Credit Scoring Models Using Soft Computing Methods: A Survey

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Abstract: *During the last fifteen years, soft computing methods have been successfully applied in building powerful and flexible credit scoring models and have been suggested to be a possible alternative to statistical methods. In this survey, the main soft computing methods applied in credit scoring models are presented and the advantages as well as the limitations of each method are outlined. The main modelling issues are discussed especially from the data mining point of view. The study concludes with a series of suggestions of other methods to be investigated for credit scoring modelling.*

Keywords: *Credit scoring, credit risk, soft computing, data mining.*

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1. Introduction

Credit risk evaluation decisions are key determinants of success for financial institutions in the lending industry due to the heavy losses associated with wrong decisions. The US sub-prime mortgage crisis reveals the impact of credit risk decisions on the economy either locally or globally. Many financial institutions suffered significant losses as a result of customers' payment defaults. Hence, the development of the credit risk decision support tools and models has an important impact on enhancing the evaluation decision by getting faster and more accurate decisions.

Credit scoring is the most commonly used technique to evaluate the creditworthiness of credit applicants with respect to their features such as age, income, and marital status. Its objective is to classify the credit applicants into two classes according to their likely payment behaviour: good applicants who are likely to repay their financial obligations and subsequently receive the credit and bad applicants who are denied because of the high probability of defaulting on their financial obligations. Many methods have been investigated by banks and financial institutions to develop accurate credit scoring models with the statistical methods being most popular.

In recent years, with the developments of financial markets, more sophisticated methods that can model non-linear, complicated, real world applications are needed. In this context, soft computing methods have been successfully applied to solve non-linear problems in engineering, business and medicine. These methods which indicate a number of methodologies used to find approximate solutions for real-world problems which contain various kinds of inaccuracies and uncertainties can be alternative methods to statistical methods. The underlying paradigms of soft computing are neural computing, fuzzy logic computing and evolutionary computing [34].

There are some studies on the application of soft computing techniques in credit scoring models. For example, Vellido *et al.* [29] surveyed the use of neural networks in business applications and included a section on credit scoring model. It illustrated some of the difficulties of credit scoring modelling such as the availability of the data and the mixed results obtained by previous research on the application of neural networks. Thomas [28] surveyed the statistical and operation research techniques used in credit scoring. It also discussed the need to incorporate economic conditions into the scoring systems.

This study aims at discussing the main modelling issues of credit scoring models built using soft computing methods and exploring the recent trends, challenges and suggesting future directions for the intelligent credit scoring modelling. Specifically, it focuses more on the growing interest of the extracting knowledge from the model for credit analysis purposes, or data mining approach to credit scoring model. Data mining is aimed to reveal useful relationships, finding useful patterns in data sets and to predict outcomes using set of computational techniques and tools [7].

This paper is organized as follows. Section 2 defines the credit scoring problem while the credit scoring models using soft computing techniques is presented in section 3. Section 4 discusses the main recent issues and challenges facing these techniques in scoring modelling. Finally, section 5 draws the conclusion.

2. Credit Scoring Problem

Credit scoring models are based on statistical or operation research methods. These models are built using historical information from thousands of actual customers. For each application, an application form and history over a fixed period are taken, and a decision on whether his history is acceptable or not, i.e., is he or she a bad customer or not, is then made. Specifically, credit scoring objective is to assign credit applicants to either good customers or bad customers, therefore it lies in the domain of the classification problem [1].

The credit scoring model captures the relationship between the historical information and future credit performance. This relation can be described mathematically as follows:

$$f(x_1,x_2,\ldots x_m)= y_n \quad (1)$$

where each customer contains m attributes: $x_1,x_2,\ldots x_m$, y_i denotes the type of customer, for example good or bad. f is the function or the credit scoring model that maps between the customer features (inputs) and his creditworthiness (output), the task of the credit scoring model (function f) is to predict the value of y_i, i.e., the creditworthiness of customer i by knowing the $x_1,x_2,\ldots x_m$, which denote the customer features such as income and age. Linear discriminant and logistic regression and their variations are the most popular methods in the credit scoring industry [9].

