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Credit Card Risk Assessment Using Artificial Neural Networks

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Abstract

In recent years, the supply and demand of the plastic currency market has been rapidly increasing, especially, for the growth rate in the credit card market. It has increased about 16 times in the last 10 years. Many banks devoted to make a large investment in credit card marketing for the sake of getting the maximum profits in the worldwide market. However, most banks are trying to reduce the requirements for credit card application in order to increase the motivation of the customers for applying their credit cards. As a result, many banks somehow ignore the risk management of credit card approval which leads to the increases of bad debt in the credit card market. When this scenario happens year by year, those banks will not get profits from the credit card market but a great loss.

In this study, a total of 113,048 entries were used which included fundamental customer data, credit card data, and customer history data from Joint Credit Information Center (JCIC) of Taiwan. We used the characteristics of artificial neural networks and grey theory to find out the potential factors of the bad credit and finally used the correlation method to find out the higher (important) relative variables (parameters) of bad credit. 80,000 entries were randomly selected as training data and the remaining 33,084 entries were used as testing data.

The experimental results shown that the accuracy of forecasting rate for the proposed early warning system was an overall of 92.7%. These results suggested that the once the collections of the new customer data were available, the proposed approach could be used as an early warning system which can be used to decrease the risk of credit card approval.

Keywords: Credit card risk assessment, artificial neural networks, self-organizing map (SOM), grey theory, electronic commerce

1. Introduction

Daily items for human beings have been developed completely and in wide array to satisfy the diverse needs of individuals, given the ceaseless advancement of technologies. The money market, an indispensable part of human livelihood, has also transformed from the “barter system” of early times, to transactions with currency, and contemporary transactions with plastic money. In Taiwan, the use of plastic money for transactions is common and everywhere. This implies that plastic money has been gradually and surely replacing cash in transactions, and has emerged as the primary form of currency. However, the excessive inflation of credit limit granted in favor of the consumers and the improper approval of credit limits by banks resulted in high debts beyond the means of the consumers for retirements and high non-performing loans for the banks. This is the problem of the so-called “credit card slaves” in Taiwan, which hit the society hard wave after wave. In light of the said issued, this paper proposes to apply the Neural Network with an attempt to map out an effective early warning system for detecting the characteristics of potential credit risks of card holders to avoid the loss of banks due to improper review and approval of credit cards.

1.1. Background and Motivation

According to Joint Credit Information Center [1], there were 3,676,000 credit cards circulated in 1995. This number increased to 45,494,000 in 2005. Similarly, credit card loans rose from NT$272,387 million in 1995 to NT$1,420,984 in 2005.

The data of loans from credit card charges and cash advances provided a clue to the reasons why banks scrambled for a share of the credit card market. The statistics of loans from credit card charges increased by 7.5 times in the decade of 1995 to 2005. The cash advance business also mushroomed by almost 15 times in the same period (Fig. 1, 2).

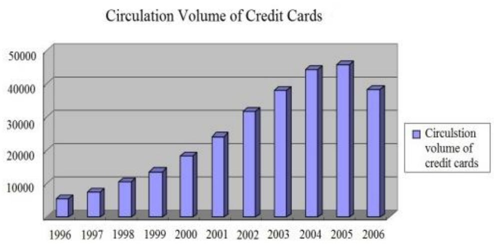

Fig. 1 Volume of Credit Cards in circulation over the years

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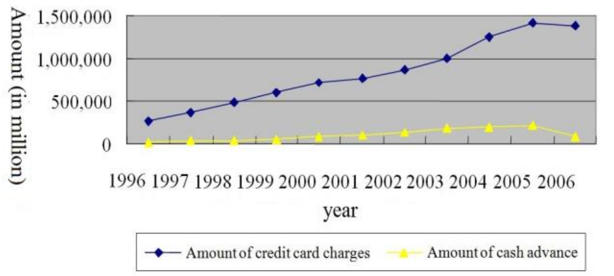

Fig. 2 Growth trend of loans from credit card charges and cash advances

Yet, the number of new cards issued, the amount of credit card loans, and cash advances significantly reduced in 2006. This phenomenon was the result of one card holder possessing many credit cards because banks tended to lower the entrance barrier for granting the applications for credit cards and cash cards in order for a larger quantity of issuance.

