results of the questionnaire have confirmed that there is indeed the assumption that background needs to be considered when searching for similarity of trademarks. Therefore, this paper proposes CNN trademark background recognition system to prevent unfair competitors from using this method to damage the image and reputation of existing trademarks.

Fig.6 shows part of the training neural network data. These data are generated using a combination of Graphis trademark database and background data sets, each background class has 1,000 data. From the previous description, there are 11 known common backgrounds, so there are a total of 11,000 training data.

Table 1 is the Validation Accuracy and the average processing cost of the network architectures neural networks. Before training for the two networks, the training

[width = 8.5cm]fig06.pdf

Figure 6 The Part of Training and Testing Generation Data

Table 1 Validation Accuracy of Networks

Architecture	Avg. Cost (ms)	Validation Accuracy
AlexNet	3.194	0.9964
VGG-16	3.254	0.9928
VGG-19	3.812	0.9936
ResNet50	4.689	0.9948
ResNet101	4.827	0.9951
GoogleNet	4.643	0.9951

Table 2 The Accuracy of Proposed System in Basic Test

Architecture	TPR	FPR
AlexNet	0.9961	0.0004
VGG-16	0.9946	0.0006
VGG-19	0.9959	0.0006
ResNet50	0.9943	0.0004
ResNet101	0.9944	0.0005
GoogleNet	0.9931	0.0007

data is augmented by horizontal and vertical flipping and 90-degree counterclockwise rotation. The input training data is divided into two parts, one part is 80% of the data used for training, and the other part is 20% of the data used for verification. In Table 1, the validation accuracy of the two network architectures is higher than 99.2%, and the difference is less than 0.4%. Therefore, the experimental results of the two networks are discussed below.

The first stage of the testing is the basic test of the proposed system, the testing data is 11,000 data independent of the training data. There are also 1,000 documents for each class. We utilize these data to test the proposed system and the results are indicated in Table 2. Table 2 is the accuracy of the proposed system, which uses network architectures for testing. The definition of true positive rate (TPR) and the false positive rate (FPR) are written as formulas (8) and (9). The average TPR and FPR of all architectures are 99.47% and 0.05%, respectively.

$$\mathrm{TPR} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})} \tag{9}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{(\mathrm{FP} + \mathrm{TN})} \tag{10}$$

Fig.7 shows the receiver operator characteristic (ROC) Curve of the overall and individual classes respectively. Area under the curve (AUC) is an indicator for evaluating system performance in ROC Curve. This indicator is obtained by integrating ROC Curve. The larger the indicator value, the better the performance of system in recognizing objects.

In the experimental results, a small number of trademarks obscured more background due to the shape of the trademark as Fig.8. The AUC indicator in different backgrounds, proposed system achieved an effect higher than 99%.

Under different designs, the area of the trademark background will also change. In order to verify the commonality of proposed system in this paper, the following are the results of the system commonality test. Fig.9 is common trademark background variations, where Fig.9(a) is original background, Fig.9(b) is background under different designs, and Fig.9(c) is generated testing data sample.

The results of the system commonality test are shown in Table 3. In some network architectures, one of the design of class 2 makes the system to misjudge as class 7 as Fig.10, which reduces the TPR. And the is still less than 1% in all architectures.

[width = 8.5cm]fig07.pdf

Figure 7 The Integrated ROC Curve of Proposed System

[width = 4cm]fig08a.pdf [width = 4cm]fig08b.pdf

(a) (b)

Figure 8 The Samples of False Positive data in Class 11. (a) False positive testing data. (b) Corresponding correct results.

Table 3 The result of system robustness testing in common trademark background variations

Architecture	TPR	FPR
AlexNet	0.9890	0.0009
VGG-16	0.9776	0.0015
VGG-19	0.9662	0.0022
ResNet50	0.9386	0.0038
ResNet101	0.9285	0.0046
GoogleNet	0.9435	0.0034

In fact, the size of the trademark that the human eye sees varies with distance. When the trademark is far away, due to the trademark is too small, people will not be able to recognize the detailed information of the trademark. Small size trademarks are reduced their features, and people use the existing knowledge of visual psychology to recognize trademarks naturally. In related work, the classic high-frequency feature extraction methods [4, 5] did not consider this situation in the image. The purpose of this article is to prevent unfair competitors from using the characteristics of visual psychology to propose auxiliary recognition methods. Therefore, the final stage of the test is to use small-size trademark images to simulate the recognition effect of distance changes.

The data used in the test are 5,861 unique trademark images in the Graphis public trademark database [24]. Among these unique trademark images, 50% randomly generated images with background trademarks through the proposed method and background. Then the 5,861 images are processed through subsample to create test data. Since the system in this article is mainly for analyzing the background, it is not suitable for searching trademarks in independent operation. Therefore, in this test, the classical high-frequency feature method [4][5] is used as the basis to compare the differences with or without the method to assist in the analysis. Table 4 is the comparison result with the classical high-frequency feature search method. From the first column of Table 4, it can be seen that the original features of the trademark are affected by the distance, which reduces the features of the image due to shrinkage, making the recognition result worse. The second column is the result

[width = 1.3cm]fig09a.pdf [width = 2.6cm]fig09b.pdf [width = 3.9cm]fig09c.pdf

(a) (b) (c)

Figure 9 Common trademark background variations. (a) Original background. (b) Background under different designs. (c) Generated testing data sample.

Table 4 The comparison with existing methods in rank-1 accuracy (%)

Methods	$a = 0.5$	$a = 0.4$	$a = 0.3$	$a = 0.2$	$a = 0.1$
[4][5]	94.0966	75.9939	44.4975	12.9329	0.7337
[4][5]+[25]	98.5327	87.4936	61.1329	24.8422	1.3479
[4][5] +Proposed	98.8910	89.8823	63.0438	30.4897	2.0304

[width = 6cm]fig10.pdf

Figure 10 Class 2 variation and class 7 prone to false negative in some network architectures

of high-frequency features combined with the existing perceptual hash algorithm in the literature [25]. The results prove that the combination of the two methods can indeed assist the recognition results. The last column is the test result of the high-frequency features with the method proposed in this article. The results show that the effect of this article is better than that of [25]. For this result, we think that the main reason is that the purpose of [25] is a method of fast image search. The method reduces most of the features of the image, so that some important information is ignored. The CNN analysis used in this article, although the main goal is to analyze the background, can maintain some high frequency information to provide recognition results. This difference makes the method proposed in this article superior to the combined method [25].

Conclusion

Trademarks are common symbols in society, and people can recognize the goods, services, organizations, and businesses they represent through these symbols. In recent years, the research directions on trademarks have been exploring on searching for similar trademarks. These discussions have also yielded good results, effectively identifying similar trademarks to prevent unfair competitors from plundering the interests of others' trademarks. However, while similar trademark tools can be found or obtained, there are still many unfair competitors using various methods to steal the credit and benefits accumulated by the original trademark efforts. Among the methods used by unfair competitors, in this article we focus on using similar or same background combination settings to make HVS generate optical illusional trademark credit and profit-stealing methods for research and discussion on news reports [15, 16] in recent years. In the description of the report [15, 16], it stated that customers did stray into the storefront of unfair competitors because of such signs with similar backgrounds. This phenomenon shows that just using a similar background may affect the image and reputation of the original trademark.

In order to confirm the hypothesis that the use of similar backgrounds can affect the original trademark, in this article we use a short-answer online questionnaire to randomly interview interviewees between 21 and 65 years old, and collect the interview results to verify the hypothesis. The statistical results of the questionnaire showed that 87.95% of the respondents believed that similar backgrounds would indeed cause confusion of trademarks and damage the image and reputation of trademarks. The results of this questionnaire support the aforementioned hypothesis, indicating that in addition to trademark graphics, the background combination of trademarks should also be considered in the protection of trademarks. However, in the past research on trademarks, the methods proposed in the literature only discussed the similarity of geometric features of trademark graphics, and did not consider the issue of similar backgrounds. Therefore, we propose a set of analysis system based on deep learning convolutional neural network for identifying the plagiarism method using a similar combination of backgrounds. This system

complements the similar background parts that were not explored in the past research to deter unfair competitors to protect the original manufacturers or reduce the chance of infringement caused by misuse by latecomers.

We use CNN technology to implement the proposed system, while using regional growth to generate training data from the trademark database and background dataset, and verify the usability of the proposed system based on experimental results. On the CNN training data, we use Graphis' public trademark database [24] and the common background combination found by the Google image search engine to generate the training neural network dataset. After completing the neural network training, a similar method is used to generate testing data which is independent of the training data to verify the feasibility of the system. In the testing result part, this article uses common AlexNet and GoogleNet CNN network architectures for system testing. The results show that the system proposed in this article can achieve a TPR more than 98% for background recognition. Then, in the system robustness test, even if the background of the trademark changes due to different panels, it can still achieve a TPR more than 98%. This result indicates that the method proposed in this article can effectively analyze the methods of using similar backgrounds to steal the credit and interests of others, protect the interests and credit of the original manufacturers, or reduce the legal problems caused by misuse by latecomers.