3. Credit Scoring Models Using Soft Computing Methods

In the credit lending industry, an improvement in prediction accuracy of even a fraction of a percent may translate into huge savings [33]. To pursue even small improvement in credit scoring accuracy, many methods have been investigated in the last decade. Artificial Neural Networks (ANNs) are the most commonly soft computing method used in credit scoring modelling.

Thirteen out of 23 of the applications of soft computing methods in credit scoring models proposed neural networks methods either as single method [33, 18, 17, 6, 21, 25, 2, 3, 4, 15 and 32] or combined with other methods [26, 22]. Some studies used neural networks as a benchmark to compare with the new proposed algorithms like evolutionary computation [24, 14] and support vector machine [20, 30, 8, 35, 23 and 13]. Recently, other methods like evolutionary algorithms and support vector machine have shown promising results in terms of prediction accuracy. In the following sections, neural networks, evolutionary computation and support vector machine are briefly described and the main characteristics of each method are mentioned.

3.1. Neural Networks

ANNs are mathematical representations inspired by the functioning of the human brain. They are composed by a number of simple processors (neurons) working in parallel, without any centralised control. The neurons are arranged in a particular structure which is usually organised in layers. A system of weighted connections determines the information flow through the network. ANNs have been extensively used in many disciplines to model complex real-world problems.

3.2. Neural Networks in Credit Scoring Literature

Neural networks have established themselves as a serious alternative to traditional statistical models and many studies have concluded that neural networks outperformed statistical methods in terms of classification accuracy [33, 6, 21, 4]. Much architecture of neural networks have been applied to develop credit scoring models. Vellido *et al.* [29] indicated that more than 75% of neural networks applications in business rely on the use of feedforward MultiLayer Perception (MLP) trained by Back Propagation (BP).

In [18], a MLP has been used to predict the payment history of credit applicants. The MLP model was compared with a commercial credit scoring model using a sample of 125 applications. Its classification accuracy ranged from 76% to 80% on the validation sample. In [6], a comparison of the predictive accuracy of two neural networks: the multiplayer perceptron and modular neural network, against that of two statistical techniques: linear discriminant analysis and logistic regression in classifying loans into good and bad was made. It was concluded that neural networks are superior only if the measure of performance is the percentage of bad loans correctly classified. If the measure is the percentage of good and bad loans correctly classified, neural network performance is comparable to those of statistical modelling techniques.

West [33] compared the classification accuracy of five ANN techniques: the MLP, Mixture Of Experts (MOE), Radial Basis Function (RBF), Learning Vector Quantization (LVQ) and Fuzzy Adaptive Resonance (FAR). Two data sets were used in this study, namely the German data set and Australian data set. Surprisingly, RBF and not MLP -which is the most used method- is the most accurate NN method. This initial result is important and needs more studies to be confirmed as most of the new proposed methods have chosen MLP as a neural networks benchmark method to compare with. To increase the accuracy of the credit scoring model, three ensemble strategies: cross-validation, bagging and boosting were applied by West *et al.* [32]. Multilayer perceptron neural network was employed as a base classifier. The idea is that an ensemble of predictors provides more accurate generalization than the reliance on a single model. The result revealed that the generalization ability of neural network ensemble was superior to the single best model for three data sets.

3.3. Neural Network Modelling Issues

3.3.1. The Lack of Explanatory Capabilities

Even though the rate classification of neural networks is high, they are being criticized for their black box nature, i.e., there is no explanation as to why certain applicants are classified as good credit group and the others as a bad credit group. In his survey, Vellido *et al.* [29] stated that the lack of explanatory capabilities is considered as the main shortcoming of applications of neural networks in business field. Moreover, Baesens *et al.* [4] pointed out that the main reason behind the lack of applying neural networks methods in credit risk evaluation industry is the lack of explanatory capabilities of these techniques and therefore the enhancement of the transparency of neural networks is one of the key factors of their successful deployment. This explanatory capability plays a pivotal role in credit-risk evaluation as the evaluator may be required to give justification as to why a certain credit application is approved or rejected. To solve this problem many methods have been proposed such as hybridization, rule extraction from trained neural network and clustering methods.

