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Assessment of Customer Credit Risk using an Adaptive Neuro-Fuzzy System

Research Article

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Abstract. Given the financial crises in the world, one of the most important issues of banking industry is the assessment of customers' credit to distinguish bad credit customers from good credit customers. The problem of customer credit risk assessment is a binary classification problem, which suffers from the lack of data and sophisticated features as main challenges. In this paper, an adaptive neuro-fuzzy inference system is exploited to tackle the customer credit risk assessment problem regarding the mentioned challenges. First of all, a SOMTE-based algorithm is introduced to overcome the data imbalancing problem. Then, several efficient features are identified using a MEMETIC meta-heuristic algorithm, and finally an adaptive neuro-fuzzy system is exploited for distinguishing bad credit customers from good ones. To evaluate and compare the performance of the proposed system, the standard German credit data dataset and the well-known classification algorithms are utilized. The results indicate the superiority of the proposed system compared to some well-known algorithms in terms of precision, accuracy, and Type II errors.

Keywords. Banking, Customer credit risk, Risk assessment, Fuzzy system.

1. Introduction

Customer credit risk assessment is one of the most important issues in banking industry, which has been attracted by a lot of researchers [1-4]. There is no doubt that due to the current financial crises, banks, first, assess customers' credit and, then attempt to lend[5]. Obviously, it is a very difficult to identify good and bad credit customers [5]. Having a reliable model is necessary to take preventive and correct actions in relation to lending to customers [6-9]. Therefore, customer credit risk assessment is one of the most important factors in preventing losses of banks and financial and economic enterprises.

Generally, customer credit risk assessment problem is a binary classification problem that divides customers into good and bad groups, hereafter, they are called good and bad customers, according to their characteristics. Lending money is accompanied by safety to the good customers; however, lending to the bad customers is risky. Given the significance of the issue, there have been many studies conducted on this topic. Initially, probabilistic models and optimization techniques including linear discriminant analysis[10], logit analysis[11], Profit analysis[12], linear programming [13], integer programming[14], K-nearest neighbor (KNN)[13], and Classification Tree[15] have been introduced. Although the aforementioned methods compute the credit risk of customers, distinguishing good customers from the bad ones is still a real challenge. Recent studies have shown that intelligent methods, e.g., neural networks [8, 16],and evolutionary algorithms, e.g., genetic algorithm [17] have more advantages than the statistical methods. Nevertheless, little research has been conducted in this area due to the lack of standard data sets[15].

Large differences between good customers' class size and bad customers' class size, which is known as data imbalancing in machine learning concept, is another important challenge of this problem. In imbalanced datasets, the size of the minority class is much less than the size of the majority class[18]. Training a classifier using the imbalanced data leads the classifier to learn the characteristics of the majority class and avoid learning the characteristics of the minority one. Consequently, the precision of the classifier for classifying the minority class is much less than the majority one. Generally, the minority class is much more important than the majority class. Here, the bad credit customers are members of the minority class. Typically, the number of bad credit customers is much less than the number of good ones. In this paper, a SMOTE re-sampling technique, introduced by Chawla et al. [19], has been utilized to solve the problem of data imbalancing. In this method, new instances have been produced artificially using over-sampling of the minority class. They have the most resemblance to the minority class instances and the least resemblance to the majority class instances. One of the most important problems with this method is overfitting[20]. To solve this problem, an algorithm aimed at finding the distribution of minority class data via data clustering algorithm has been introduced in order to produce artificial samples with respect to the distribution of the minority class. Deploying the algorithm over our imbalance dataset reveals that bad customers' class size reaches to good customers' class size.

High dimensionality of data is another challenge of the customer credit risk assessment problem. Therefore, a feature selection method based on the Memetic algorithm [21] is introduced to tackle this problem. The aim of the algorithm is extracting a subset of features affecting more on the identification of good and bad credit customers. The Memetic algorithm is a meta-heuristic evolutionary algorithm that uses a simple KNN(K-nearest neighbor) classifier in order to define the fitness function and tries to select the effective and efficient features. In the proposed algorithm, the micro-genetic algorithm is exploited for local search and the precision of the KNN algorithm is used to define the fitness function. Simplicity, linear time complexity, and space complexity are the three reasons for choosing KNN algorithm to calculate the fitness function. Considering some qualitative features, an adaptive neuro-fuzzy system is used to classify good and bad credit customers and the membership functions,

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fuzzy rules, and other parameters which are learned using the balanced German credit card dataset.