This article is aimed at the optical illusion problem of visual psychology, and we propose a method of protecting trademark interests. Therefore, in the future, we can study other situations where HVS may cause misjudgments to make the system of protecting trademark credit and reputation more perfect.

List of abbreviations

- HVS: Human vision system. In digital image processing, video processing and computer vision expert technology, it is a model for processing biological and psychological processes that have not yet been fully understood.
- CNN: Convolutional neural network. A class of deep neural network, commonly applied to analyze two-dimensional signal processing, such as visual imagery.
- TPR: True positive rate. Evaluation index, indicating the probability of correct recognition of the system.
- FPR: False positive rate. Evaluation index, indicating the probability of system error recognition.
- ROC Curve: receiver operator characteristic curve. It is a coordinate diagram analysis tool used to select the best signal detection model or set the best threshold in the same model.
- AUC: Area under the curve. In the ROC curve, an indicator to evaluate the strengths or weaknesses of the model.

Availability of data and materials

Trademark database is available online at http://www.graphis.com/logos/

Competing interests

The authors declare that they have no competing interests.

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Author's contributions

Conceptualization, K.M.H.; Methodology, K.M.H.; Investigation, K.M.H., L.M.C. and T.W.C.; Resources, L.M.C. and T.W.C.; Writing–Original Draft, K.M.H., L.M.C. and T.W.C.; Writing–Review & Editing, K.M.H.; Funding Acquisition, K.M.H.; Supervision, K.M.H.;