- Neuro-Fuzzy system: one of the solutions to overcome the lack of the transparency in neural networks is to combine them with fuzzy systems. The term "fuzzy systems" refers mostly to systems that are governed by fuzzy IF–THEN rules. The IF part of an implication is called the *antecedent* whereas the second, THEN part is a *consequent*. A fuzzy system is a set of fuzzy rules that converts inputs to outputs. The fuzzy inference engine combines fuzzy *IF–THEN* rules into a mapping from fuzzy sets in the input space *X* to fuzzy sets in the output space *Y* based on fuzzy logic principles. In [22], a neuro-fuzzy algorithm called ANFIS was used to build a comprehensible credit scoring model which outperformed Multidimensional Discriminant Analysis (MDA) in terms of accuracy. Furthermore, the neuro-fuzzy approach was found flexible, more tolerant of imprecise data and can model non-linear functions of arbitrary complexity. The main limitations of this method lay in the computational cost due to the curse of dimensionality i.e., the exponential increase of the fuzzy rules when the number if input increase and the fact that ANFIS is applied only for Takagi Sugeno type which is less comprehensible than the Mamdani fuzzy type. The latter type of fuzzy system was applied by [26] to develop a comprehensible credit scoring model with fuzzy rules. The performance of neuro-fuzzy was compared with that of neural networks. Three data sets were used in this study. The result obtained from the study illustrated the trade-off between the classification performance results and understandability of the result obtained. Neural networks outperformed neuro-fuzzy systems in terms of classification accuracy, on both training and testing data while neuro-fuzzy systems are understandable by any user since they are in IF-THEN rule form. A comparison between Takagi-Sugeno and Mamdani types in terms of performance and comprehensibility was investigated by [10]. The result showed that the credit scoring model developed by neuro-fuzzy Takagi Sugeno type was more accurate and less comprehensible than the ones developed by neuro-fuzzy Mamdani type. These two types of inference system vary somewhat in the way outputs are determined. The Mamdani generates a comprehensible descriptive fuzzy rule set with a fuzzy set output while Takagi Sugeno generate fuzzy rules with linear or constant output. The latter method is widely used in dynamic and complex systems while Mamdani type is more suitable for data analysis and data mining problems.
- Clustering methods: some studies used the visualization capabilities of Self Organized Map (SOM) for exploratory data analysis. Huysmans *et al.* [15] used this method in the first step to offer data analysts an easy way for exploring data. Two data sets from Benelux financial institutions were used in this study. To enhance the classification accuracy of the initial model, two ways for integrating SOMs with supervised classifier were proposed. The first technique consists of improving the predictive power of individual neurons of the SOM with the aid of supervised classifiers. The second technique is similar to a stacking model in which the output of a supervised classifier is entered as an input variable for the SOM. The result found that the integration of a SOM with a supervised classifier is feasible because of the powerful visualization capabilities of SOMs for exploratory data analysis and the percentage of correctly classified applicants of these integrated networks is better than what can be obtained by employing solely a SOM.
- Rules extraction from trained neural networks: another approach to overcome the lack of explanatory capabilities of neural networks is to extract the rule sets that mimic the decision process of the trained neural network. Three different methods have been discussed in [4] for comparatively extracting rules from a NNs: NeuroRule, Trepan and Nefclass. The aim of this study was to investigate the performance of these methods to generate meaningful as well as accurate rule sets for credit risk evaluation problems. The

performance of these methods was compared with the C4.5 algorithm and logistic regression. All these methods were applied to three real credit databases: German credit and two data sets from Benelux financial institutions. Both NeuroRule and Trepan yield very good classification accuracy when compared to the popular C4.5 and logistic regression. Furthermore, it was concluded that NeuroRule and Trepan were able to extract very compact trees and rules for all data sets. Subsequently, a decision table technique was used to represent the rule set in intuitive graphical format that allows for easy consultation by the user. One of the drawbacks of using these techniques is that the rule set extracted does not capture the learned knowledge very well [26].