After the "Credit Card Slaves" storm, banks have learned their lesson. They changed from focusing on the quantity of card issuance to screening for clients with good credit standing and therefore attempted to construct an efficient early warning system under objective conditions to reduce non-performing loans. This remains the motive of this study.

1.2. The Objective of Study

This study adopts the method of data mining whereby the potential credit risks of credit card clients are explored based on the characteristics of neural network clustering. In practice, the personal information of clients, the borrowing records of the clients at Joint Credit Information Center (JCIC) and the patterns of spending by credit card holders and the payment records are included for analysis for finding out the factors related to bad credit of card holders and delinquency in payment. These factors will be used as the variables in the analysis for constructing an early warning system for credit evaluation.

1.3. Literature Review

Literature on risk management in the financial sector will be introduced in this section. Theories of the neural network model also will be discussed here.

1.3.1. Risk Management

Risk literally means the possibility of suffering loss. Risk can be managed through identification, analysis, and responding measures.

Risk can be analyzed from the perspectives of general causes, the probability of occurrence, the effect of risk, and the damage or loss that is caused (converted into monetary form). Rosenbloom (1972) defined risk as "the uncertainty of the occurrence of loss" 0, Webster's Dictionary defined risk as the opportunity of damage or loss or being in danger. These definitions focused on the possibility of a negative result. Further. Williams & Henis (1981) pointed out that: Risk management is the management method through identification, assessment and control of risk at minimal cost in order to minimize the loss that is caused 0.

Focusing on risk management of banks, Lin (1997) proposed a few principles [4]: (1) Properly evaluate the influences of different risks on the profitability of banks and these influences shall be subject to good financial management; (2) Properly evaluate the capacity of the bank management in early warning of the banking sector and assessment of the strength and weakness of the bank; (3) understand the capacity of the bank in assuming risks on the basis of the competitive advantage of the bank in the industry and take the changes in the macro economic environment under control in pursuing its goal with relevant adjustment of risk level; (4) Viable risk management and monitoring systems will be necessary: (5) Good management and the training of good professionals.

Risk management is important to enterprises of any industry. Better risk control will help to lower the intensity of loss.

1.3.2. Neural Network Model

A Neural network is one form of artificial intelligence and is a data processing system imitating the biological neurotic system. With large number of linked artificial receptive neurons, this system imitates the learning capacity of a biological neurotic system and simulates learning and memory through a parallel computation framework. It is applied to categorization, reflection, identification and optimization functions.

The neural network system is a simulation of the biological neurotic system in operation through ceaseless learning and correction of data for correct output. The neural network system features large volume of parallel processing, non-linear output, and multiple layering in forecasting. The Processing Element (or PE) is the fundamental component unit of the neural network system and the processing unit can be subcategorized as input and output values. The sum of the output values from each layer is the input value of the upper layer. Generally, the function of the product of the input value and weighed links is expressed in the following equation:

$$A = f(net) = f\left(\sum_i W_{ij} X_i - \theta_j\right)$$

A=the output signal of neural network PE
X_i=External input of data
net=Cluster function
θ_j=Threshold value of neural network PE

W_{ij}=the linked weights of all neural network PE in between data paths of the PE. The symbol denotes the strength of the effect of the ith PE of the former layer on the jth PE of the latter layer.

f is the transfer function of neural network PE. It is the conversion of the sum of another PE input value and the linked weights to output value through the PE conversion function. The Conversion function usually sorts out the output value like the Sigmoid Function and is mathematically expressed as:

$$f(net) = \frac{1}{1+exp^{-net}}$$

The output of S function fall between 0 to 1, and the S function input/output curve is usually skewed. Therefore, the net signal is very small and approaches zero. At this point, the output value approaches infinity. If net is a positive value and approaches infinity, the output value approaches 1. Besides, another commonly used conversion function is hyperbolic tangent function and its output is also in an S shape, and is mathematically expressed as follows:

$$f(net) = \frac{exp^{net} - exp^{-net}}{exp^{net} + exp^{-net}}$$

The hyperbolic tangent function is symmetrical with its original point and is a function with output function between -1 and 1. This function works faster than other neural functions in computation for results [5].

1.3.3. Neural Network Model

This section gives an introduction on the application software, techniques, and relational analysis. The clustering techniques and neural network algorithm used Clementine of SPSS proposed by Kohonen. Grey Relational Analysis is adopted for the sampling process of card users in poor credit standing.