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Figure 1a

Example 1

Animals 1

Figure 1b

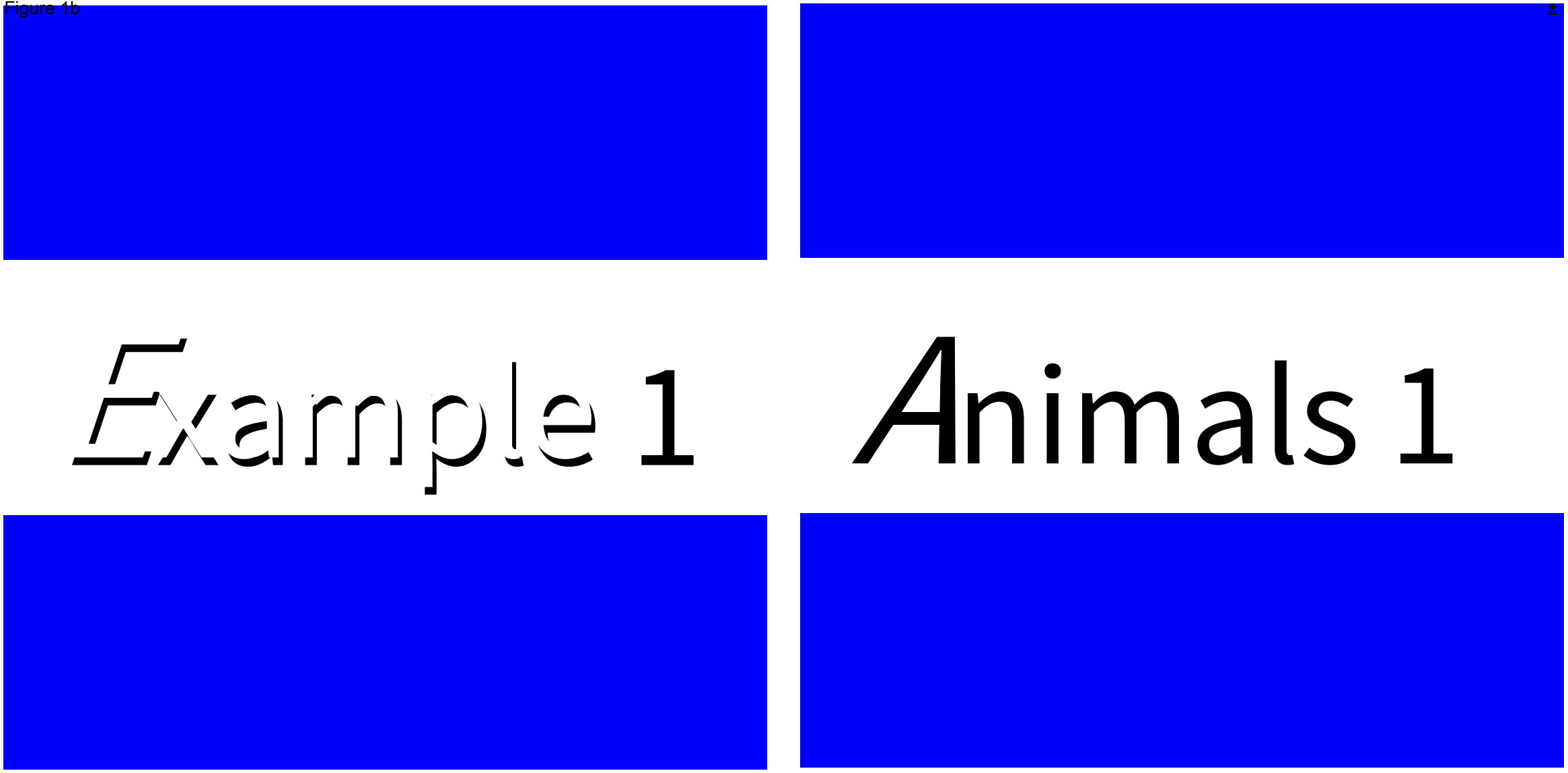

Figure 2a

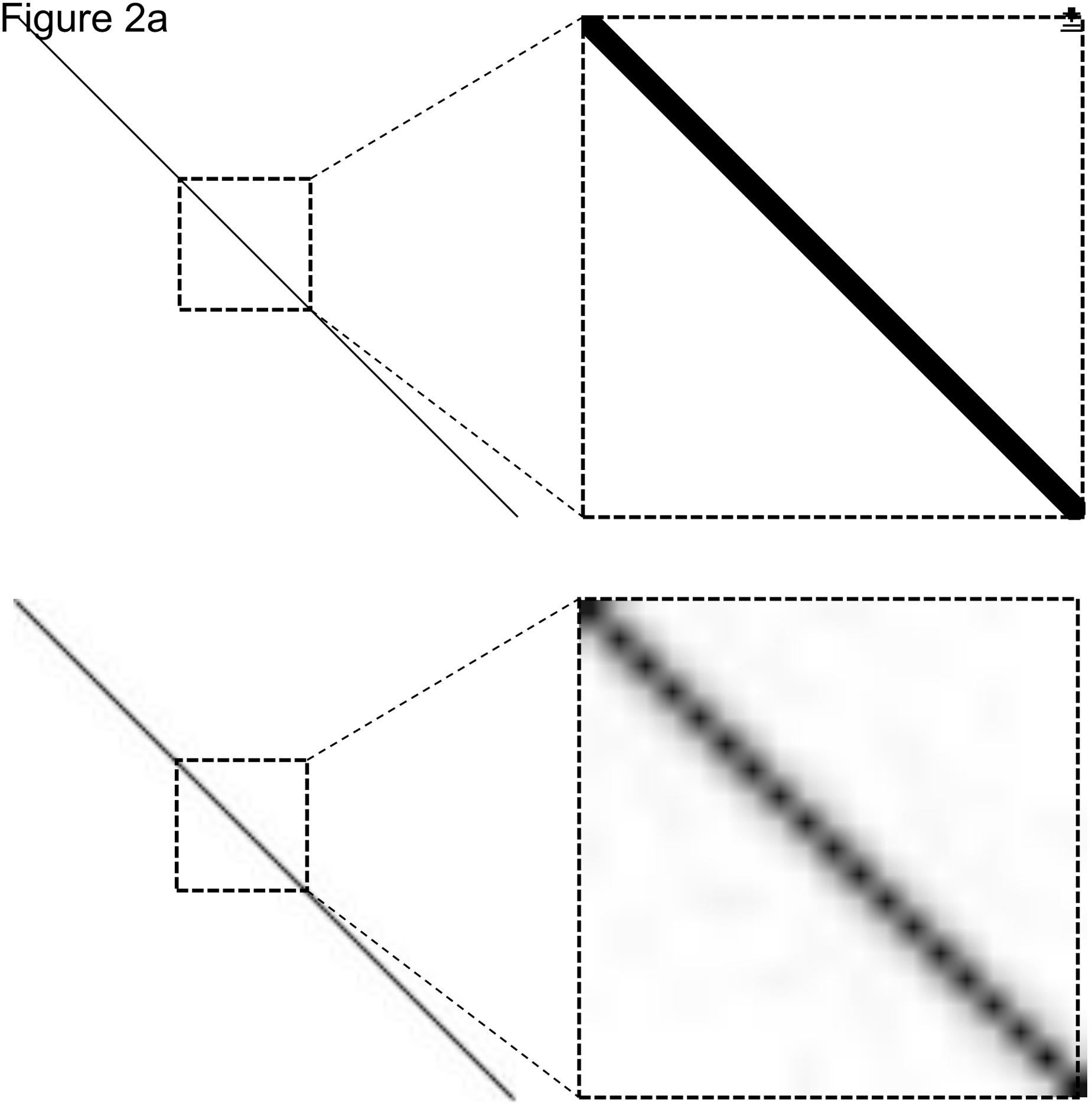

Figure 2b

Click here to

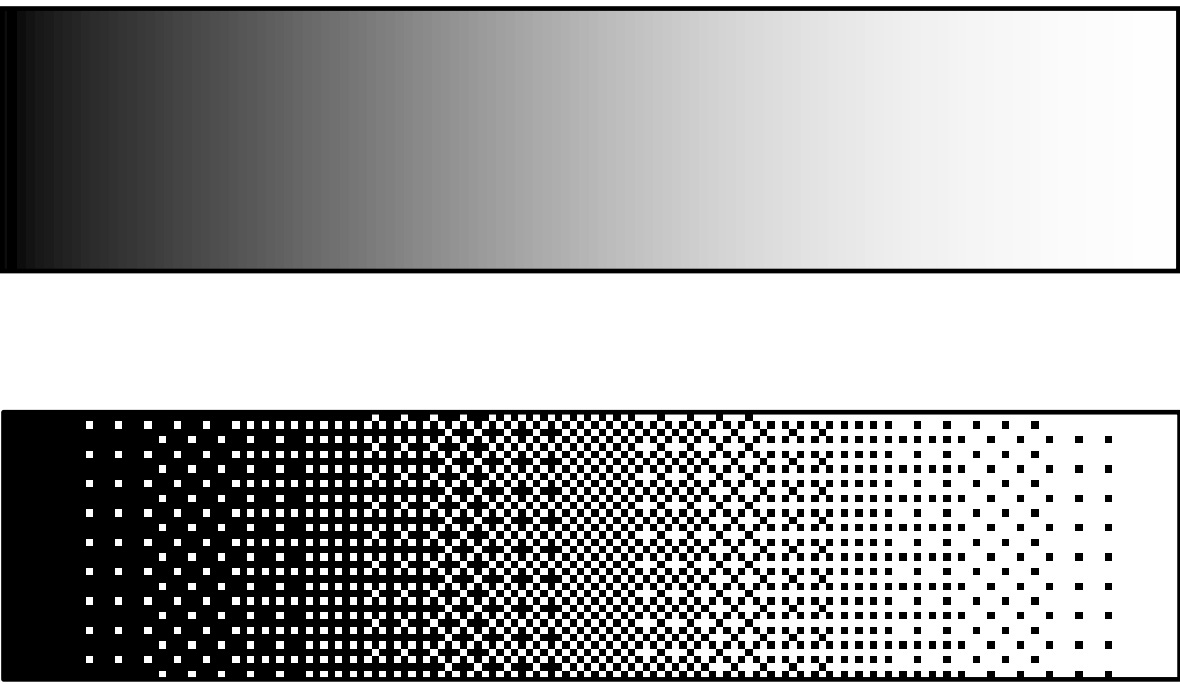

Figure 3

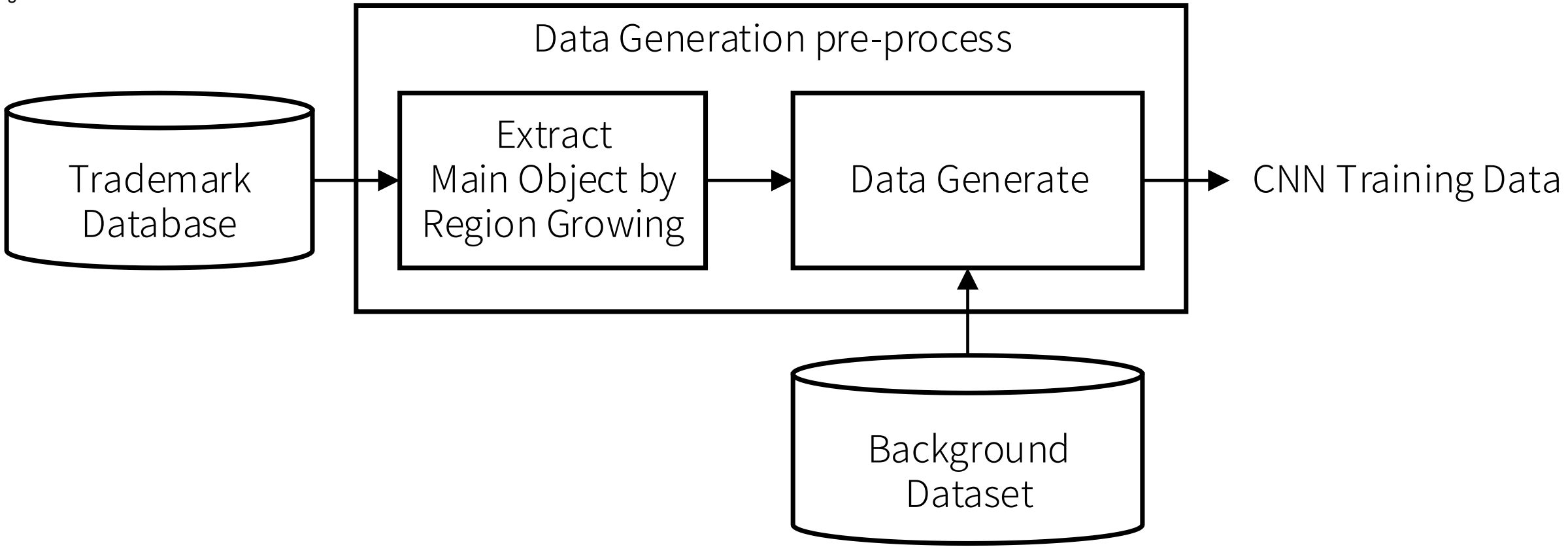
Data Generation pre-process
Trademark Database
Extract Main Object by Region Growing
Data Generate
CNN Training Data
Background Dataset

Figure 4

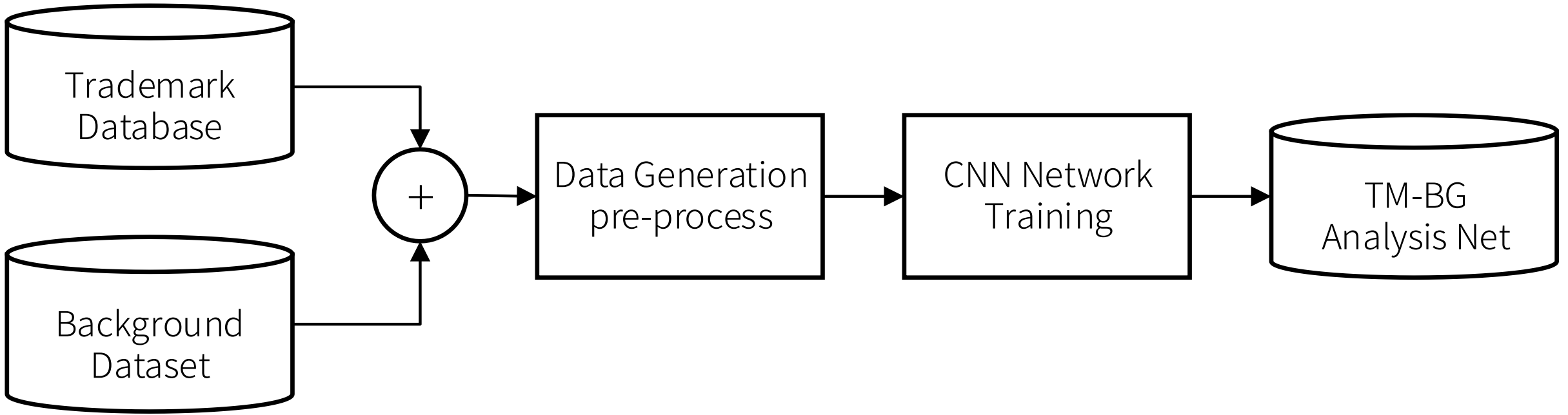
Trademark Database
Background Dataset
+
Data Generation pre-process
CNN Network Training
TM-BG Analysis Net