3.3.2. Neural Networks Parameters Selection

The performance of neural networks depends on the adequate setting of the network parameters. The lack of a formal method for selecting the most suitable parameters is a major drawback that may affect the prediction accuracy of the neural networks. In [31] and [16], Genetic Algorithms (GAs) have been applied to determine the optimal topology of NNs. Another study [19] used evolutionary techniques to define the adequate values of RBF parameters. The performance of the proposed model was compared with other models such as support vector machine and NNs models. The results were superior in terms of prediction accuracy but the processing time required was longer than the other models. The conception time is largely reduced as the main network parameters were automatically defined by the GA while a trial and error technique is used in the other models of NNs.

3.4. Evolutionary Computation

Evolutionary computation searches for the optimal solution by a number of modifications of strings of bits called chromosomes. The chromosomes are the encoded form of the parameters of the given problem. In successful iterations (generations), the chromosomes are modified in order to find the chromosome corresponding to the maximum of the fitness function. Each generation consists of three phases: reproduction, crossover, and mutation.

3.4.1. Genetic Algorithm

After the success of neural network in developing accurate credit models, many studies have investigated the application of genetic algorithm as a potential alternative to neural network or statistical methods. It was found in [5] that GA approach was better than linear discriminant analysis, logistic regression and a variety of neural networks in terms of classification accuracy. One drawback to use GA is the considerable computational cost and the lack of comprehensibility. To make the evolutionary model more comprehensible different methods have been proposed.

One of the best solutions to overcome this problem is to combine the powerful learning of genetic algorithm with the description capabilities of fuzzy logic. Hoffman *et al.* [10] proposed a genetic fuzzy for credit scoring and compared it with neuro-fuzzy algorithm NefClass. The result showed that the performance of the genetic fuzzy algorithm is better than the neuro-fuzzy whereas it is less comprehensible than the descriptive rule inferred by neuro-fuzzy classifier NefClass.

Recently, a data mining approach is adopted in developing credit scoring model. Hoffmann *et al.* [11] proposed two evolutionary fuzzy rule learners: an evolution strategy that generates approximate fuzzy rules, whereby each rule has its own specific definition of membership functions and a genetic algorithm that extracts descriptive fuzzy rules, where all fuzzy rules share a common, linguistically interpretable definition of membership function. The performance of evolutionary fuzzy rule learners was compared with that of Nefclass; a neuro-fuzzy classifier and a selection of well-known classification algorithms on four data sets: German data set, Australian data set and two data sets from Benelux financial institutions. The result showed that the genetic fuzzy classification compares favorably with the other classifiers yields about the same classification accuracy across different data sets.

3.4.2. Genetic Programming

Another type of evolutionary computational techniques, Genetic Programming (GP), has been used by [24] to build an accurate credit scoring model with two data sets: the German credit data set and Australian data set. The accuracy of the model was compared with other models using techniques like: neural networks, decisions trees, rough sets, and logistic regression. The result showed that the new model outperforms the other models in terms of accuracy.

Another study conducted by Huang *et al.* [14] proposed a model using two-Stage Genetic Programming (2SGP) to deal with the credit scoring problem by incorporating the advantages of the IF–THEN rules and the discriminant function. 2SGP was compared with GP, MLP, Classification And Regression Tree (CART), C4.5 algorithm, rough sets, and Logistic Regression (LR) using the two real-world data sets. The first data set, called the German credit data set, and the second called the Australian data Set. The result showed that 2SGP outperforms other models. However, GP, ANNs and logistic regression can also provide the satisfactory solutions and can be other alternatives. The accuracy of the induction-based approaches (decision trees and rough set) is inferior to the other approaches.