1.3.4. Clustering Technique

Clustering is the method through which data with the same or similar characteristics are grouped. Clustering is a form of non-monitoring learning skill and in the process of clustering the distance between each data and the center of the cluster will be mapped out. Clusters of the shortest distance to the center will be formed into the same group.

The main feature of clustering is that no attribute has been assigned to the data and clustering is directly conducted. After the clustering process, the clusters will be based on the results of clustering to trace the characteristics of the cluster elements and the criteria for clustering. Taking this study as an example, the symptoms of clients with potential risk are unclear before the process. Therefore, clustering is used for digging out the characteristics of different clusters. With the different intensifies of the clusters, different weights are assigned to construct a system for forecasting clients with bad credit standing.

The Self-Organizing map Neural Network, or SOM, was proposed by Kohonen (1988) [6]. In brief, this system is a network framework with 2 layers, the input layer and output layer (or competitive layer). The characteristic of SOM is to search the characteristics of the targets and reflect the vector of any dimension to a one or two dimensional map (Fig. 3.2). The output layer neurons will base on the characteristics of the input and display in the output space in topological structure. This map reflects the characteristics of the input vector. Therefore, this is called SOM. The strength of the neural network proposed by Kohonen is that it is a parallel neural network structure and provides the characteristics of analysis and the relation of the organizations. Therefore, it has high confident level as a technique of categorization.

Assuming there are K neurons in this network.

If WkT (n) X (n) = max kT Wi (n) X (n)

i=1, 2,…A

This means that the Kth neuron is the ultimate winner. Adjustment of the chain values

$$W_k(n+1) = \begin{cases} W_j(n) + \eta\left(X(n) - W_j(n)\right) & if\ j = k \\ W_j(n) & \end{cases}$$

where, X=(X1,X2,...,Xp)T means the input vector of the network;

Wj=[Wj1,Wj 2,...,Wjp]T, represents the chain value vector of the jth neuron. P represents the dimension, and η is the parameter of learning rate, n represents the dispersion time. Usually, each chain value of the neuron will be normalized with growing rate at 1. Therefore, the rule for sorting out the winner could be corrected as:

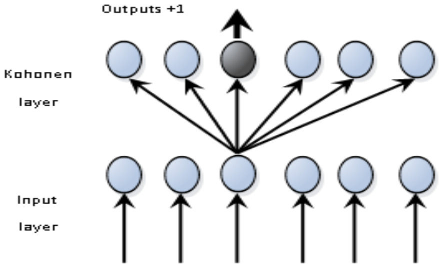

Fig. 3 Dimension Kohonen Model

If $\|X-W_k\| < \|X-W_j\|$, then neuron k will be the winner until the formation of the characteristic map (Fig. 3).

1.3.5. Clustering Technique

Teng (1982) proposed the Grey System Theory for studying the cognition of human beings on different research and things from simple to sophistication. It is just like the waves in the sea coming one after another. In other words, many things are neither absolutely black (blank) nor white (fully transparent) to human beings. Instead, it is in a state of grey (half understood and half unknown), which implies that information is not complete or cannot be described in full detail [7].

Grey Relation Analysis is refers to certain degree of association between 2 elements of the systems or events. If the elements become congruent due to changes, the association between the two is high, or vice versa.

Degree of association is the variance of the geometric shapes of the curves. Assuming a reference value X0, and N comparative values, then X1, X2,⋯, Xn, the relational coefficient ξ (Xi) of each comparative value matrix and the reference value can be expressed by the following equation:

$$\xi_i(k) = \frac{\min_i \min_k |X_0(k) - X_i(k)| + \zeta \max_i \max_k |X_0(k) - X_i(k)|}{|X_0(k) - X_i(k)| + \zeta \max_i \max_k |X_0(k) - X_i(k)|}$$

ζ (Zeta) is the differentiation coefficient and $0 < \zeta < 1$ while , implies that it is the smallest absolute value between two values (comparative and reference values). After the comparison of all values is completed, the smallest value of the small values is sorted and marked as Δ min.

Similarly, represent the greatest absolute value between two values (comparative and reference values). After the comparison of all values is completed, the greatest value of the great values is sorted and marked as Δ max.

