A Facial Feature Extraction and Classification Model for Loan-Default-Detection

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Abstract: The purpose of this paper is to make a new trial to explore the influence factors of loan default in Internet finance loan business. A facial feature extraction and classification model is proposed. The optimal facial feature extraction algorithm is obtained by comparing four commonly used facial feature extraction algorithms and certain facial features based on physiognomy are selected and classified in 117, 507face images. An experimental study with the help of the proposed model is conducted to explore the correlations between loan defaults and Internet finance loan users' classified facial features based on physiognomy. The findings are as follows: among male Internet finance loan users, short eyebrows are related to default and eye angle, nose height-to-width ratio (nHWR), lip thickness and facial width-to-height ratio (fWHR) are positively related to default behavior and the mouth length is negatively related to default; among female Internet finance loan users, eyebrows angle, eyes angle, lip thickness and facial width-to-height ratio are positively correlated to default and mouth length is negatively correlated with default. Additionally, the conclusion of that male fWHR is positively related to default of the proposed study is echoed with the research results of [1] and [2].

Keywords: loan default, physiognomy, internet finance

1. INTRODUCTION

Taking advantage of the Internet, China's Internet financial loan business has developed rapidly. The most important thing in developing personal loan business is the control of personal credit risk [3]. However, how to effectively identify the risk of personal default from large-scale data is the key to the development of Internet financial loan business.

Most studies focused on the identification of Internet financial loan default risk are based on social data [4], basic personal information [5], [6], historical lending data [7], etc. Moreover, few studies focused on hidden information resources, face images. Human face, as one of the biological characteristics of human beings, contains much information. Since ancient Greece, Westerners have read information from people's faces [8] and in ancient China, physiognomy was deeply rooted in politics, culture, economy, and people's daily lives [9]. The thought that the face reflects one's personality could be found in every ancient culture, and reached its prime in 19th century physiognomy [10]. Many companies also used physiognomy as one of main tools for evaluating candidates, such as AT&T, IBM, etc. Moreover, in the research field of the detection of loan default in Internet finance, face images are not mined and exploited. Reference [1] and [2] found that men's facial width-to-height ratio(fWHR) was related to deceptive behavior and women's fWHR wasn't related. The conclusion inspires us and we wonder that whether do the facial features like fWHR have correlations with the loan default in Internet finance?

In the proposed study, we expect to explore the role facial features play in loan default in Internet finance. In the background of big data, conventional data analysis tools are not appropriate to extract and classify the facial features automatically in the large scale of face images. With the development of artificial intelligence, the technologies of computer visualization and image processing make it possible. A facial feature extraction and

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classification model is proposed consisting of facial feature extraction and facial feature classification. By means of the model, the correlations between facial features and loan default can be found in the large scale of face images.

2. LITERATURE REVIEW

2.1 The research on facial features

Human face contains much information. Since ancient Greece, Westerners have read information from people's faces and in ancient China, physiognomy was deeply rooted in politics, culture, economy, and people's daily lives [8]. Modern psychological studies have revealed that people tend to evaluate others on their appearance and then proceed to interact with them based on first impressions [9]. And it has been established that faces play a central role in people’s everyday assessments of other people [10]. In contemporary, researchers still make effort to seek the implicit information in faces.

People have believed in and practiced physiognomy, the art of reading traits from faces [10]. According to the theory of "San Ting Wu Yan" [11], reference [12] selected facial features based on physiognomy and determined corresponding classification standards, finding out the correlations between facial features and personality traits. Reference [13] studied the relationship between the facial width-to-height ratio(fWHR) of 968 young CEOs on Standard & Poor's and their financial policies. It was found that CEOs with larger fWHR were more radical in their financial policies. It was show in [1] and [2] that men with larger fWHR were more likely to cheat and there is no correlation between fWHR and deceptive behavior among women.

On the whole, these research achievements all indicated that the face contains much information and has the correlation with human behavior. Although these conclusions were not verified in large scale of data, it could be seen that these conclusions had the potential of application and practical value.

2.2 The research on loan default in Internet finance

Risk control is the key to decreasing default rate and the core of healthy development in Internet finance. Exploring the influence factors of loan default in Internet finance, researchers made great effort.