3.5. Support Vector Machine

SVM is a powerful learning method based on recent advances in statistical learning theory. It is widely used for classification and regression problems due to its promising empirical performance. Recently, many studies have used SVM in credit scoring with promising results. Li *et al.* [20] developed a loan evaluation model using SVM to identify potential applicants for consumer loans. The experimental results revealed that SVM surpasses neural network models in generalization. As the other machine learning, a major problem is that the SVM is a complex function and then it is incomprehensible for human. To overcome this problem, [23] proposed a comprehension credit scoring using SVM by rule extraction technique. Rules can be extracted from a trained SVM that are interpretable by humans while maintaining as much of the accuracy of the SVM as possible. The results obtained showed that this technique loses only a small percentage in performance compared to SVM and therefore this technique ranks at the top of comprehensible classification techniques. A data mining approach is applied by Huang *et al.* [13] to get credit scoring model with relatively few input features. This study used three strategies to construct the hybrid SVM-based credit scoring model. Two credit data sets were used to evaluate the methods applied. The experimental results demonstrated that the proposed methods achieve accuracy identical to that of neural network, genetic programming and decision tree classifier. Additionally, combining genetic algorithm with SVM classifier can be used for simultaneously feature selection task and model parameters optimization. A direct search method has been applied by [35] to optimize the parameters of SVM model. The resulting model has been compared with other three parameters optimization methods, namely grid search, Design Of Experiment (DOE) and GA. The results revealed the ability of direct search to select effective, accurate and robust SVM credit scoring model.

Baesens *et al.* [3] made a study of 17 different classification algorithms using eight different real-life data sets. Some of the data sets originate from major Benelux and UK financial institutions. The classification methods were linear regression (and its quadratic variant), logistic regression, linear programming, four variants of vector support machines, four variants of classification trees, two variants of nearest neighbours, neural net, naive Bayes and tree augmented naive Bayes. The experiments were conducted on eight real-life credit scoring data sets. The classification performance was assessed by the Percentage Correctly Classified (PCC) cases and the area under the receiver operating characteristic curve AUC.

It was found that the Radial Basis Function (RBF), least-squares support vector machine (LS-SVM) and NNs classifiers yield very good performance in terms of both PCC and AUC. However, it has to be noted that simple, linear classifiers such as Linear Discriminant Analysis (LDA) and LOGistic Regression (LOG) also gave very good performances, which clearly indicates that most credit scoring data sets are only weakly non-linear. Only a few classification techniques were clearly inferior to the others.

4. Some Modelling Issues

4.1. Data Limitation

There is a lack of data in the field of credit scoring modelling for the academic community [18]. There are two data sets which are made public from uci repository of machine learning database. The first data set called German credit data set was provided by Prof. Hofmann in Hamburg and the second data set is the Australian credit data set provided by Quinlan [27]. Both of the German and Australian data sets were used by many studies [3, 4 11, 13, 14, 23, 24, 32, 33, 35] to compare the performance of different models. Some authors [2, 6, 8, 10, 15, 17, 18, 20, 21, 22, 25, 26, 30] used data sets from other banks. Baesens *et al.* [3] used rich data sets composed of eight real-life credit scoring data sets from Benelux, UK, German and Australian financial institutions. There are relatively few studies that used many data sets. Thus, more data sets should be made publicly available for academic researchers and cooperation between them and the financial institutions are needed.

4.2. Data Preprocessing

The data preprocessing is an important step in the modeling process. The objective is to derive a set of data, which is expected to be a representative sample of the problem to be modeled. A preprocessing stage was applied by [12] to isolate the unrepresentative data sample in the data set using hybrid SOM-K means clustering methods and then used the neural networks to construct the credit scoring model. The aim of this stage is to increase the effectiveness of the neural networks learning process by using representative and consistent data set. The results show that the preprocessing stage is valuable in building credit scoring of high effectiveness.

4.3. Variable Selection

Variable selection or feature selection is the problem of choosing a small subset of features that is sufficient to describe the target concept. The objective of the variable selection in credit scoring model is to obtain a model with low dimensionality.

Most of the intelligent credit scoring models developed have used the independents variables provided by the banks without modifications. Variables selection may affect the performance of the model and using a formal method for choosing the most suitable customer variables for the model may improve the accuracy and reduce the complexity of the model by eliminating the non-relevant variables. In [13], inputs selection has applied technique to build a less complicated credit scoring model with relatively few inputs.