Relational coefficient ξ (Xi) can be simplified and expressed as

$$\xi_i(k) = \frac{\Delta\min + \zeta\Delta\max}{\Delta\mathrm{oi(k)} + \zeta\Delta\max}$$

Furthermore, the relational coefficient may vary at different points of the reference value and the comparative value along the curve, and there is more than one value of the degree of association. Therefore, if all the points along the curve are linked and make it a relational coefficient value, this will be the mean of such value and is expressed by ri. The equation of degree of association ri will be:

$$r_i = \frac{1}{N} \sum_{k=1}^{N} \xi_i(k)$$

Finally, after adding up all relational coefficient values and then dividing by the total number of values, we get the degree of association.

Due to the demands on credit card risk assessment and prediction capability of artificial neural networks, there are many literatures regarding the deployment of novel techniques on the problem of credit card risk assessment in recent years [8-10].

2. Experiment

2.1. Study Sample

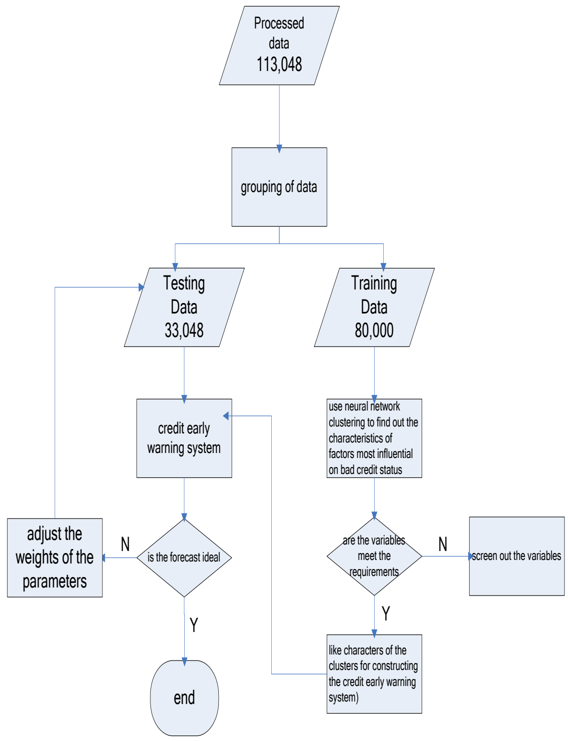

Fig. 4 Flow figure of constructing the early warning system

Samples of this study included the master file of card holders, credit card payment record information, and the information of JCIC, which made up a total of 113,048 entries. Thirteen variables are sorted and the samples are divided into Training Group and Testing Group. 80,000 samples were selected at random for the Training Group. The characteristics of bad credit standing of this group are traced through neural network analysis. Weights were assigned to these characteristics for constructing an objective client credit evaluation system. The remaining 33,084 samples were subject to testing under the Testing Group (Fig. 4). The result from forecasting is compared with the actual bad credit status clients of the banks exemplified by failure to renew credit cards or confirmed by the processing banking officers. If the variance between the forecast and the actual result is wide, it means that more influential factors exist and additional weight shall be assigned in the scoring. The same principle is applied for repeated adjustment of weights. If the forecast approximates the ratio of clients in poor credit standing, it means the characteristics of the variables used in this study are sufficient to forecast clients of potentially poor credit status.

2.2. The Benchmark for Banks to Make Judgment on Poor Credit Status

Different banks have different criteria for judging poor credit status of clients. Banks who provided sample for this study offered both internal and external information for judging poor credit status of clients. They are: I. Internal information: this is the information available from the database of the banks and includes: 1) Loan information of the bank – overdue cash card accounts of more than 15 days of delinquency for the last payment. 2) Loan information of the bank – overdue loan accounts of more than 30 days of delinquency for the last payment. 3) Marked by the bank as GD (1~9) unemployed/insufficient incomes. 4) Marked by the bank as GF (1~9) declared legally incompetent. 5) Marked by the bank as GL (1~9) to be assisted by guarantor for settlement.6) Marked by the bank as GM (1~9) bearing information on assignment of right to debts for repayment. 7) Marked by the bank as GN (1~9) retirement of loans by a relative. 8) Total loans from the bank exceed approved limits. II. External Information: this includes information of the clients from other banks, JCIC transaction record, loan record and payment record. External information usually contains the followings: 1) Loan information –unusual credit approval. 2) Loan information – record of declined account. 3) There were more than 3 “insufficient payment for the minimum” or “overdue account for payment in full” of credit cards over the last six months. 4) Delinquency of cash card payment for more than 31 days (inclusive) over the last six months. 5) Delinquency of consumer loans for than 31 days (inclusive) over the last six months. 6) Supplementary/special mention information indicated as unemployed/insufficient incomes. 7) Supplementary/special mention information from JCIC indicated declared legally incompetent. 8) Supplementary/special mention information from JCIC indicated assignment of right to debts for retirement of loans. 9) Supplementary/special mention information from JCIC indicated retirement of loans by a relative. 10) Total loans from other banks exceed approved limits.