We use the standard German credit card dataset (UCI machine learning dataset repository) containing the information of 1000 credit card owners in order to evaluate and compare the proposed system with well-known methods. The dataset was prepared by the University of Berlin[22]. Two scenarios have been followed in the experimental studies. 1) Investigating the parameters of the proposed system. 2) Comparing the proposed system with well-known algorithms, namely, Support Vector Machine (SVM), Decision Tree, K-Nearest Neighborhood (KNN), and Multi-Layer Perception (MLP) algorithms. As the experimental analyses show, the proposed algorithm outperforms its counterparts in terms of precision, accuracy, and Type II Error.

The rest of the paper is organized as follows. Section 2 reviews related works. Section 3 describes the proposed system which contains SMOTED-based algorithm, Memetic algorithm, and ANFIS system as well. Experimental studies, which follow two main evolution scenarios is presented in Section 4, and finally Section 5 draws some conclusion.

2. Related Work

Yu et al. presented an intelligent agent-based fuzzy Group Decision Making (GDM) model as a multi-criteria decision-making tool for assessing credit card risks. They evaluated a simple numerical model with three real-world dataset of UK, German, and Japanese credit cards, which achieved acceptable results[23]. Johan et al. studied the accuracy of the ensemble classification methods in identifying risky credit card customers. They used ensemble classification methods of Bagging, Boosting, and Random Forest[24].

Onick et al. introduced a new method for feature selection, calculated efficient features in the standard German credit card dataset, and used the decision tree classifier to classify customers. They combined the Consistency Subset Eval feature selection method with the best first search method and obtained maximum classification precision of 72.6. In the feature selection phase, 14 features of 20 existing features were selected [26]. Orski's et al. introduced a new heuristic algorithm called HGA-NN that combines genetic algorithm and an artificial neural network. This algorithm improved the scalability of credit card customer risk assessment by identifying a subset of the efficient features. The performance of the proposed classifier is evaluated by real-world credit data set collected at a bank in Croatia. The results are very promising[25]. Mohammadi et al.[26]suggested a method based on artificial neural networks for classifying credit card data in Germany. They, first, calculated the optimal number of hidden neurons using the Mean Squares Error (MSE) and, then, used ROC curve to determine a suitable cutting point that has a high precision and a better performance to classify "bad" class.

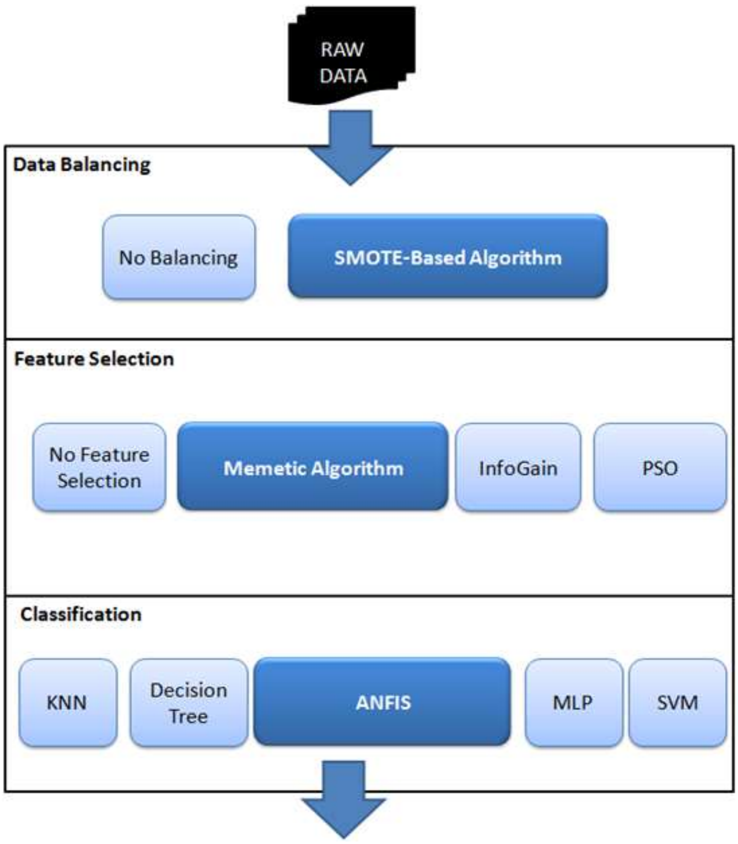

Fig. 1. The architecture of the proposed algorithm

3. Proposed System

Figure 1 depicts the architecture of the proposed system which consists of three main phases of data balancing, feature selection, and classification. Two methods of no balancing and SOMTE-based algorithm are presented here for solving data imbalancing. The PSO, Memetic, and the Information Gain-based algorithms have been introduced for the feature selection phase. Finally, the KNN, Decision Tree, MLP, and SVM algorithms have been introduced for the classification phase.