Peer-to-peer (P2P) lending is a representative of Internet finance, allowing individuals to directly lend to and borrow from each other on an Internet-based platform. It is noted that the user's borrowing success rate was related to the voluntary disclosed information, even if the disclosed information by the user was not confirmed [5]. Moreover, it was presented that people who seem to be trustworthy were more likely to get a loan and not likely to default [14]. In China, Internet finance loan business developed rapidly and the research about risk identification has become the focus. Reference [15] analyzed the data collected from Renrendai (A P2P platform in China) with Probit model. It was shown that high-education users had low loan default rates and higher loan scores.

In summary, the existing research is mostly based on personal basic information, including gender, age, education, social network and so on, to study influence factors of loan default in Internet finance.

3. METHOD

The model in proposed study integrates facial features extraction and facial features classification based on physiognomy, which is a combination of computer vision and physiognomy. In order to achieve a better understanding of the proposed model, an illustration of the framework is shown in Figure 1. In the following sections, the model and its components are described in detail.

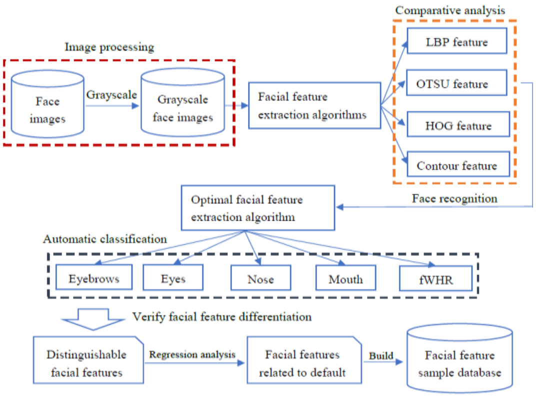

Figure 1. Facial feature extraction and classification model and experiment process

3.1 Facial feature extraction

Before applying the algorithms, face images will be converted to be gray scale images. Facial feature extraction is an important step and the facial features extracted by different texture descriptors have different performances.

To gain the optimal facial feature extraction algorithm, several commonly used algorithms are applied and compared, which are LBP, OTSU, HOG and facial feature point. Figure 2 shows the extracted features by different facial extraction algorithms. Limited by the policies of privacy protection, the face images used in this paper are all from Jaffe database as the substitute for real user's face image.

Figure2. The facial features extracted from different facial feature extraction algorithms

3.1.1 LBP

LBP is an effective texture description operator, which can extract the local neighbor texture information of grayscale image. LBP calculates the binary relations between each pixel in the image and its local neighbor points in the grayscale. The binary relationship is weighted into a LBP code according to certain rules. The LBP code is defined in equation (1).

$$LBP\ (x_c, y_c) = \Sigma_{(P=0)}^{(P-1)} s(g_P - g_C) 2^P \tag{1}$$

In equation (1), g_c represents the gray pixel value at the center position $(x_c y_c)$ in the 3*3 region, and g_p represents the gray pixel value at other positions in the region. The center pixel is compared with neighboring pixels, and a binary value of 1 for neighboring pixels and 0 for smaller pixels is generated.

3.1.2 OTSU

The OTSU algorithm is an efficient algorithm in image binarization, which is an adaptive threshold determination method, and also known as the Otsu threshold segmentation method. When the grayscale of image is L, the number of pixels with the grayscale value i is n_i. Then, the total number of pixel points is $N = n_0 + n_1 + \cdots + n_{L-1}$, and the probability that the grayscale value i is $P_i = \frac{n_i}{N}$, where $P_i \geq 0$, $\Sigma_{i=0}^{L-1} P_i = 1$. According to the threshold t, the image is divided into two categories which are C_0 and C_1, where $c_0 = \{0, 1, \ldots, t\}$, $C_1 = \{t+1, t+2, \ldots, L-1\}$. The probabilities of ω_0 and ω_1 are $\omega_0 = \Sigma_{i=0}^{t} P_i$ and $\omega_1 = 1 - \omega_0$. The grayscale mean values of μ_0, μ_1 and images $\mu_0 = \Sigma_{i=0}^{t} iP_i / \omega_0$, $\mu_1 = \Sigma_{i=t+1}^{L-1} iP_i / \omega_1$ and $\mu = \Sigma_{i=0}^{L-1} iP_i$. The formula of inter-class variance between C_0 and C_1 can be obtained in equation (2).

$$\sigma^2 = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 \quad (2)$$

3.1.3 HOG

The main purpose of this method is to define an image as a group of local histograms. The process for implementing the HOG descriptors is as follows.