Further to the aforementioned internal and external information, other special requirements are availed to the banks for reference: 1) No renewal of credit cards for student card holder who holds more than 3 cards. 2) Supplementary proof of financial capacity is required if the total unsecured loans exceeds 22 times of monthly salary. 3) If any of the said conditions applies to particular clients of the bank in credit judgment, such client shall be classified as “no card renewal” client.

2.3. Analysis of the Clustering Results

The clustering characteristics of the Kohonen model are adopted and cross computed with all input variables. The result showed that each cluster shows their resemblance. Under this method, there are 22 clusters grouped. Data for the 22 clusters are permuted in sequential order. Clusters ranked at the higher echelon of the hierarchy are the variables denoting clients in better credit standing, and vice versa.

The table of variables ranking showed that the top 6 poor credit accounts, clusters 6, 9, 14, 18, are congruent with the 6 clusters confirmed by the banks as in poor credit status through ranking and manual confirmation (therefore renewal of cards is declined). Therefore, this study further explores the factors and characteristics of the 4 clusters for poor credit standing. They will be listed as the reference in subsequent forecasting of clients of poor credit standing. The relations between the variables and the status of bad credit are expressed in terms of grey relation (Fig. 5).

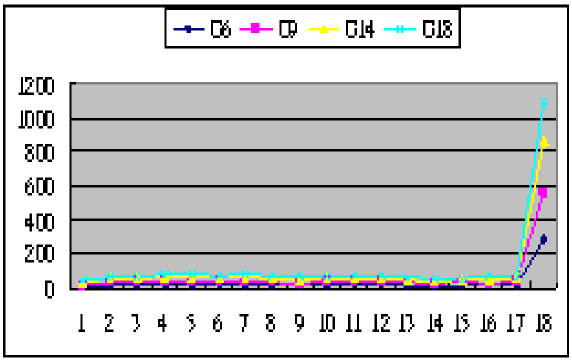

Fig. 5 Forecasting on clusters of bad credit status

We can see the comparison of relations between the clusters and the factor values directly from Fig. 5. In this study, cluster 18 is used as a control for comparison. Grey relation analysis is introduced as follows: I. Standardization: The characteristics are sorted through analysis under the Kohonen model. The data of the 4 clusters are listed (the primary data indicated the ranking among the clusters. The greater value of the data, the poorer the credit status). II. Find out the maximum variance of the clusters and the minimum variance, for finding out the maximum value and the minimum value , we must first find out the "Mapping of variance" Table for the maximum value of variance as =1.59, which means Δ max=1.59. The minimum variance is =0 and is expressed by Δmin=0. III. Calculation of relational coefficient: it is ξ i (k).

Assuming ζ =0.5, then the relational coefficient of X1 and X0, ξ i (k), can be expressed as follows:

$$\xi_1(1) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{01}(1) + \zeta\Delta\max} = \frac{0 + 0.5 \times 1.59}{0 + 0.5 \times 1.59} = 1 \tag{1}$$

$$\xi_1(2) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{01}(2) + \zeta\Delta\max} = \frac{0 + 0.5 \times 1.59}{0.74 + 0.5 \times 1.59} = 0.64 \tag{2}$$

$$\xi_1(3) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{01}(3) + \zeta\Delta\max} = \frac{0 + 0.5 \times 1.59}{0.57 + 0.5 \times 1.59} = 0.57 \tag{3}$$

$$\xi_1(4) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{01}(4) + \zeta\Delta\max} = \frac{0 + 0.5 \times 1.59}{0.40 + 0.5 \times 1.59} = 0.5 \tag{4}$$

The same principle applies to the computation of all other variables.

$$r_i = \frac{1}{N} \sum_{k=1}^{N} \xi_i(k) \tag{5}$$

IV. Calculate for the value of: the degree of association between comparative value X1 and corresponding reference value X0.

$$r_1 = \frac{1}{4} \sum_{k=1}^{4} \xi_1(k) = \frac{1 + 0.64 + 0.57 + 0.5}{4} = 0.5723$$

The same principle applies to the computation of all other variables.