In the following, the SOMTE-based algorithm is explained and, then, Memetic-based and adaptive neuro-fuzzy system, ANFIS, is expressed.

3.1. Data balancing

The objective of customer credit risk assessment is to predict bad credit customers. Since the number of bad credit customers is much less than good ones, the classes are imbalanced. In order to solve data imbalancing, an algorithm which is based on SMOTE method produces artificial instances regarding bad credit customers' distribution, is proposed. Hence, the minority class is, firstly, clustered by k-means algorithm. Then, artificial instances are constructed by SMOTE algorithm for every cluster. Finally, the aforementioned steps continue until the number of the minority class members equals to the number of the majority class members. Figure 2 shows the SOMTE-based algorithm.

```
Input:  D:  Imbalance Dataset  , k: the number of  clusters
// default value is 2
Output:  Balanced Dataset
Function Balancing_algorithm (D, k)
begin
     [min]=Minority (D)
     [max]=Majority(D)
     While  size(min) < size(max)
     begin
          [c1,c2,...,ck]=kmeans(min, k)
          For i=1 to k
          begin
               Min= min + SMOTE (ci)
          end
     end
end
```

Fig.2. SOMTE-based algorithm pseudo-code

Where *Minority(.) and* Majority *(.)* functions return the minority and majority class members, respectively. *kmeans()* runs *kmeans* algorithm in order to cluster the minority class members. *SMOTE(.)* function is used to construct artificial instances for every cluster found by *kmeans* function.

The lack of attention to the distribution of minority class members is one of essential drawbacks of the SMOTE method[20]. Therefore, SMOTE method usually makes classifiers over fit on training data. To overcome this problem, the distribution of minority class members is, first, determined by Kmeans clustering algorithm, and, then, artificial instances for every cluster are produced by SMOTE algorithm. Here, the number of clusters is set 2. Although the SMOTE algorithm utilizes continuous features to generate artificial instances, hereby, discrete features are dealt with. In order to adopt SOMTE algorithm for discrete features, one of the discrete values is randomly selected based on its frequency in the corresponding cluster.

3.2. Feature Selection

The Memetic algorithm, which is known as an extension of the genetic algorithm, runs a local search over the population generated by the genetic algorithm to find the appropriate solutions[27]. Figure 3 depicts a flowchart of the Memetic algorithm.

The Genetic algorithm is a population-based meta-heuristics approach. It has successfully been applied to various optimization problems. However, immature premature convergence is an important feature of the genetic algorithm that makes this algorithm incapable of searching multiple solutions of the problem domain. A memetic algorithm is known as an extension of the genetic algorithm. It uses a local search technique to reduce the risk of the immature convergence. Local search leads to an escape from local optima in the algorithm [30]. Different search algorithms could be utilized as local search algorithms[28] [30]. One of the mostly used and efficient algorithms is a micro-genetic algorithm.

In this paper, a memetic algorithm, which uses a micro-genetic algorithm for local search is exploited in order to determine the sophisticated features. A binary n-dimensional vector is used as a chromosome where n is the number of features.

To define a fitness function, a simple classification algorithm, here KNN, with low execution complexity is utilized while its precision is used as a fitness value. KNN does not require a training phase and tries to classify with K-nearest neighbors of an input instance. The assumption is that k is considered to be 3. Moreover, a two-point crossover operator is used as a crossover operator. The fitness function is computed by Eq.1.

$$fitness(ch) = Precision\big(KNN(3)\big) \qquad (1)$$

Where *ch* is an input chromosome and *Precision (.)* function calculates the precision of the clustering results.

3.3 Classification

Fuzzy logic solutions are based on linguistic uncertain expressions. Zade[29] founded the fuzzy logic for modeling complex systems. Fuzzy systems have already had great success in solving complex problems such as control problems [30-35]. However, the main problem is the lack of a systematic process to design fuzzy controllers. Artificial neural networks can learn a structure from a set of inputs/outputs. Therefore, many researchers make use of the Adaptive Nuro-Fuzzy inference system, called ANFIS, which combines a neural network and a fuzzy inference system to solve complex problems. ANFIS parameters can be learned with the help of the artificial neural network.