Figure 5

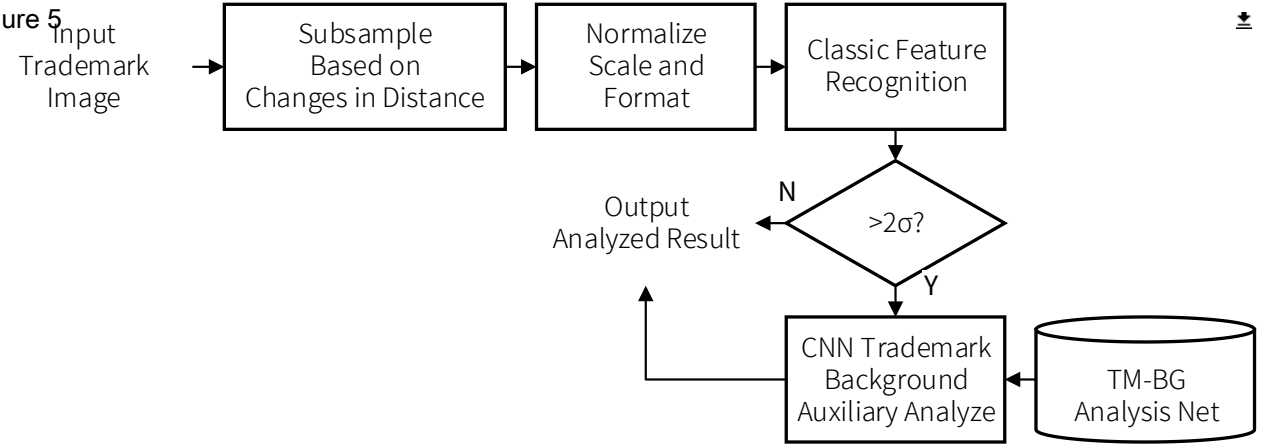
Input
Trademark
Image
Subsample
Based on
Changes in Distance
Normalize
Scale and
Format
Classic Feature
Recognition
>2σ?
N
Output
Analyzed Result
Y
CNN Trademark
Background
Auxiliary Analyze
TM-BG
Analysis Net

Figure 6

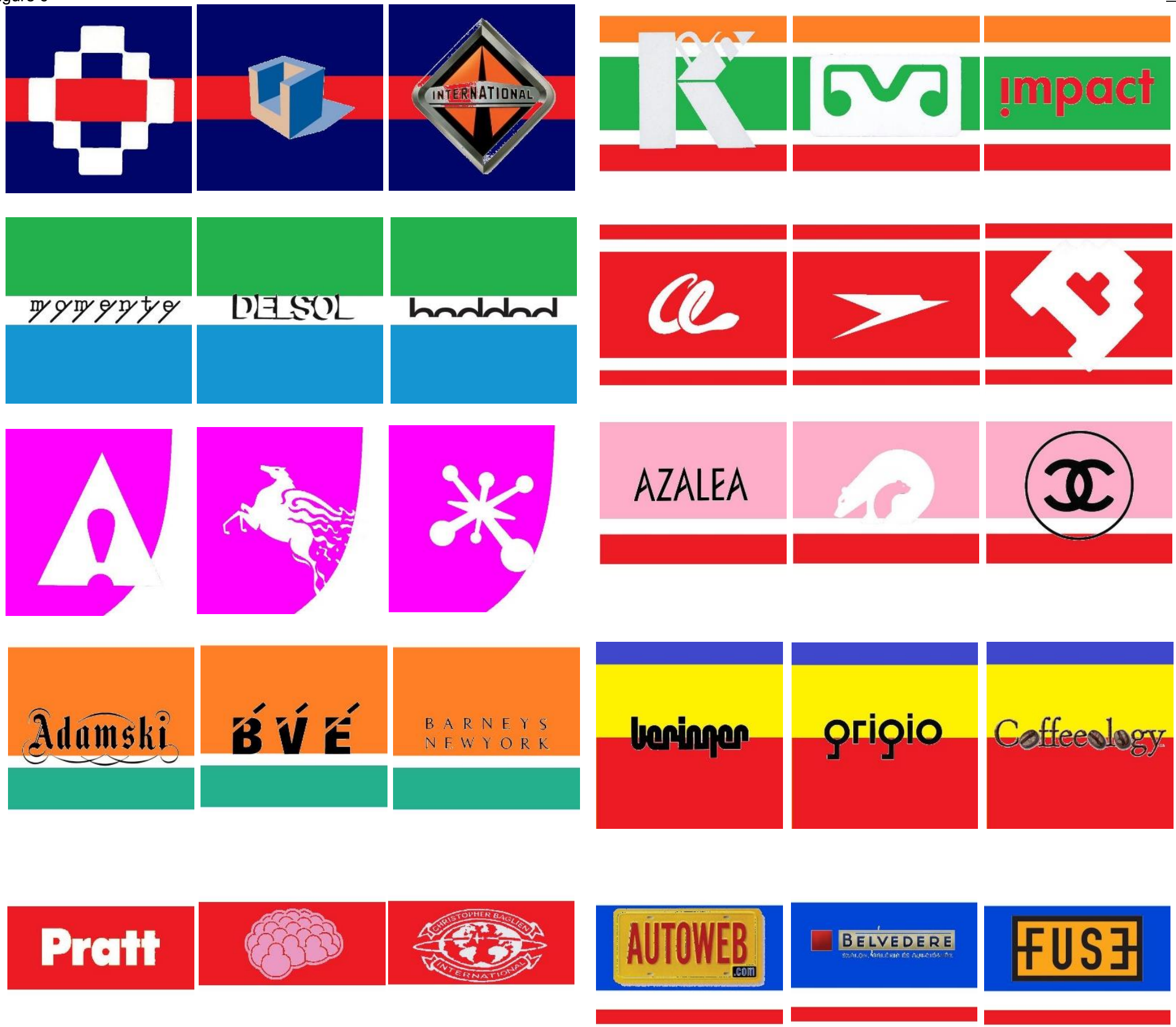
INTERNATIONAL
impact
momente
DELSOL
AZALEA
Adamski
BVÉ
BARNEYS NEW YORK
beringer
grigio
Coffeeology
Pratt
CHRISTOPHER BAGLIEN INTERNATIONAL
AUTOWEB .com
BELVEDERE
FUSE

Figure 7

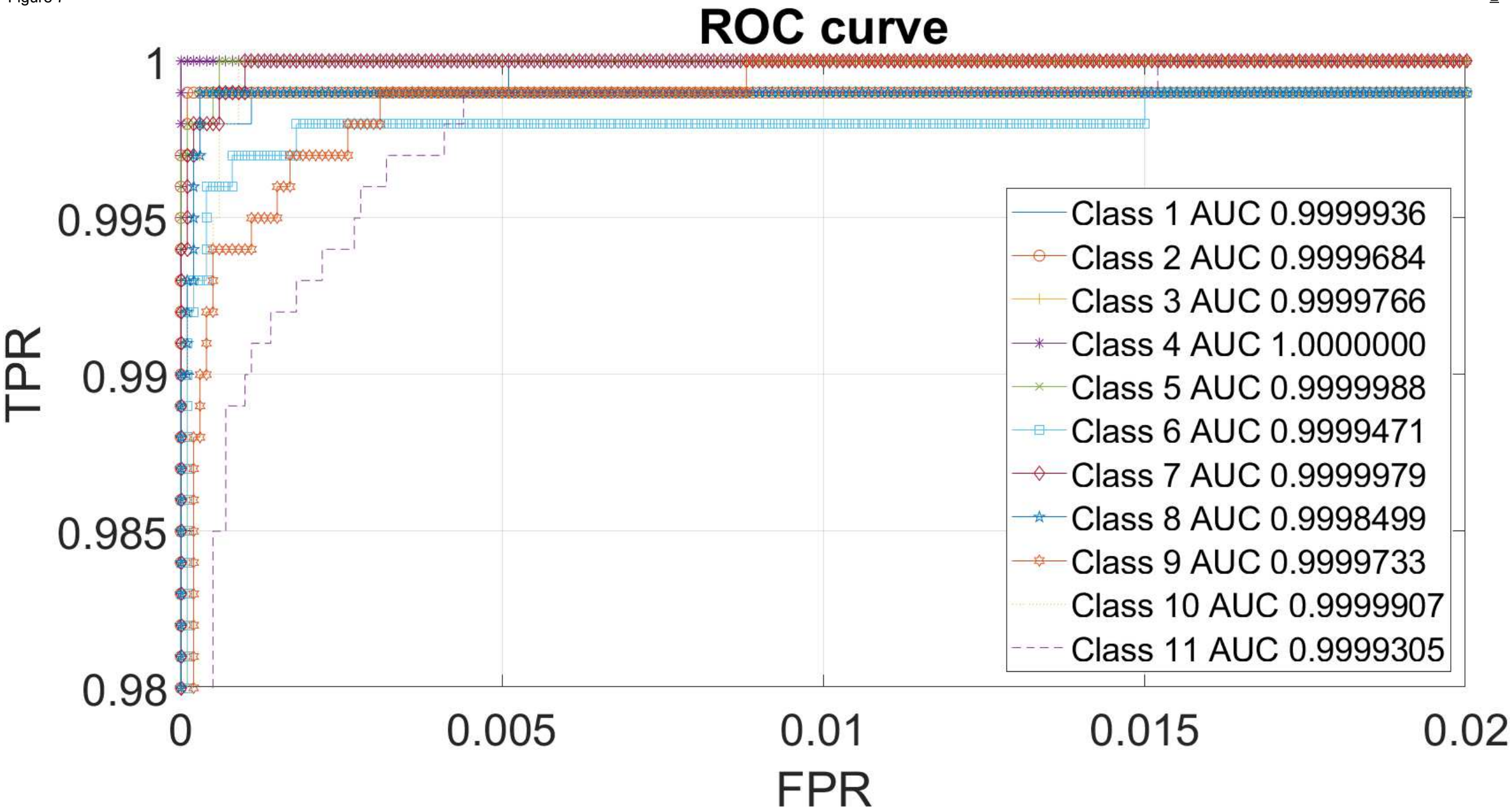
ROC curve
TPR
FPR
1
0.995
0.99
0.985
0.98
0
0.005
0.01
0.015
0.02
Class 1 AUC 0.9999936
Class 2 AUC 0.9999684
Class 3 AUC 0.9999766
Class 4 AUC 1.0000000
Class 5 AUC 0.9999988
Class 6 AUC 0.9999471
Class 7 AUC 0.9999979
Class 8 AUC 0.9998499
Class 9 AUC 0.9999733
Class 10 AUC 0.9999907
Class 11 AUC 0.9999305