V. The above results are ranked in sequential orders and the following result is yielded.

r4>r5 >r6> r7> r8> r13> r2> r14> r9 >r11> r16> r12> r1> r15> r1> r17> r3

2.4. Construct the Early Warning System

Mapping of variables for judgment (Fig. 6) can be given the benchmark for mark deduction of each variable. For example, the factor of "cash advance", if the data field is "Y", it means 8% of the scores for this factor shall be deducted. The sample principle applies to the computation of all other variables.

The User Interface of the early warning system (Fig.7) for the forecasting of potential risks of credit card holders.

Enter the ID card number of the card holder and press "activate for scoring", the system will retrieve the data of this holder from the database and process each count of data for determining if they meet the default standards. The total scores for this ID will be shown in the field of "TOTAL SCORE". And recommendation will be shown in the field of "ADVICE RESULT", including the recommendation for "renewal of card" or "no renewal", and so forth.

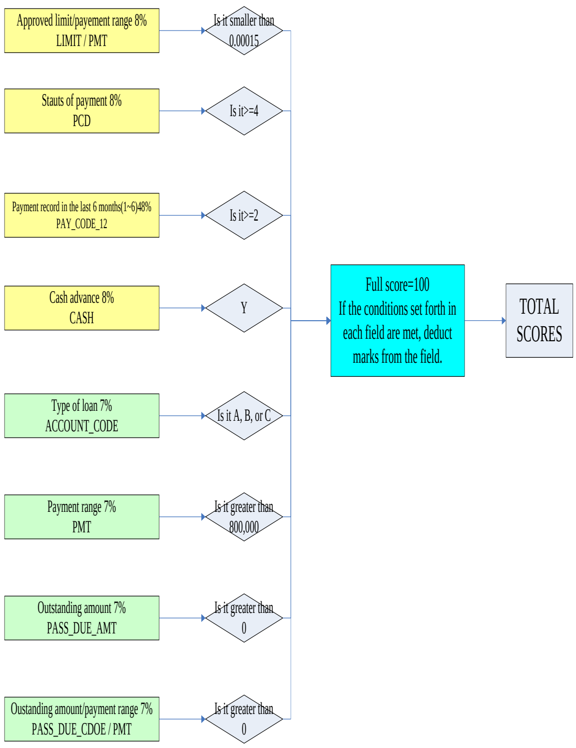

Fig. 6 Mapping of variables for judgment

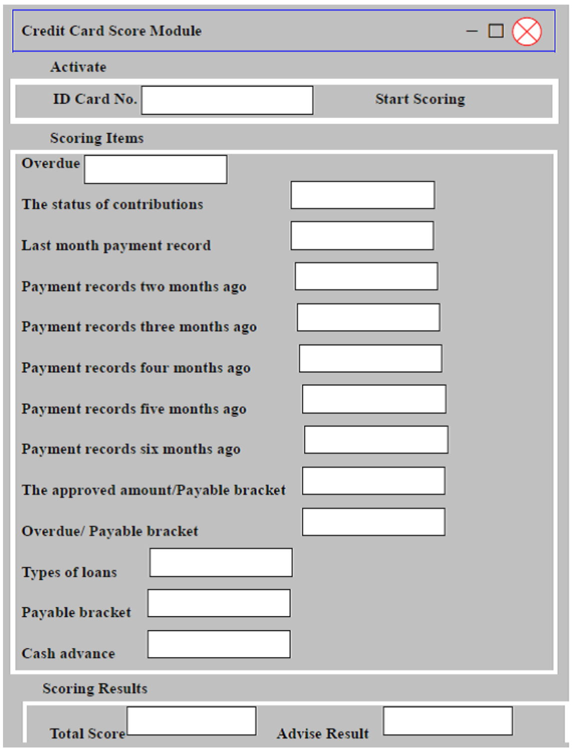

Fig. 7 The user interface of the early warning system

3. Conclusions

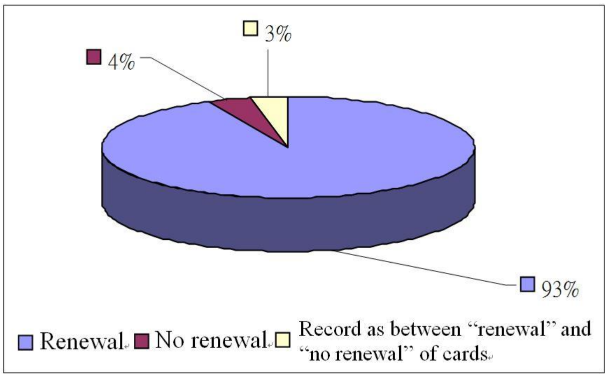

Fig. 8 Distribution of "renewal" and "no renewal" accounts judged by the banks

Currently, each bank has its own method of evaluation in credit risk management. For transparency of information, each bank can access to the database of JCIC for the information of its clients on loans with other banks, credit information and related payment record. Banks can be more accurate in forecasting credit risk if they could have more complete information. In this study, the common fields and data of JCIC are adopted, and the clients of the banks are subject to analysis with the data provided. Neural network system and grey relation analysis are applied to find out the variables possibly related to poor credit status of clients. This section gives a description on the empirical findings of this study. Fig. 8 is the population distribution of the clients for deciding the renewals of cards in the Testing Group. The distribution shows that 93% of all samples constituted clients being granted the renewal of cards. Only 4% of the clients are determined as "no renewal" of cards due to poor credit standing. There are 3% of the samples judged by the banks as "no renewal" after supplementary information on financial position has been provided, and shown in the credit record as between "renewal" and "no renewal" of cards (Fig. 8).