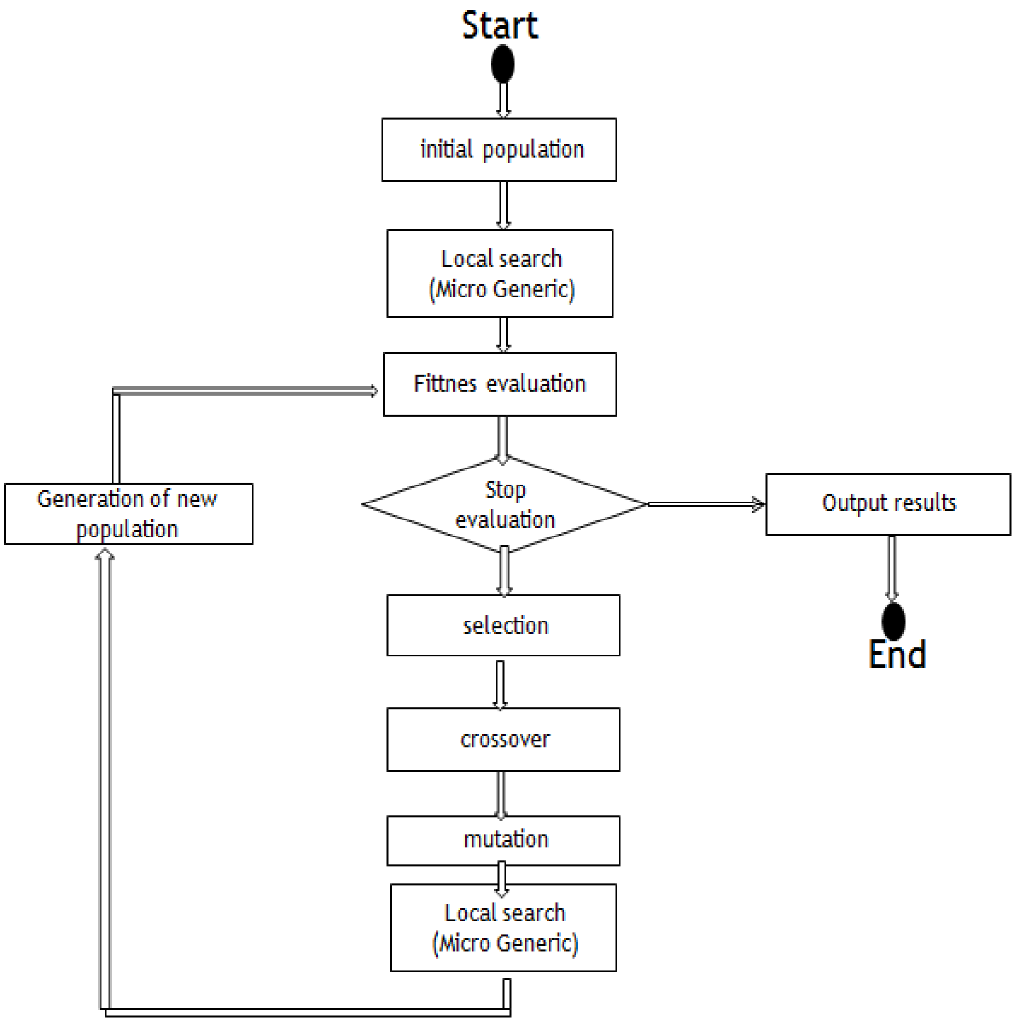

Fig.3. A flowchart of the Memetic algorithm

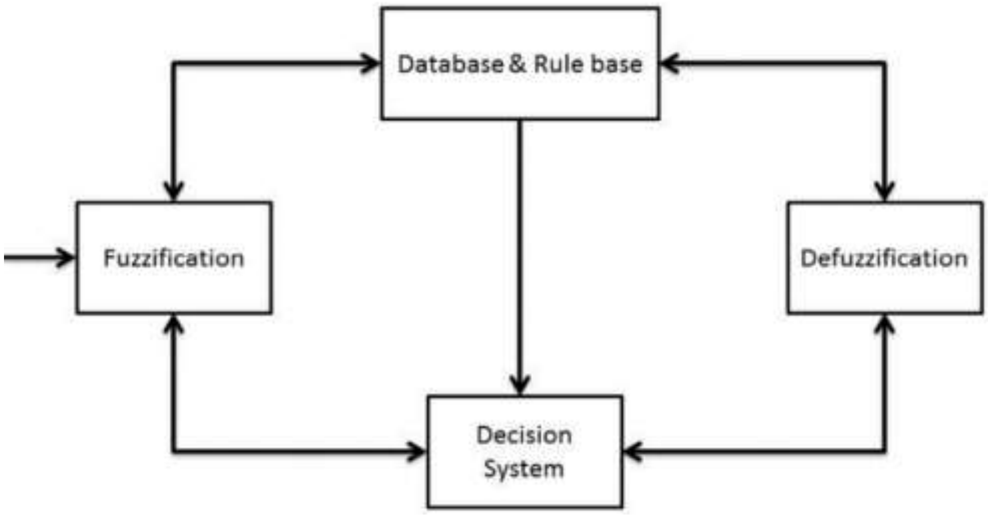

Fig.4. Fuzzy system architecture

3.3.1 Structure of ANFIS

ANFIS is a rule-based system consisting of three conceptual components. 1) A knowledge based component contains fuzzy if-then rules.2) A data base component contains membership functions. 3) An inference component combines fuzzy rules in order to produce results.

To design an ANFIS system, the first step is to determine the membership functions of system parameters. The second step is to define fuzzy rules, and the third step is to determine the output characteristics, e.g., the membership function.

Backward Propagation and Hybrid-learning algorithms are two learning algorithms which are used to determine membership functions as well as learning fuzzy rules. Figure 4 illustrates the overall structure of a fuzzy system, ANFIS, which includes a multi-layer feed-forward network system that uses neural network learning algorithms and a fuzzy inference to map an input space to an output space. ANFIS benefits from the capability of learning parameters, building structure, and classifying instances. The main characteristic is learning fuzzy rules from numerical data or experts' knowledge. The most important problem that ANFIS suffers from is the time consuming learning.

The proposed system utilizes an ANFIS in order to tackle customer credit risk assessment problem. It uses the capability of the artificial neural network to learn membership functions and fuzzy rules. Outputs are also calculated by reasoning capability of fuzzy logic. The Hybrid-learning algorithm and subtractive function are used to determine ANFIS structure (Details of the algorithm and its mathematical background are given in [32]).

For clarity and simplicity, we assume that a fuzzy inference system includes x, y inputs, and z output. The two following fuzzy rules are expressed for first-order Sugeno Inference.