Figure 8a


PLAYHOUSE
INTERNATIONAL PICTURES
restaurant
MECCA
SUNDANCE PRESERVE

Figure 8b

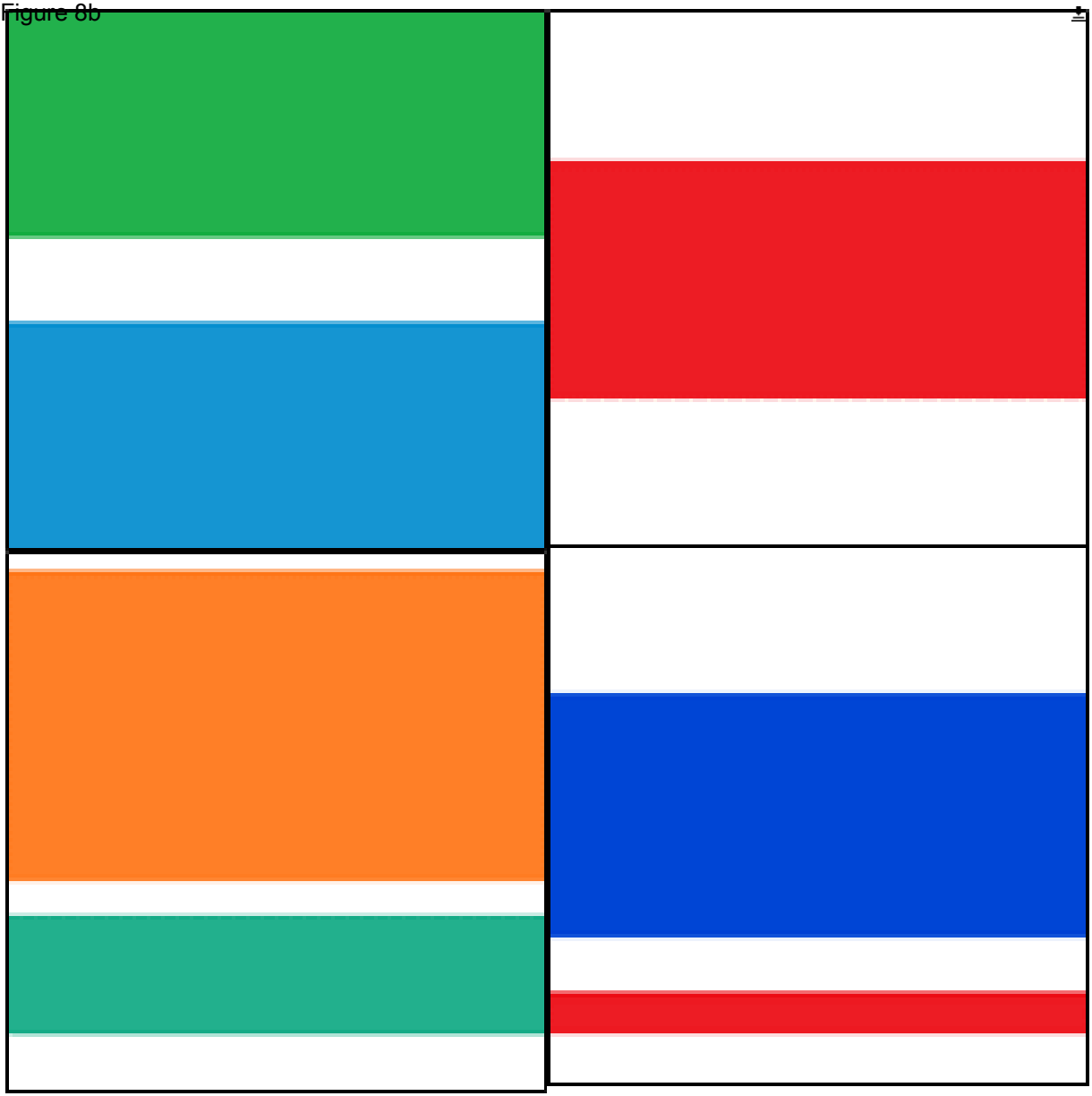

Figure 9a

Figure 9b

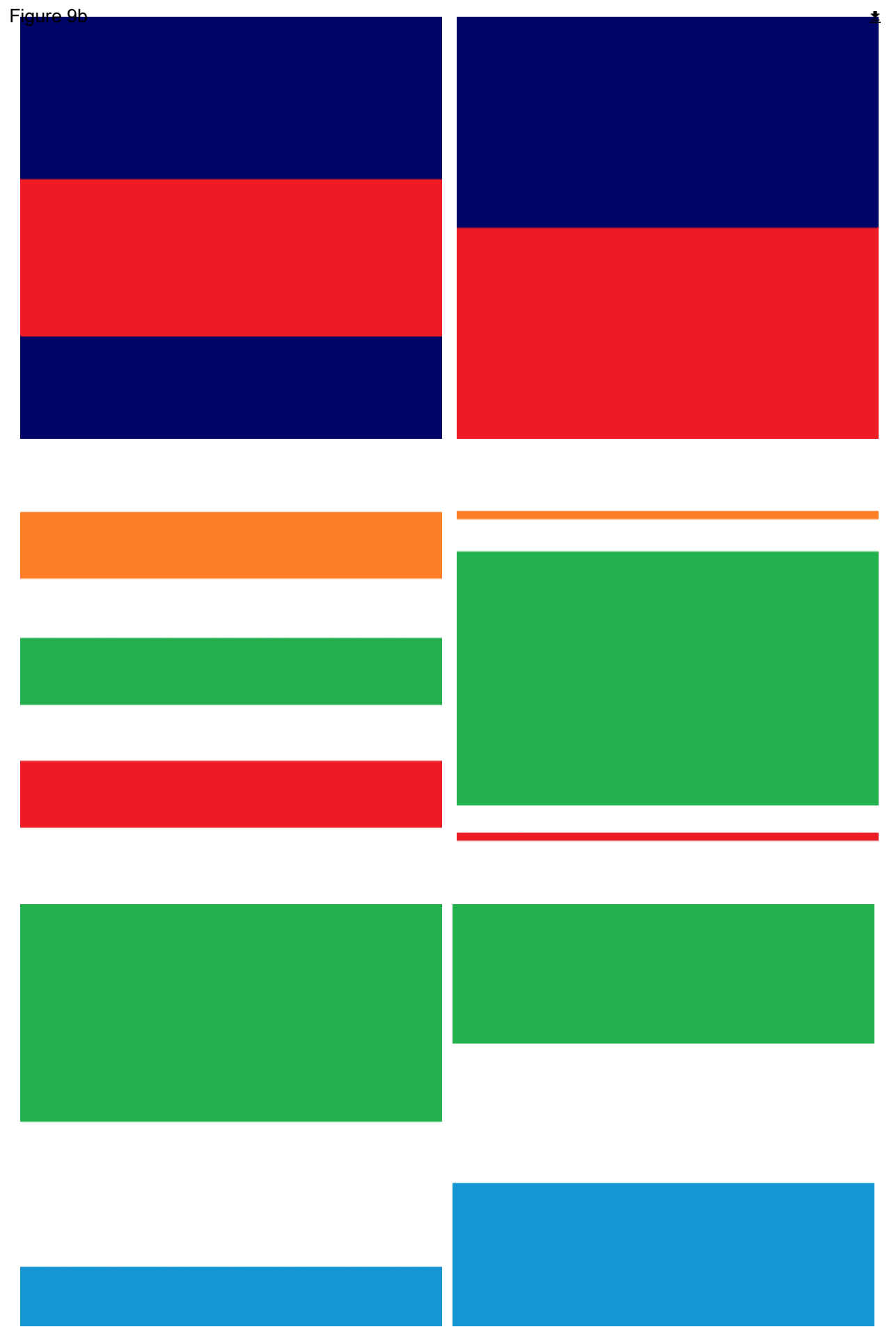

Figure 9c

Figure 10

Figures