Table 1 shown that T1 stands for forecasted "renewal of card" in this study while T2 stands for "renewal of card" determined by banks. F1 stands for forecasted "no renewal of card" in this study while F2 stands for "no renewal of card" determined by banks. (T1,T2)(※ Noyr 2) the forecasting rate is 91.21%, and (F1,F2) the forecasting rate is 1.46%. The total of the two is 92.67%, which means that the forecasted results under the early warning system are congruent with the actual judgment of the banks.

In Table 2, 49% of the forecasted clusters (T1, F2) were randomly selected by banking professional for verifying the credit status of the card holders. The findings indicated that of the 160 samples being selected (Note 3), 33.33% are indeed in good credit standing but were erroneously judged by the banks as "no renewal of card". This would be significant loss of the banks for losing such good potential clients.

Further, 1.82% of the forecasted clusters (F1, T2) in Table 3 are subject to analysis. The findings indicated that of the 60 randomly selected samples (Note 4), 33.39% are indeed clients in potential poor credit status but erroneously judged by the banks as "renewal of card" clients. In other words, the proportion of bad debts from 1/3 of these clients is much higher than other clients. The banks shall pay attention and take precautions.

This study has led us to know that banks have shortcomings in making judgment on renewal or no renewal of cards. This study also helps to explore a group of marginal clients falling in between "renewal" and "no renewal" and associated strongly with bad credit status, which is critical for decision of renewal or no renewal. This could be served as reference for the banks in the evaluation of credit card clients.

Table 1 Comparing the forecasted rate of the early warning system

Banks / This study	T2	F2
T1	91.21%	5.49%
F1	1.84%	1.46%

Table 2 T1F2 Distribution of Sample Clustering

T1F2(160 samples)				
	Renewal	%	No renewal	%
Judged by banking officers	53	33.33	106	66.67

Table 3 F1T2 Distribution of Sample Clustering

F1T2(60 samples)				
	Renewal	%	No renewal	%
Judged by banking officers	20	33.90	39	66.10

※Note 1: "No renewal for student cards" refers to the same student who holds more than 3 credit cards or applies for credit cards with more than 3 banks at the same time. If these conditions are met, the banks shall treat this group of clients as potentially in poor credit status and determined as "no renewal of card".

※ Note 2: (T1, T2) in this study stands for: (T1) forecasted as "renewal of card" and (T2) the judgment of the banks is also "renewal of cards", and so forth.

※Note 3: At the proportion of 5.49% of all samples, 10% or 160 samples are selected at random.

※Note 4: At the proportion of 1.82% of all samples, 10% or 60 samples are selected at random.

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