$$Rule1: \ IFxisA_1 \text{ and } y \text{ is } B_1 \text{ THEN } f_1 = p_1x + q_1y + r_1 \quad (2)$$

$$Rule2: \ IFxisA_2 \text{ and } y \text{ is } B_2 \text{ THEN } f_2 = p_2x + q_2y + r_2 \quad (3)$$

Where x,y are crisp inputs to node i, A_i and B_i are linguistic labels (low, medium, high) that are specified by membership functions and p_i, q_i and r_i are consequence parameters. An ANFIS system includes five layers that are described in brief.

Layer 1 (Input layer): In this layer, a membership degree is computed by a membership function. Every output node, denoted by$O_i{}^l$ is calculated by Eq.4 and Eq.5.

$$O_i{}^1 = \mu_{A_i}(x) for i = 1,2 \quad (4)$$

$$O_i{}^1 = \mu_{B_{i-2}}(x) for i = 3,4 \quad (5)$$

where μ_{A_i} and μ_{B_i} are respectively membership functions of the fuzzy sets A_i and B_i. Various membership functions including Trapezoidal, Triangular, and Gaussian can be used to calculate membership degrees. Here, the Generated bell-shaped membership function which calculated by Eq.6 is used.

$$O_i{}' = \mu_{A_i}(x) = \frac{1}{1 + ((x - c_i)/a_i)^{2bi}} \quad (6)$$

Where $O_i{}' \in [0,1]$ are membership functions parameters which are called premise parameters.

Layer 2 (Rule Layer): In this layer, And/Or operators are used to compute an output for every rule. This layer output, denoted by $O_i{}^2$(Firing Strength), is the multiplication of the previous layers membership functions which is represented by Eq.7.

$$O_i{}^2 = \omega = \mu_{A_i}(x)\mu_{B_i}(y) i = 1,2 \quad (7)$$

Layer 3 (Average Layer): In this layer, Firing Strength of each rule is calculated by Eq.8.

$$O_i{}^3 = \overline{\omega}_i = \frac{\omega_i}{\sum \omega_i} i = 1,2 \quad (8)$$

Layer 4 (Consequent Layer): This layer uses Eq.9 to calculate the participation of i^{th} rule to produce output.

$$O_i{}^4 = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_i y + r_i) \quad i = 1,2 \quad (9)$$

Where $\{p_i, q_i, r_i\}$ are the output parameters of a Sugenofuzzy system.

