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A hybrid model for estimating the probability of default of corporate customers

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Abstract

Credit risk estimation is a key determinant for the success of financial institutions. The aim of this paper is presenting a new hybrid model for estimating the probability of default of corporate customers in a commercial bank. This hybrid model is developed as a combination of Logit model and Neural Network to benefit from the advantages of both linear and non-linear models. For model verification, this study uses an experimental dataset collected from the companies listed in Tehran Stock Exchange for the period of 2008–2014. The estimation sample included 175 companies, 50 of which were considered for model testing. Stepwise and Swapwise least square methods were used for variable selection. Experimental results demonstrate that the proposed hybrid model for credit rating classification outperform the Logit model and Neural Network. Considering the available literature review, the significant variables were gross profit to sale, retained earnings to total asset, fixed asset to total asset and interest to total debt, gross profit to asset, operational profit to sale, and EBIT to sale.

Keywords

Credit risk, Default, Hybrid model, Logit model, Neural network.

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Introduction

One of the most critical challenges the banks are facing today is credit risk. Lahsasna, Ainon and Wah (2010) emphasized that credit risk decisions are key determinants for the success of financial institutions because of huge losses that result from wrong decisions. In fact, risk estimate is the major factor contributing to any credit decision, and the inability to precisely determine risk adversely affects credit management. In addition, risk influences both approved and unapproved financing decisions (Bekhet & Eletter, 2014). Approved customers may be unable to repay their obligation, so poor evaluation of credit risk can cause money loss. Conversely, in rejecting a customer, there is a risk of losing a potentially profitable customer to competitors and the risk of opportunity cost (Bekhet & Eletter, 2014). Wu *et al*. (2010) suggest that credit risk assessment is the basis of credit risk management in commercial banks and provides the basis for loan decision-making. Hence, credit risk evaluation is essential before making any lending decision (Bekhet & Eletter, 2014).

Due to the significance of credit risk, a number of studies have proposed embracing statistical modeling in banks to improve their risk assessment models and hence increase the prediction accuracy of existing models (Akkoc, 2012; Al-Kassar & Soileau, 2014; Jones & Hensher, 2004; Permachandra, Bhabra & Sueyoshi, 2009; Yalsin, Bayrakdaroglu & Kahraman, 2012; Vuran, 2009; McKee & Lesenberg, 2002). Artificial Neural Networks, genetic algorithms, genetic programming, support vector machines, and some hybrid models have been used to evaluate credit risk with promising results in terms of performance accuracy. Using data mining techniques in application evaluation would improve credit decision effectiveness and control loan officer tasks, as well as save analysis time and cost (Bekhet & Eletter, 2014).

Although numerous studies have been conducted in this field, improving the prediction accuracy of models is important because it may prevent considerable losses. Also, numerous models have been proposed to solve credit rating problems but they have the following drawbacks: (1) lack of explanatory power; (2) reliance on the restrictive assumptions of statistical techniques; and (3) numerous variables, which result in multiple dimensions and complex data (Chen & Cheng, 2013). To overcome these shortcomings, this study applies a hybrid model that solves the practical problems in credit rating classification. In fact, the purpose of the current study is to explore the effectiveness of a new hybrid credit scoring model in a commercial bank in Iran. Neural Network (NN) and Logistic Regression (Logit) models were combined and a new hybrid model was developed in this paper. The paper also aims to investigate the superiority of the new hybrid model over Logit and NN models in screening out potential defaulters.

The structure of the paper is as follows: Section 2 reviews the literature, Section 3 describes the methodology and models, Section 4 presents the experimental results, and, finally, Section 5 presents conclusions and recommendations for further research.

Literature review

Over the years, failure prediction or financial distress models have been much discussed in accounting and credit management literature. Since the late 1960s, when Altman (1968) and Beaver (1966) published their first failure prediction model, many studies have been devoted to the search for the most effective empirical method for failure prediction. David Durand (1941) was the first to recognize that one could use the same techniques to discriminate between good and bad loans. Not only in developed but also in developing countries, researchers have attempted to construct a good failure prediction model.

Credit scoring model is a decision support system that helps the managers in financial decision-making process. With a rapid development in credit industry, credit scoring models have been used in decisions related to credit admission evaluation (Chen & Huang, 2003). Credit scoring is a group of decision making models and their underlying techniques which provide support for lenders while providing credit for customers (Heiat, 2012; Thomas, Edelman &

Crook, 2002). The objective of the credit scoring model is to determine credit applicant's capacity to repay financial obligations by evaluating the credit risk of a loan application (Emel *et al*., 2003; Lee *et al*., 2002) and it is necessary to rely on models and algorithms rather than human judgment in consumer lending because of the vast number of decisions involved (Khandani, Kim & Lo, 2010). In fact, credit rating is the assessment of the creditworthiness of issuers or issues and involves a hierarchical ranking process by which credit is classified into different risk categories by credit rating agencies. Credit rating agencies, such as S&P, Moody's, and Fitch, assess the capacity of entities to fulfill their financial commitments.

Recently, many papers have been published comparing different scoring techniques (for example, Logit analysis, Neural Network, and Decision Trees) on the same dataset, i.e. Bell, Ribar & Verchio (1990), Altman, Marco and Varetto (1994), Curram and Mingers (1994), Kankaanpää and Laitinen (1999). In addition, some attention has been paid to the comparison of the performance of different types of failure prediction models (Mossman *et al*., 1998).