The first is to calculate the gradient. Horizontal $G_x(x,y)$ and vertical $G_y(x,y)$ image gradients are calculated as follows. In equation (3), $H(x,y)$ represents the pixel density at (x,y) point.

$$\begin{cases} G_x(x,y)=H(x+1,y)-H(x-1,y) \\ Gy(x,y)=H(x,y+1)-H(x,y-1) \end{cases} \quad (3)$$

The second is to calculate the orientation histograms. Horizontal $G_x(x,y)$ and vertical $G_y(x,y)$ image gradients are used to calculate the gradient magnitude $G(x,y)$ and gradient orientations $D(x,y)$ are calculated in equation (4) and (5).

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \quad (4)$$

$$D(x,y) = tan^{-1}(\, G_y(x,y)/G_x(x,y)) \quad (5)$$

Then, the gradient histogram is built. The image is divided into several non-overlapping cells and 9 bins evenly spaced over 0°~180°. The histogram of bins is used to calculate the gradient of each cell. Several non-overlapping cells are grouped into blocks. Lastly, the features are obtained after normalization processing and combined.

3.1.4 Facial feature point

The facial feature point detection refers to detecting the location of key points in face, mainly including five parts which are eyes, eyebrows, the nose, the mouth and the cheek. The number of required feature points is about 60. This paper selects the face recognition package in Python as a tool for facial feature point detection. The package is used to detect facial points, which applies the convolutional neural network to training detection model. In this paper, the facial feature points extracted are drawn into lines to form the face contour feature as the facial feature extracted.

3.2 Facial feature classification

3.2.1 Eyebrows

The length of the eyebrows is determined by two extended baselines, which are from both sides of nose to canthus [15]. The specific baseline is shown in Figure 3(a). The angle of the eyebrows is determined by the endpoints of the eyebrow’s both sides and the highest point of the eyebrow, which is a fixed value. It is shown in Figure 3(b).

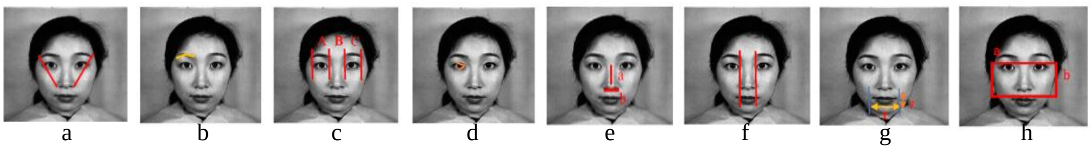

Figure 3. The classification of facial features

According to the two baselines, the length of the eyebrows is divided into four categories: long eyebrows, short eyebrows, standard eyebrows, and upward eyebrows. If exceeding the baseline, the eyebrows are defined as long eyebrows. Otherwise they are short eyebrows. If the end point of eyebrows is just on the baseline, the eyebrows is defined as standard eyebrows.

3.2.2 Eyes

Reference [15] defined the distance between the eyes as a benchmark, as shown in Figure 3(c). The shapes of eyes are divided into large eyes and small eyes. If the size of A area is smaller than B area, the eyes are defined as small eyes. If the size of A area is larger than B area, they are big eyes. At the same time, the angle between the highest point, the lowest point and the right endpoint of the left eye, as shown in Figure 4, is selected as a supplement indicator for measuring the size of eyes. Figure 3(d) shows the standard for dividing the size of eyes and the way to measure the angle.

3.3.3 Nose

The nose height-to-width ratio(nHWR) is the indicator to measure the size of the nose, as shown in Figure 3 (e). A represents the length of nose bridge and b represents the length of the tip of nose.

3.3.4 Mouth

The mouth can be divided into large mouth and small mouth [15]. As shown in the Figure3 (f), two straight lines are drawn from the inside point of iris to calculate the size of mouth. If the corner of the mouth exceeds the line, it is a large mouth. Otherwise, it is a small mouth. The horizontal distance between the corners of the mouth is used as a compared index to measure the size of the mouth. As is shown in Figure3 (g), the thickness of lip is proposed as the supplement feature of mouth. The vertical distance between the upper and lower part of the mouth is an index to measure the thickness of the lip.