Layer 5 (Output Layer): This layer calculates the final output of the fuzzy system by summing all input signals from previous layer through Eq8. Hence, the output obtained by Eq.9 is converted to the precise value.

Table 1. The training parameters of the proposed method

Parameter	Value
Membership Function	Gauss-12
AND method	Prod
Imp.method	Min
Aggr.method	Max

Table 2. Inputs, variance and mean of membership functions of each input

Input	Range	Gauss (μ,σ)
over-draft (O_D)	[1...4]	[0.62, 2.0]
credit usage (C_U)	[4...96]	[12.6, 42.6]
credit-history (C_H)	[1...5]	[0.81, 2.2]
Purpose (P)	[1...10]	[1.6, 3.6]
Credit amount (C_A)	[1...5]	[0.58, 2.1]
Average credit balance (A_B)	[1...5]	[1.2, 2.5]
Employment (E_S)	[1...6]	[0.98, 3.2]
Installment rate (I_I)	[1...3]	[0.28, 1.1]
Personal status (P_S)	[1...6]	[0.99, 2.9]
Other debtors / guarantors (O_G)	[1...3]	[0.50, 1.2]
Residence since (R_S)	[1...3]	[0.64, 1.4]
Property (PR)	[1...5]	[0.51, 1.3]
Age (A)	[1...2]	[0.28, 1.0]
Other payment plans (O_P_P)	[1...2]	[0.52, 1.5]
Housing (H)	[1...2]	[0.03, 1.5]

The artificial neural network is trained by Hybrid-learning algorithm which is a combination of gradient descent and the least Squares methods. The gradient descent method is used to learn nonlinear parameters (a_i, bi, c_i) and the least squares method is employed to learn the linear output parameters (p_i, q_i, r_i).The antecedent parameters such as membership functions parameters are used to build fuzzy rules. Since the input variables must be partitioned in multiple clusters, the structure of the input layers should be carefully determined. Therefore, the subtractive fuzzy clustering function is used to construct fuzzy rules. Table 1 reports the initial values of training parameters.

The proposed method has 15 inputs. Table 2 reports the variance and the mean of their membership functions.

4. Experimental Studies

Three methods based on Memetic, PSO, and Info-gain algorithms are explored to determine sophisticated features which reported by Table 3. Moreover, five classifiers of MLP, K-Nearest Neighborhood (KNN), Decision Tree, and Support Vector Machine (SVM) are exploited to classify good and bad credit customers.

Three evaluation criteria, namely, accuracy, precision, and Type II error are used to evaluate the proposed system and compare the results with other well-known systems. Type II error calculates the rate of the good credit customers who have been classified incorrectly in the bad credit customers. Type II error is computed by Eq.10.

$$TypeIIerror = \frac{FN}{FN + TP} \tag{10}$$

4.1. Dataset

The standard German credit card dataset, which includes information from 1000 credit cards is utilized. This dataset is related to a bank in Germany and it is collected and adjusted by the University of Berlin. It contains imbalance data about customers and their behaviors, which entails 21 features. Every customer is labeled as "good" or "bad," which represents good or bad credit customers. The good credit customer class includes 700 instances and bad credit customer class contains 300 samples. In the preprocessing phase, artificial instances for minority class are constructed by the proposed algorithm (Section 3.1) and the sophisticated features are selected by the proposed algorithm (Section 3.2). Table 3 reports the list of features, their type, and description.

4.2. Configuration

A 10-fold cross validation is used to evaluate the proposed method. Tables 4 and 5 show the parameters of Memetic and SMOTE algorithms, respectively. Algorithms are implemented on MATLAB with a Core i5 CPU and 8 GB main memory.