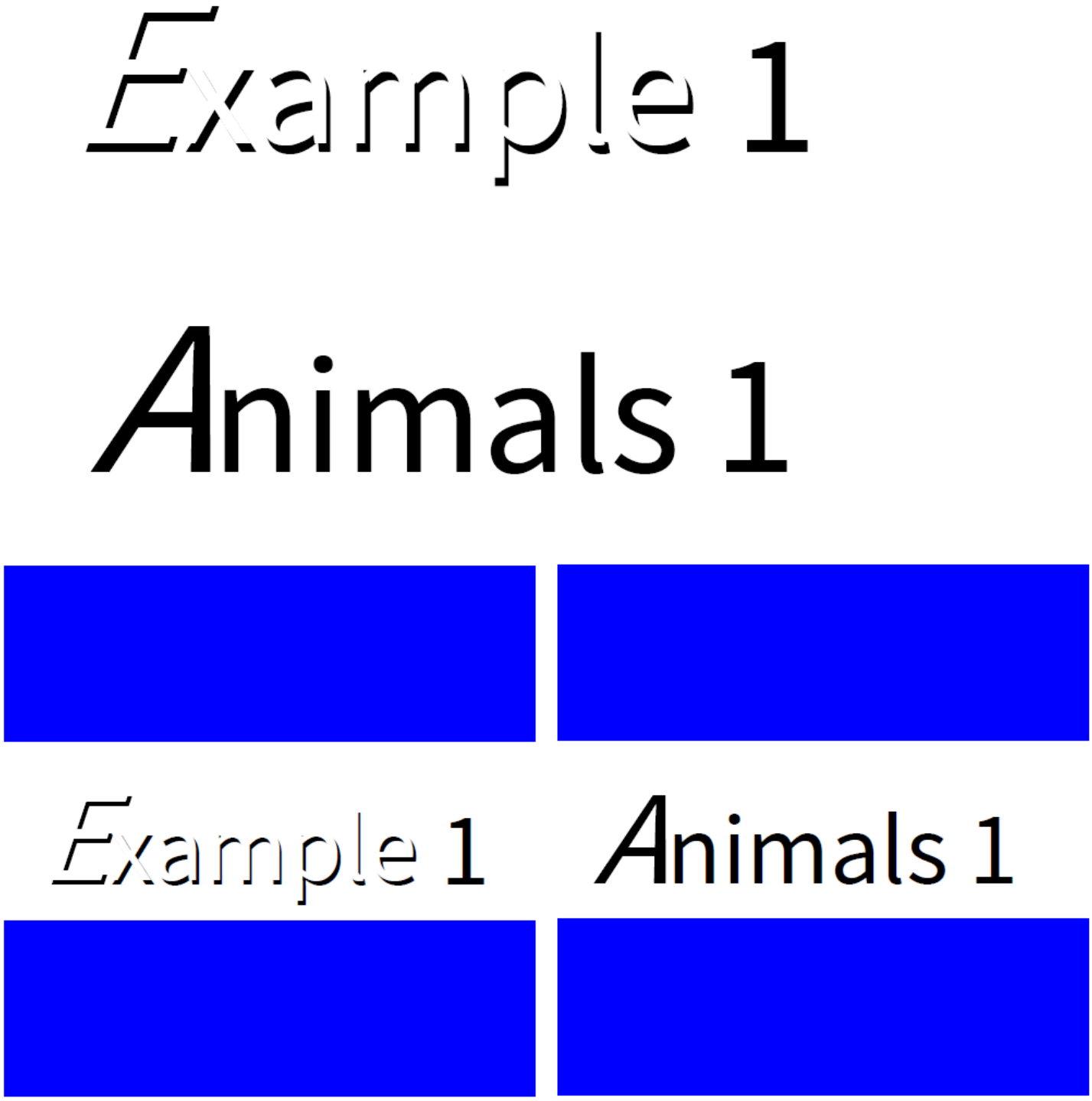

Figure 1

Example tradenark. (a) Without background. (b) With background.

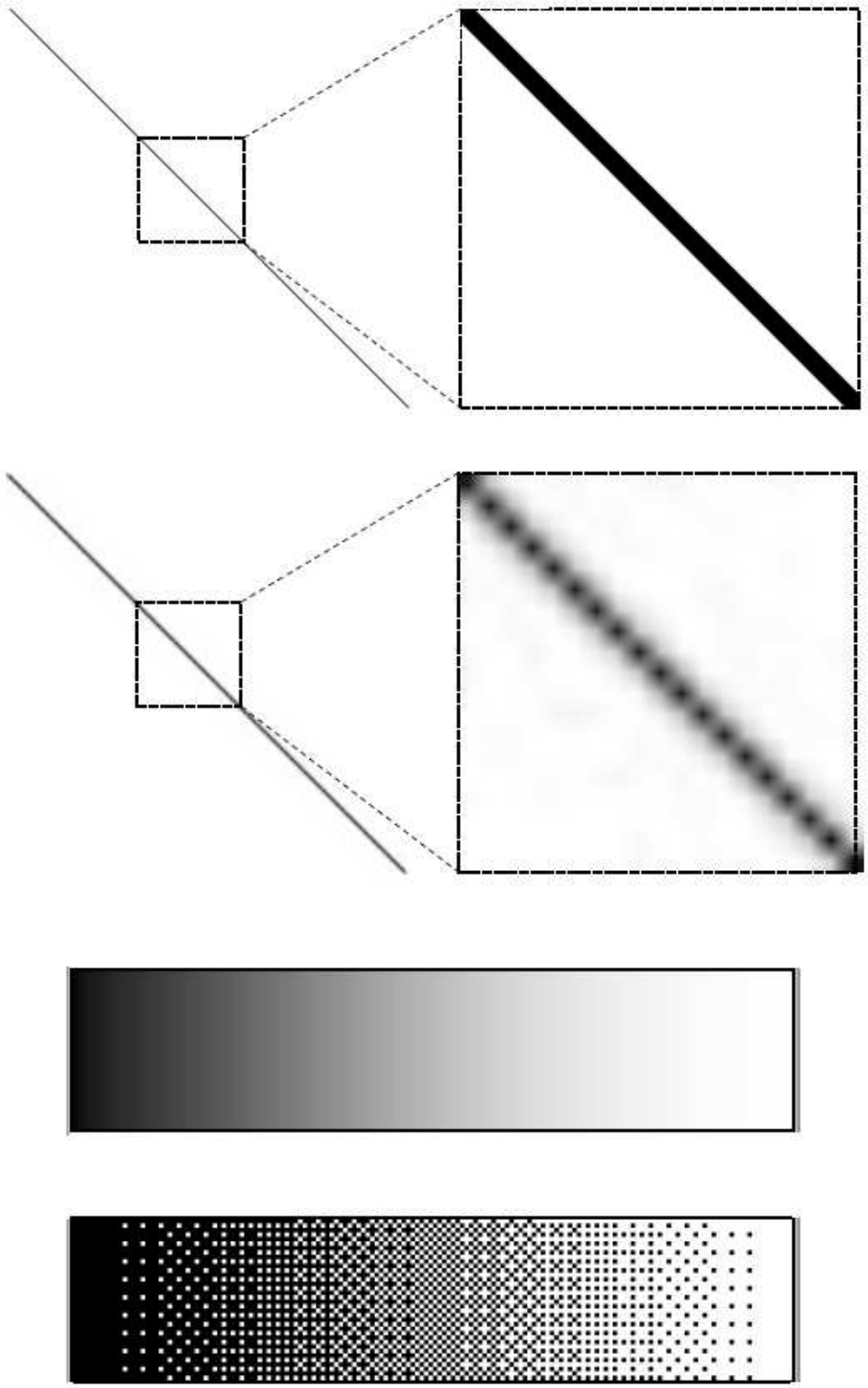

Figure 2

The Exist Techniques of Using Optical Illusion. (a) JPEG Image Compressing. (b) Halftoning.