3.3.5 Facial width-to-height ratio

As shown in Figure3 (h), bizygomatic width is calculated as the maximum horizontal distance from the left facial boundary to the right facial boundary. Upper face height is calculated as the vertical distance from the highest point of the upper lip to the highest point of the eyelids. Facial width-to-height ratio(fWHR) was calculated as width divided by height [2].

4. EXPERIMENTS

In this section, face images are converted to be gray scale images and four different facial feature extraction algorithms are used in order to perform a comprehensive evaluation. The accuracy of face recognition is a standard to determine the optimal algorithm. According to classification standards, facial features are classified automatically by the location of facial features extracted by the optimal facial feature extraction algorithm. Then, the facial features without differentiation are filtered. Based on the filtered facial features, the logistics regression is employed to find out the correlations between facial features and loan defaults.

4.1 Datasets

The face images in experiments are provided by an Internet financial loan institute in China, which are generated from the users' identity authentication link. We stress that face images used in the experiment are all classified and the users' privacy are protected.

The face images are all self-portraits, containing credit-worthy users and loan default users. Credit-worthy users are those who pay loan back on time, and loan default users are those whose repayment are overdue more than 30 days. The number of face images is 117,507, where 104,776 are good customers who pay loan back on time and 12,731 are bad customers who default.

4.2 Evaluation

Considering robustness, accuracy and the subsequent classification, we hold that extracted facial features must be distinct, face contours must be complete and the obtained effective facial feature images must be more. Based on that, we use a trained face recognition classifier to judge the performances of facial feature extraction algorithms. The extracted facial features are the inputs of the classifier and the accuracy of face recognition is the output. As shown in Table Ⅰ, the performance of HOG feature is the best.

Table Ⅰ. The recognition accuracy of each facial feature extraction algorithm

Facial feature extraction algorithm	The accuracy of recognized face images
LBP	64.818%
OTSU	51.488%
HOG	97.463%
Facial feature points	97.149%

OTSU is a method to determine the threshold of image binarization segmentation. According to the grayscale characteristics of the image, it is divided into foreground and background. When the difference between foreground and background is larger, the probabilities that the foreground and the background are misclassified is smaller. In experiments, we find that when the scene where user shoots is not bright, the algorithm can't segment the facial features well. On the contrary, the part of the face is divided into the background, resulting in severe image distortion and very poor performance in datasets. It shows that the performance of the algorithm is easy to be affected by illumination and not robust. At the same time, we find that the LBP is easily affected by the user's shooting angle and the direction of the light, which leads to the missing information of many parts in faces and some specific parts blurred. HOG algorithm can extract the contour information of faces better and gain the best accuracy, but it can’t extract the information of the specific part of the face well. If the illumination of the image is dark and some parts of the face is the same as the illumination background, the algorithm cannot split this part which makes key information of the face lost. From the Table Ⅰ, it can be seen that the accuracy of facial contour feature extracted by facial feature point algorithm is very close to the HOG feature, only 0.314% difference. By comparing the facial feature images, it is shown that the key parts in HOG feature are not distinct and the boundary of feature is vague. On the contrary, the facial contour feature extracted by facial feature point algorithm can describe the contour of key parts in face well and present the information in face. Additionally, distinct facial features of key parts are vital to subsequent facial feature classification.

Considering the recognition accuracy, the robustness and the subsequent facial feature classification, the facial feature algorithm is chosen as the optimal facial feature extraction algorithm. The point positions of each selected facial feature can be gained by facial feature point algorithm, which are expressed in the form of two-dimensional coordinates. According to the point positions of facial features and classification standards, the facial features can be classified automatically.

4.3 Results and discussion

In Table II, it can be found that none of users’ eyebrow features is standard eyebrow. Therefore, the standard eyebrow feature is removed, only leaving three features which are long eyebrow, short eyebrow and upward eyebrow. In term of the shape of eye, the work finds that the classification standard proposed by [15] is not appropriate in this experiment. In Table II, there are 114,195 users who have big eyes, and no users’ eye shape is small. The feature is discarded after consideration. Additionally, there are 113,713 users who are big mouths, and only 482 users are small mouths. However, the number of features varies greatly. Hence, we decide to rule out this feature. After preliminary screening, we retain facial features such as eyebrow shape, eyebrow angle, eye angle, nHWR, mouth length, lip thickness and fWHR.