Table 3. Features

Features	**Qualitative/ Quantitative**	**Description**
Over_draft (S_C)	Qualitative	Status of existing checking account
Credit Usage (D_M)	Quantitative	Duration in month
Credit history (C_H)	Qualitative	Credit history
Purpose (P)	Qualitative	---
Credit amount (C_A)	Quantitative	Credit amount
Average credit balance (A_B)	Qualitative	Savings account/bonds
Employment (E_S)	Qualitative	Present employment since
Installment rate in percentage of Disposable income (I_I)	Quantitative	Installment rate in percentage of disposable income
Personal status and sex (P_S, S_E)	Qualitative	Personal status and sex
Other debtors / guarantors (O_G)	Qualitative	Other debtors / guarantors
Residence since (R_S)	Quantitative	Present residence since
Property (PR)	Qualitative	Property
Age (A)	Quantitative	Age in years
Other Payment plans (O_P_P)	Qualitative	Other installment plans
Housing (H)	Qualitative	Housing
No. existing credits (E_C)	Quantitative	Number of existing credits at this bank
Job (J)	Qualitative	--
No. dependents (N_D)	Quantitative	Number of people being liable to provide maintenance for
Telephone (T)	Qualitative	--
foreign worker (F_W)	Qualitative	foreign worker

Table4. Setup parameters of the memetic algorithm

Parameters	**Values**
Initial population	50
No. of iterations	20
Crossover	Two point
Crossover rate	0.8
Mutation rate	0.02

Table5. Setup parameters of SMOTE

Parameter	**Value**
Rate	3
Number of neighbors	5

Table 6. Results of different methods of classification of credit card dataset in Germany

Methods	Accuracy	Precision (Good)	Precision (Bad)	Type II Error
Null+Null+MLP	72.3	78.9	54	47.6
Null+Null+DT	70.7	76.3	51.5	61
Null+Null+SVM	68.7	69.6	0	100
Null+Null+KNN	69.4	76.5	48.8	58.3
MLP[2]	70.17	77.9	50.4	53
DT[2]	74.37	78	60.6	58
SVM[2]	75.57	78.6	63.7	56.6
SMOTE+PSO +MLP[36]	70.8	71.3	70.8	30.4
SMOTE+PSO+DT[36]	72.2	72.8	71.8	26.7
SMOTE+PSO +SVM[36]	56.6	60.2	54.9	27.8
SMOTE+PSO+KNN[36]	66.2	69.4	67.6	37.7
Null+Info_Gain+MLP	74.6	80	58.8	44.5
Null+Info_Gain+DT	72.9	78.4	55.9	55.6
Null+Info_Gain+SVM	68.5	69.5	0	100
Null+Info_Gain+KNN	70.9	77	52	57.3
MLPNN [26]	79	85	64	33
SMOTE+MA+MLP	70.8	70	71.6	30
SMOTE+MA +DT	71.35	69.8	73.2	29.5
SMOTE+MA+SVM	72.5	72.9	72.3	25.1
SMOTE+MA+KNN	73.72	71.9	75.9	30
SMOTE+MA+ANFIZ	78.10	78.65	76.91	**24.3**

4.3 Comparison of the proposed method with other methods

Table 6 reports the results of the evaluation and comparison of different methods. Here, the name of each method consisting of the three parts of data balancing method, feature selection method, and classification method. For example, SMOTE + MA + NF uses SMOTE algorithm to data balancing, Memetic algorithm to select the features, and ANFIS to classify. Moreover, DT, MLP, and KNN are Decision Tree, Multi-Layer Perception, and k-Nearest Neighborhood, respectively. MA, PSO, and Info_Gain, respectively, are Memetic Algorithm, Particle Swarm Optimization, and Information-Gain algorithm for feature selections.

As it can be seen in Table 6, four methods of Null+Null+MLP,Null+Null+DT, Null+Null+SVM, and Null+Null+KNN that do not use the balancing and feature selection algorithms have very disappointing results. The greatest accuracy (72.7%), type II error (47.6%), and bad class precision (54%) are obtained by Null+Null+MLP.

In Null+Info _ Gain+MLP, Null+Info _ Gain+DT, Null+Info_Gain+SVM, and Null+Null+MLP methods, the Information gain method is used to select the sophisticated features without data balancing. Fifteen sophisticated features are selected for classification in four methods. Null+Info _ Gain+MLP gained the greatest accuracy (74.6%), bad class precision (58.8%), and type II error (44.5%). MLP neural network is used to classify. As reported by Table 6, Null+ Info _ Gain+MLP outperforms Null + Null+MLP in terms of accuracy (+ 2.3%), bad class precision (+2.2%), and type II error (+ 8%).