4.4. Other Methods to Be Investigated

There are some methods which have not been investigated such as: evolutionary-neuro-fuzzy methods which are the result of adding evolutionary computation to neuro-fuzzy system. The combination of three different methods can overcome the limitation of a simple hybrid. For example, neuro-fuzzy methods may suffer from the local optima whereas genetic-fuzzy method has the disadvantage of being time consuming. By using evolutionary-neuro-fuzzy methods, the problem of local optima and time consuming can be overcome. Another promising method is multi-objectives genetic algorithms as it is suitable for systems that have conflicting objectives. In the case of credit scoring models, we have two conflicting objectives; the first one is to increase the classification accuracy while the second is to reduce the complexity of the models. Through this method maximum trade-off can be found and different levels of accuracy-complexity can be chosen.

4.5. Modelling Objectives

In most of the studies, the objective of developing credit scoring models using soft computing method was to achieve higher classification accuracy than the existing models. Recently, the transparency of the models is becoming a more important criterion for a practical credit scoring model that can be deployed in the lending industry. In Table 1, we have divided the studies based on their objectives into two categories: the studies whose objective is only to build a powerful model and the second category comprises studies those whose objective is to develop an accurate and transparent model. As shown in Table 1, the number of studies whose objective is performance and transparency is increased from 16.6 % (between 1992-2000) to 41% of the total number of studies (between 2001-2007).

The transparency in the model is generally defined as the ability to describe the relations between the customer features and their creditworthiness in an easy way; generally in the form of IF-THEN rules. The transparency degree of the model is measured by the compactness of the rule base, the number of rules that map the model behaviour and the number of antecedents in the rule base. In the majority of studies, some important features of the model needed by real-life applications are neglected because of the computer science background of the researchers. So the need of cooperating between the two disciplines; computer science and finance may have good benefits on the credit risk evaluation systems developments. A recent trend in the credit risk evaluation system is to evaluate the profit that can be gained from the customer before his delinquency rather than measuring the probability of defaulting or non defaulting on their financial obligations, hence more attention should be paid to the development in the interest of the banking and finance community and more techniques should be developed to face the newest modelling challenges.

5. Conclusions

In the last fifteen years, the application of soft computing techniques in credit scoring modelling have attracted more attention and many credit scoring models have been developed using single methods like neural networks, genetic algorithms or hybrid methods like neuro-fuzzy or genetic fuzzy. Some of these methods have been introduced and the main advantages and disadvantages have been discussed. Neural networks, genetic algorithms and support vector machines have been reported to be the most accurate methods as compared to the other methods. The classification accuracy is the key determinant of success in financial lending industry. During the last few years, many studies have been conducted to overcome the main drawback of the soft computing methods which is the lack of interpretability. This survey illustrated different approaches used to overcome this problem. Among the approaches used are extraction rules from neural networks, using hybrid methods like neuro-fuzzy or genetic-fuzzy or using unsupervised neural networks learning methods like self-organizing map. This study has shown the benefits of using hybrid methods to overcome some limitations of the single methods. By using fuzzy system, artificial methods like neural networks, genetic algorithms and support vector machine become transparent techniques.

Another issue is the classic trade-off between the accuracy and transparency or complexity of the systems, for example neural networks are more accurate and less transparent than neuro-fuzzy models and also genetic algorithms are more accurate and less transparent than genetic-fuzzy systems.

Some other hybrid methods like evolutionary-neuro-fuzzy methods or multi-objectives genetic algorithms have not been investigated in the credit scoring models.

Table1. Methods used in developing credit scoring models.