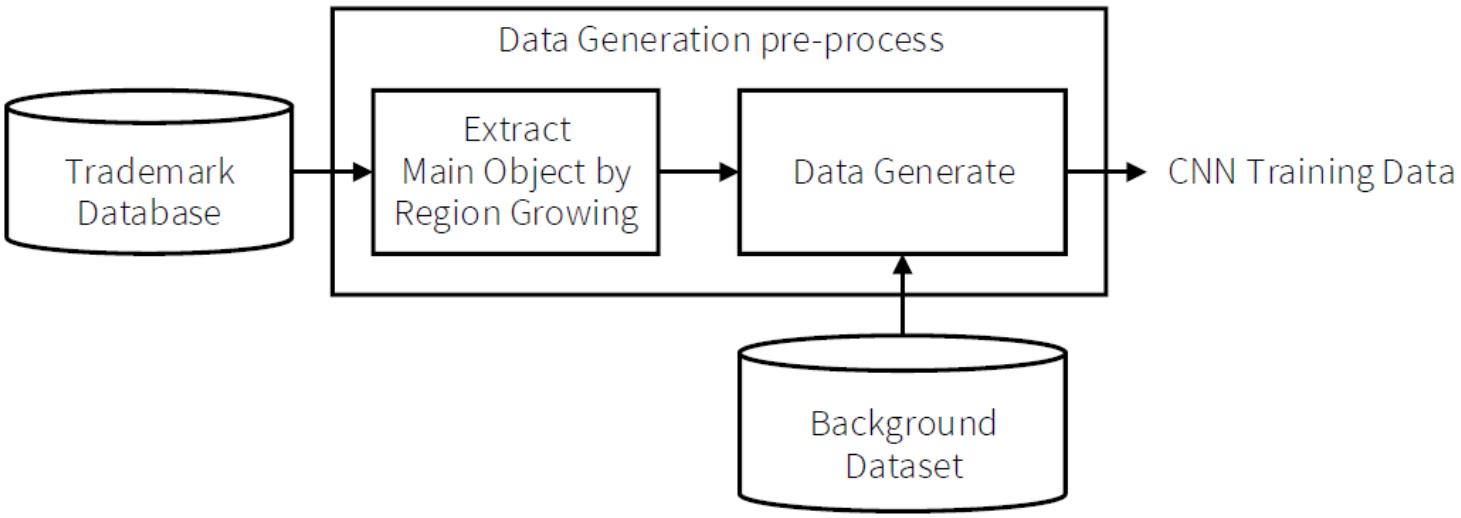

Figure 3

The Block Diagram of Pre-processing

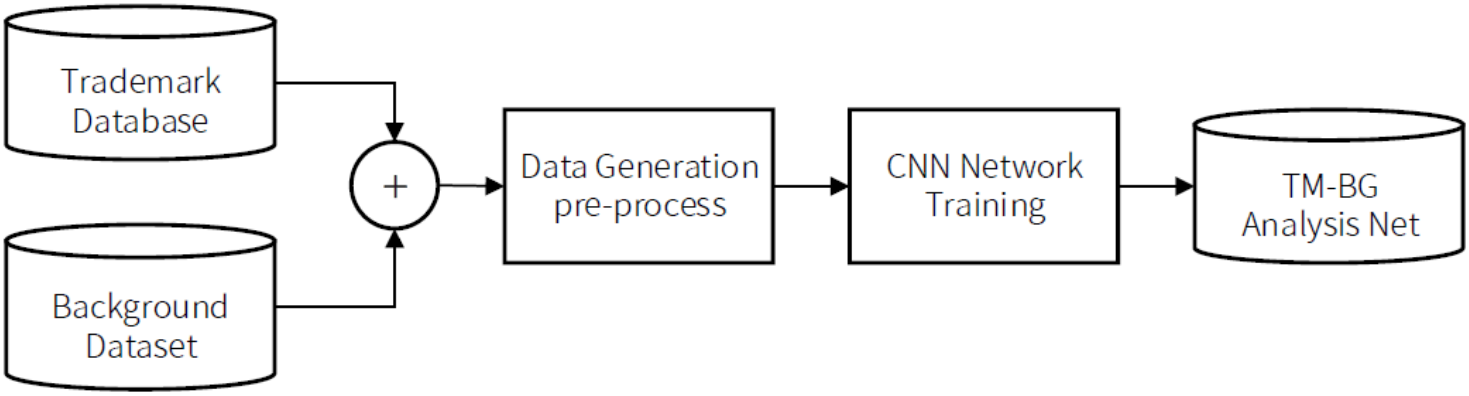

Figure 4

The Block Diagram of Proposed CNN Training

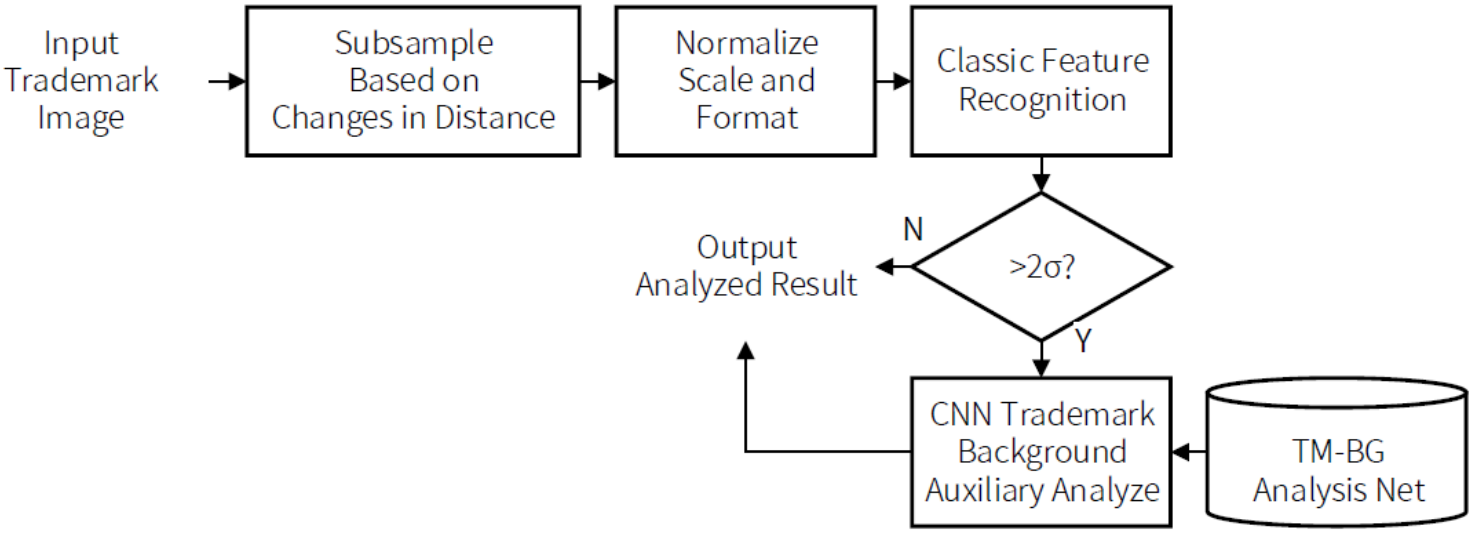

Figure 5

The Flow Chart of Proposed Analyzed System

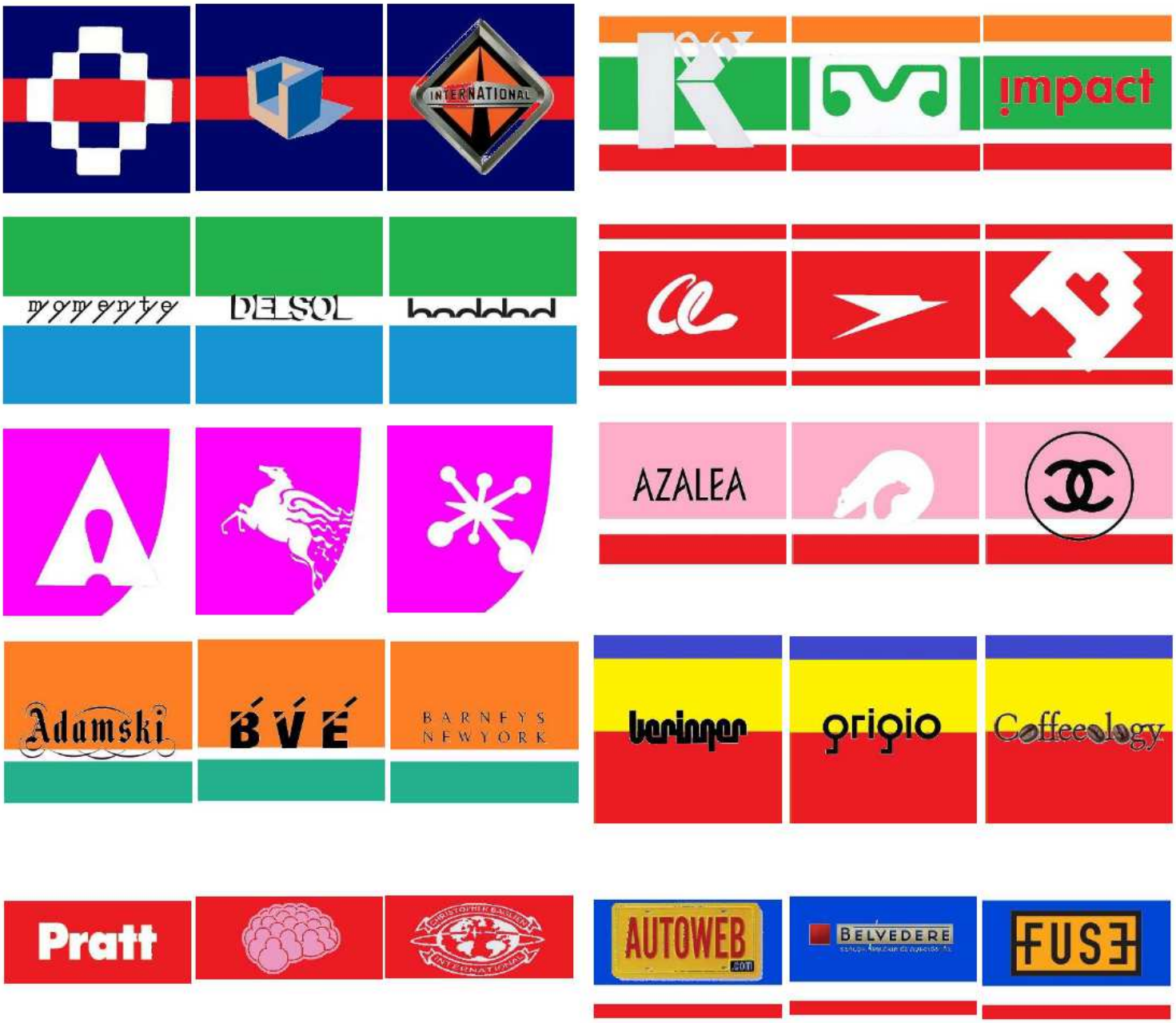

Figure 6

The Part of Training and Testing Generation Data

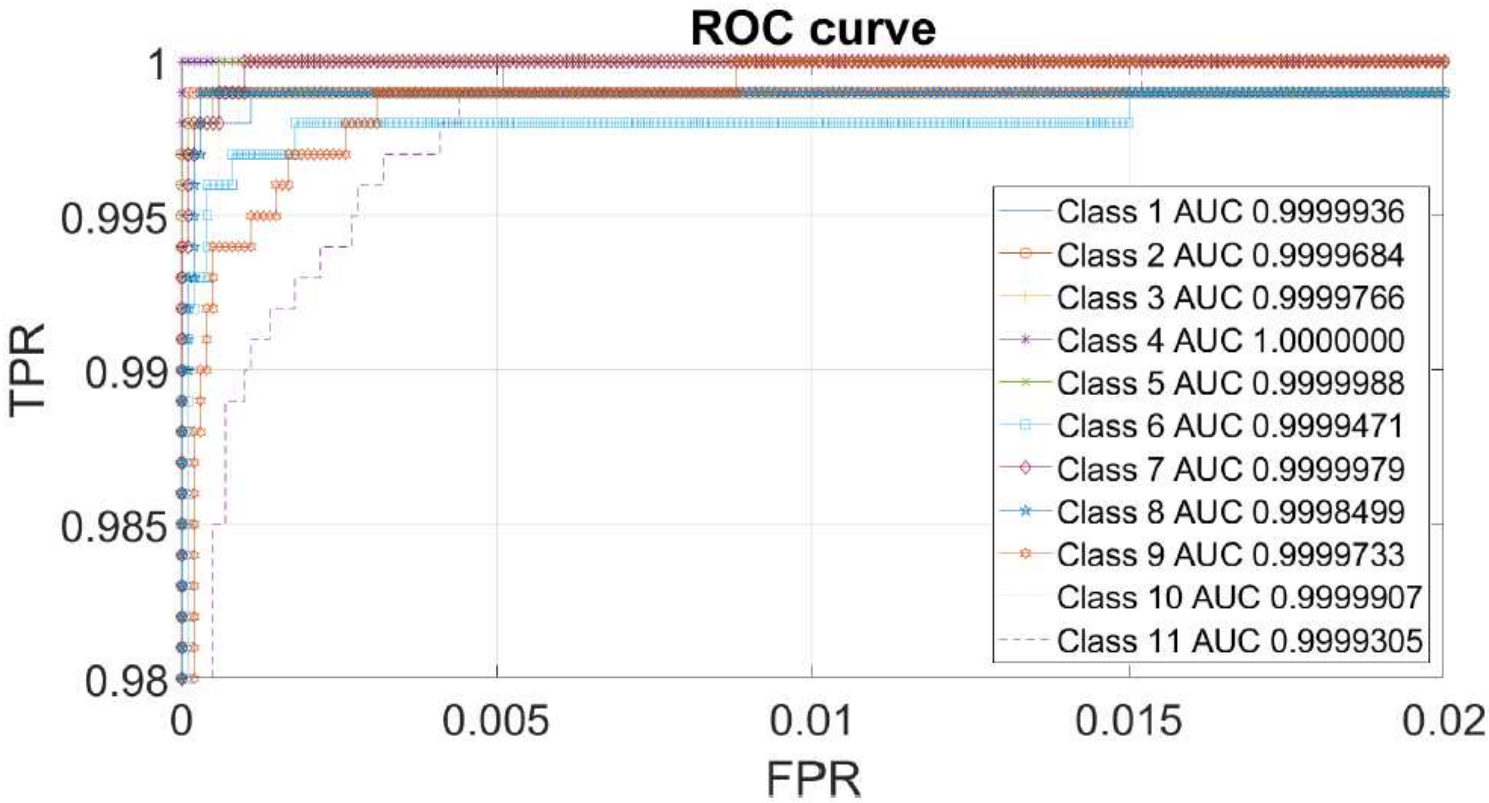

Figure 7