Three classifiers of SVM, MLP, and Decision Tree are used as classifiers [2]. The greatest accuracy (75.17%), type II error (74.13%), and bad class precision (56.6%) are obtained by SVM. In [33], accuracy and type II error are improved. The Decision Tree classifier obtained the greatest accuracy (72.7%), bad class precision (71.80%), and type II error (26.7%). As feature selection was done by PSO in this method, The Decision Tree dealt with less and more efficient features. Therefore, the model complexity has been reduced and the result has improved. Neural network was used in [28]. It had the greatest accuracy (79%) and good class precision (85%) in comparison to other algorithms.

In the proposed system, the algorithm introduced in Section 3.1 is used for data balancing and Memetic algorithm is used to select sophisticated features. This method is implemented with five different classifiers. The best results are obtained by to SMOTE + MA + ANFIS method in terms of accuracy (78.1%), precision (76.91%), and type II error (24.5%). The SMOTE + MA + ANFIS outperforms SMOTE + MA + SVM in terms of accuracy (+ 4.56%), precision (+ 4.61%), and Type II error (+ 0.8%). As reported by Table 6, the proposed method of SMOTE + MA + ANFIS outperforms [18] in terms of accuracy (- 0.9%), good class precision (+1%), bad class precision (+ 12.91%), and type II error (+ 8.7%). Moreover, the proposed SMOTE + MA + ANFIS method is better than [16] in terms of accuracy (+ 5.9%), good class precision (+ 5.85%), bad class precision (+ 5.11%), and Type II error (+ 2.5%).

Table 7. Comparison of the feature selection algorithms

	Features	Feature Selection Algorithms		
		MA	PSO	Info Gain
1	Over-Draft (O_D)	●	●	●
2	Credit Usage (C_U)	●	●	●
3	Credit-History (C_H)	●	●	●
4	Purpose (P)	●	●	●
5	Credit amount (C_A)		●	●
6	Average credit Balance (A_B)	●	●	●
7	Employment (E_S)	●	●	●
8	Installment rate (I_I)	●		
9	Personal status (P_S)	●		●
10	Other debtors / guarantors (O_G)	●	●	●
11	Residence since (R_S)	●	●	
12	Property (PR)		●	●
13	Age (A)	●	●	●
14	Other payment plans (O_P_P)			●
15	Housing (H)	●	●	●
16	Existing Credits (E_C)	●		
17	Job (J)		●	●
18	No. Dependents (E_C)		●	
19	Telephone (T)	●	●	
20	Foreign Worker (F_W)	●		●

Table 7 reports features selected by Info_Gain, PSO and MA. "Property magnitude", "Other payment plans", "Job", and "Number of dependents" were not selected as the sophisticated features.

The noticeable point is that the "Job" feature is not selected, while the two other methods have chosen this feature as an effective feature. Moreover, the "Residence since" feature is selected by MA, but it is not selected by other methods. Figure 5 illustrates the comparison results of the proposed system with other methods in terms of training time complexity.

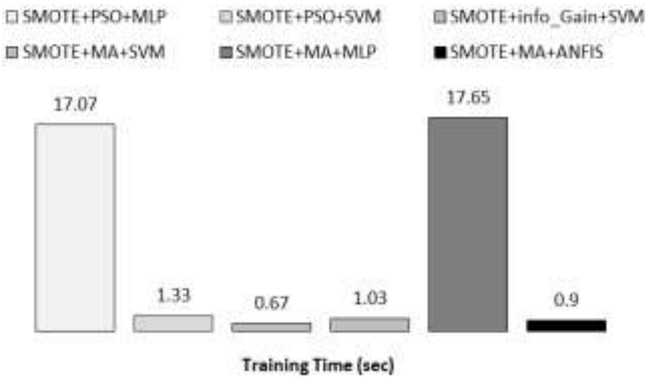

Fig..5. Comparison of different methods in terms of the training time.

Training methods of SMOTE + MA + SVM, SOMTE+Info_Gain+SVM and SMOTE + MA + ANFIS spend 1.0, 0.67, and 0.9 seconds, respectively. Therefore, the method SMOTE + MA + ANFIS has provided better quality results and is faster than others in terms of the training time except SOMTE + Info_Gain + SVM.

5. Conclusion

Customer credit risk assessment problem is a binary classification problem. We propose an adaptive neuro-fuzzy network system using MEMETIC algorithm for feature selection and SMOTE-based algorithm for data balancing. Experimental results which are conducted on the standard German credit card dataset indicate the superiority of the proposed system compared to the well-known systems in terms of accuracy, precision, type II errors, and training time complexity.

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