Paper	Objectives	Soft Computing Method	Classification Algorithm	Benchmark Method	Data Set
[33]	Perf		MLP, MOE, RBF, LVQ, FAR	LDA, LRA , KNN, NN, KDE, CART	(1) Australian credit (2) German credit
[18]	Perf	ANNs	MLP	Statistical methods.	125 applicants
[17]	Perf		MLP	/	(1) Visa Gold. (2) Visa Classic.
[6]	Perf		MLP, MNN.	LDA. LRA	(1) Credit union L, (2) Credit union M, (3) Credit union N
[21]	Perf		MLP	MDA	(1) Credit Union Data
[25]	Perf		MLP	/	(1) List of Companies.
[2]	Perf		MLP	MDA	(1) credit unions
[3]	Perf		LDA, QDA, LOG, LP, RBF LS-SVM, Lin LS-SVM, RBF SVM, Lin SVM, NNs, NB, TAN, C4.5, C4.5rules, C4.5dis, C4.5rules dis, KNN10, KNN100.		(1) Bene1, (2) Bene2, (3) UK1, (4) UK2, (5) UK3, (6) UK4, (7) Australian credit, (8) German credit
[4]	Perf-trans		C 4.5, C 4.5rules, Pruned NN, Neurorule, Trepan, Nefclass and logistic regression		(1) German credit (2) Bene1 (3) Bene2
[15]	Perf		SOM+Supervised classifier.	/	(1) Bene1, (2) Bene2
[32]	Perf		Ensemble strategy of NNs	MLP	(1) Australian credit, (2) German credit, (3)Bankruptcy data
[20]	Perf	SVM	SVM	NNs	(1) Taiwan data
[8]	Perf		LS-SVM	OLS, OLR, MLP	(1) BankScope data
[35]	Perf		Direct Search-SVM	LDA, QDA, LogR, DT, k-NN	(1) Australian credit, (2) German credit.
[30]	Perf		Fuzzy-SVM	LRA, LOG, MLP, SVM	(1) UK corporations Data. (2) Japanese credit card (3) credit data set
[23]	Perf-trans		SVM rules extraction	C4.5, logit, SVM, Trepan, G-REX	(1) Australian credit, (2) Bene-C
[13]	Perf		SVM+GA	BPN, GP, C4.5	(1) Australian credit (2) German credit
[24]	Perf	Evolutionary Algorithms (EA)	GP	NNs, DT, C4.5, rough sets, LRA	(1) Australian credit (2) German credit
[14]	Perf-trans		2SGP	GP, MLP. CART, C4.5. K-NN, LRA	(1) Australian credit (2) German credit
[26]	Perf-trans	Neuro-Fuzzy (NF)	NF	NNs	(1) credit card data
[22]	Perf-trans		ANFIS	MDA	(1) Nine credit unions
[10]	Perf-trans	Evolutionary-Fuzzy (EF)	GF	NF, Nefclass,C4.5	(1) Benelux data set
[11]	Perf-trans		GFS Approx, GFS Desc	Fisher, Bayes., ANN, C4.5, Nefclass	(1) Australian credit (2) German credit (3) Bene1 (4) Bene2

Key to Table 1

ANFIS	Adaptive Network based Fuzzy Inference Systems
Bayes	Bayes' classification rule
C4.5	Decision Trees Algorithm
C4.5rules	C4.5 with rules set
CART	Classification And Regression Tree
FAR	Fuzzy Adaptive Resonance
GF	Genetic-Fuzzy
GFS Approx	Genetic Fuzzy System inferring Approximate fuzzy rules
GFS Desc	Genetic Fuzzy System inferring Descriptive fuzzy rules
GP	Genetic Programming
2SGP	Two Stages Genetic Programming
KNN	K Nearest Neighbor
KDE	Kernel Density Estimation
LOG	LOgistic Regression
LP	Linear programming
LDA	Linear Discriminant Analysis
LRA	Linear Regression Analysis
MDA	Multiple Discriminant Analysis
Nefclass	Neuro-Fuzzy CLASSier
NF	Neuro-Fuzzy
NNs	Neural Networks
MLP	Multi-layer Perceptron
MNN	Modular Neural Networks
MOE	Mixture of Experts
LVQ	Learning Vector Quantization
RBF	Radial Basis Function
Perf	Performance
QDA	Quadratic Discriminant Analysis
SOM	Self Organizing Map
SVM	Support Vector Machine
RBF LS-SVM	Radial Basis Function least-squares support vector machine
Lin LS-SVM	linear least-squares support vector machine
RBF SVM	Radial Basis Function support vector machine
Lin SVM	Linear support vector machine
TAN	Tree Augmented Naive Bayes
Trans	Transparency

Finally, the transparency and the knowledge extracted from credit scoring models will be an important feature in any intelligent credit scoring systems because it will help for understanding the lending process, the relations between customer features and their creditworthiness and improving the decision making process.

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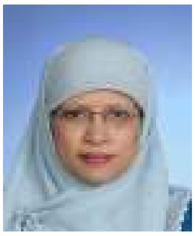

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