Table II. Statistical results of each facial feature

Eyebrow	Long eyebrow	Short eyebrow	Upward	Standard eyebrow
Amount	94, 897	19, 058	240	0
Eye	Small eye		Big eye	
Amount	0		114, 195	
Mouth	Big mouth		Small mouth	
Amount	113, 713		482	
	Mean	Max	Min	S.D.
fWHR	2.116	3.816	1.461	0.200
Eyebrow angle	134.459°	167.040°	115.258°	15.404°
Eye angle	44.868°	90°	1.122°	7.737°
nHWR	1.232	2.094	0.489	0.189
Length of mouth	68.304	482	8	7.737
Thickness of mouth	28.661	265	4	8.741

Due to the facial differences between men and women, we decide to separate male and female samples. The filtered facial features are used as independent variables, and loan defaults serve as a dependent variable. Logistic regression is performed on male samples and female samples respectively to explore the correlation between facial features and users' defaults. The results are shown in Table Ⅲ.

Table Ⅲ. The results of Logistics regression. Value labeled with the symbols *, **, and * are significant at the 10% level, the 5% level and the 1% level. Reference categories: eyebrow 0, for long eyebrow.**

Male	**Correlation**	**p-value**	**Female**	**Correlation**	**p-value**
Short eyebrow	0.16754	0.00***	**Short eyebrow**	-0.022	0.634
Upward	0.015	0.950	**Upward**	-0.040	0.920
Eyebrow angle	-0.069	0.696	**Eyebrow angle**	0.457	0.026*
Eye angle	0.365	0.003**	**Eye angle**	0.575	0.011*
nHWR	0.545	0.00***	**nHWR**	0.094	0.643
Mouth length	-2.76	0.00***	**Mouth length**	-4.991	0.00***
Lip thickness	2.384	0.00***	**Lip thickness**	2.400	0.00***
fWHR	0.907	0.00***	**fWHR**	0.732	0.00***

We find that the female users' short eyebrow and upward eyebrow ($p > 0.05$) have no correlation with loan default compared with the long eyebrows. By contrast, the male users' short eyebrow ($p < 0.05$) is correlated with loan default. Female users' eyebrow angle ($p < 0.05$) is related to loan default. The larger the eyebrow angle, the higher the probability of loan default. In male users, the eyebrow angle is not related to default. Both male and female users' eye angle ($p < 0.05$) are correlated with loan default. The larger the eye angle, the higher the probability of loan default. At the same time, male users' nHWR is positively related to loan default. In female users, there is no such correlation between nHWR ($p > 0.05$) and default. In male users and female users, the length ($p < 0.05$) of the mouth are all negatively correlated with loan default. And the thickness ($p < 0.05$) of the lip is all positively correlated with loan default in male and female users. Male users' fWHR is positively correlatedly with loan default, which echoes the conclusion made by [1] and [2] that the male with larger fWHR are more likely to have unethical behaviors. In terms of fWHR, it was found that the relationship between deceptive behavior and fWHR in female didn't exist. Moreover, we find that the female fWHR ($p < 0.05$) is relevant to loan default and the female fWHR with higher fWHR are more likely to default behavior [1], [2].

5. CONCLUSIONS AND FUTURE RESEARCH

To explore the role facial features that played in Internet finance loan default in a novel way, this paper presents a facial feature extraction and classification model. By means of the model and corresponding standards, several facial features based on physiognomy are classified automatically. To ensure the robustness and accuracy of the model and requirements of subsequent classification, the researchers compared several facial feature extraction algorithms and experimented in 117, 507 face images to obtain the optimal facial feature extraction algorithms. After consideration and analysis, the facial feature point algorithm is chosen as the optimal facial feature extraction algorithm

The work was further developed by logistics regression between filtered facial features and loan defaults. It was presented that female users' eyebrow angle, eye angle, mouth length, lip thickness and fWHR had correlations with the loan default. Moreover, it was found that the relationship between deceptive behavior and fWHR in the female didn't exist and only existed in the male [1], [2]. The conclusion that men with larger fWHR were more likely to have deceptive behaviors was consistent with the finding in this paper. There are some limitations to this work. The first topic is the improvement of facial feature extraction algorithm. Second, selected facial features based on physiognomy in the paper are not comprehensive and more facial features based on physiognomy can be chosen and experimented.

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