The Integrated ROC Curve of Proposed System

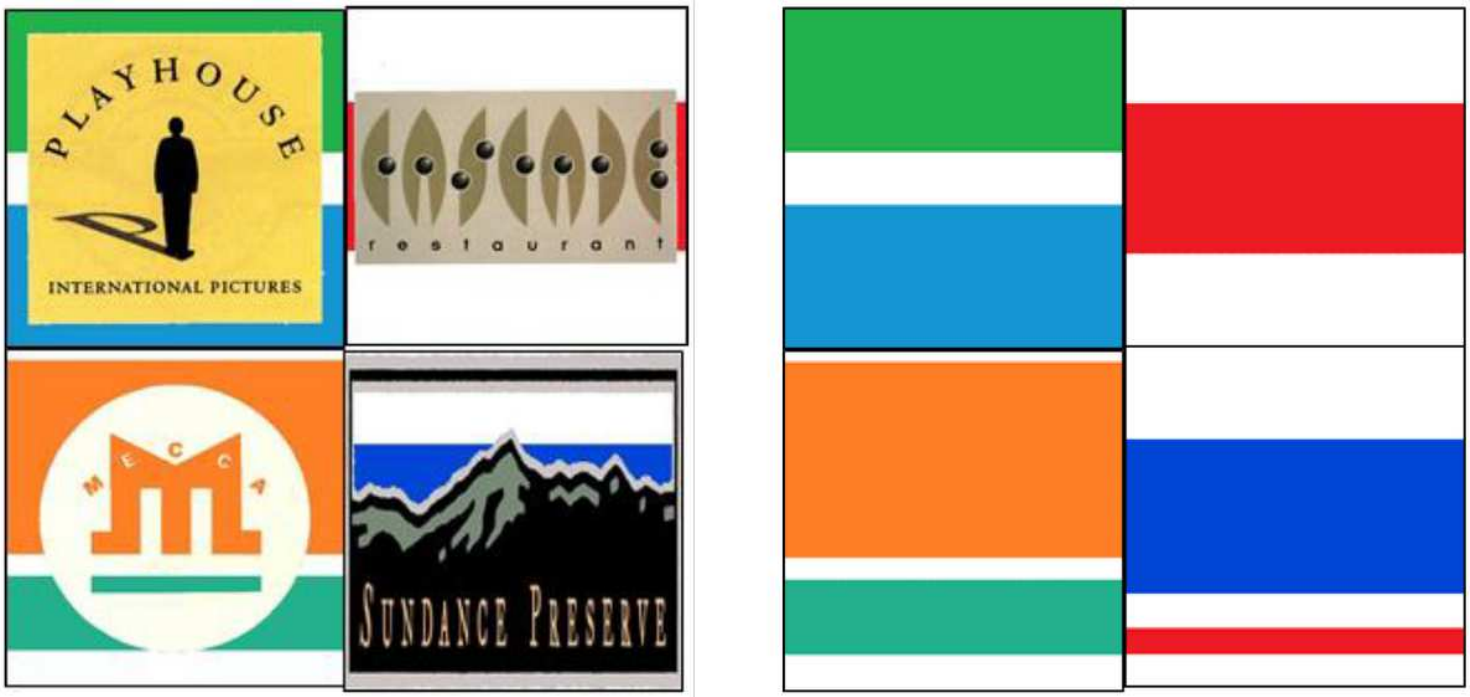

Figure 8

The Samples of False Positive data in Class 11. (a) False positive testing data. (b) Corresponding correct results.

Figure 9

Common trademark background variations. (a) Original background. (b) Background under different designs. (c) Generated testing data sample.

Figure 10

Class 2 variation and class 7 prone to false negative in some network architectures