This highlights the need for an accurate decision support model for credit admission evaluation. A small improvement in the accuracy of the credit decision might reduce credit risk and translate it into important future savings (Chen & Huang, 2003; Hand & Henley, 1997; West, 2000; West, Dellana & Qian, 2005; Tsai & Wu, 2008; Lahsasna, Ainon & Wah, 2010). Normally, a credit scoring model is built using statistical techniques such as linear discriminant analysis (LDA) and logistic regression (LR) or artificial intelligence (AI) techniques such as support vector machines (SVMs) and Neural Networks (NN).

Apart from reasons of profitability, the use of advanced credit scoring techniques is also stimulated by the internal risk measurement and assessment processes that have become increasingly important, especially in the context of the Basel II capital accord (Gestel *et al*., 2005).

Since the aim of this paper is presenting a new hybrid model, first of all, we review credit rating papers using Logit or NN models. In this review, we investigate the type I error (error of classifying failed firms as non-failed), the type II error (error of classifying non-failed firms as failed), overall predictive accuracy, number of samples for estimating the model and testing, time period, and country of research.

Table 1 categorizes some results of previous studies in credit risk, which have used Logit model or Neural Network.

Statistical models are based on the firms' financial characteristics presented by financial ratios. The selection of financial ratios that best predict financial distress has two approaches in the literature: inductive and deductive. The inductive approach, used in Beaver (1966), Altman (1968), and many other studies (Altman & Narayanan, 1997; Dimitras, Zanakis & Zopounidis, 1996), starts by forming a very wide range of possible variables and then reduces this range to a limited number of variables using statistical techniques.

The inductive-approach studies, applied across industries and countries, dominate the research streams of NN models despite its lack of a theoretical basis. The deductive approach provides theoretical explanations for the process of business failures or the features of the firms' financial situation as the basis for selecting model predictors.

An empirical test is subsequently conducted to justify the model. For instance, Wilcox (1971) provided a theoretical model to explain why certain ratios should be good predictors of failure and obtain better predictive results. The cash flow-based models examined the benefit of the information on firms' operating cash flows in predicting financial distress but concluded that the benefit was small (Casey & Bartczak, 1985).

A large number of ratios have been proposed in the literature. The Courtis's (1978) survey identified 79 financial ratios used in prior business failure studies. Also, Kaminski, Wetzel and Guan (2004) showed that 16 out of the 21 selected financial ratios were significant for effectively identifying fraudulent firms. Nevertheless, financial leverage, capital turnover, asset composition, and firm size are found to be significant factors associated with fraudulent financial reporting (Persons, 1995).

Table 1. Summary of previous studies

No.	Author and Year	Model	Predictive Accuracy			No. of sample		Research Scope		
			Type I error	Type II error	Overal Accuracy	Estimation	Test	Time period	Country	Firm Type
1	Altman *et al*. (1994)	NN	13.8%	10.6%	NA	1212	450	1985-1992	Italy	Manufacturing
2	Ohlson (1980)	Logit	12.4%	17.4%	NA	2163	NA	1970-1976	US	Manufacturing and Service (except trans. & financial)
3	Jones & Hensher (2004)	Logit	2.3%	2.2%	95.6%	NA	NA	1996-2000	Australia	Different Industries
4	Aziz *et al*. (1988)	Logit	14.3%	2.1%	91.8%	98	NA	1971-1982	US	Different Industries
5	Back *et al* (1996)	Logit NN	13.5% 5.3%	13.5% 0.0%	96.5% 97.3%	74	NA	1986-1989	Finland	Different Industries
6	Beynon & Peel (2001)	Logit	16.7%	23.3%	80.0%	60	30	NA	UK	Manufacturing
7	Brockman & Turtle (2003)	Logit	NA	NA	85.0%	NA	NA	1989-1998	US	Different Industries
8	Coats & Fant (1993)	NN	10.6%	2.1%	95.0%	282	NA	1970-1989	US	Different Industries
9	Dimitras *et al*. (1999)	Logit	7.5%	12.5%	90.0%	80	38	1986-1993	Greece	Different Industries
10	Foreman (2002)	Logit	14.3%	0.0%	97.4%	77	14	1999	US	Telecommunication
11	Jo *et al*. (1997)	NN	NA	NA	83.8%	542	NA	1991-1993	Korea	Different Industries
12	Kahya & Theodossiou (1999)	Logit	33.0%	16.0%	77.2%	189	NA	1974-1991	US	Manufacturing and Retail
13	Keasey & McGuinness (1990)	Logit	14.0%	14.0%	86.0%	86	30	1976-1984	UK	Different Industries
14	Laitinen & Laitinen (1998)	Logit	17.1%	22.0%	80.5%	82	NA	1986-1991	Finland	Manufacturing
15	Lin & Piesse (2001)	Logit	12.5%	8.9%	87.0%	77	NA	1985-1994	UK	Different Industries
16	McGurr & DeVaney (1998)	Logit	NA	NA	67.2%	112	NA	1989-1993	US	Retail
17	Neophytou *et al*. (2001)	Logit NN	4.2% NA	8.3% NA	93.8% 93.8%	102	52	1988-1994	UK	Manufacturing
18	Pompe & Feelders (1997)	NN	NA	NA	73.0%	288	288	1988-1994	Belgium	Construction
19	Stone & Rasp (1991)	Logit	NA	NA	72.3%	108	108	NA	US	NA
20	Theodossiou (1991)	Logit	NA	NA	94.5%	363	138	1980-1984	Greece	Manufacturing
21	Ward (1994)	Logit	NA	NA	92.0%	227	158	1984-1988	US	Different Industries (execpt financial services)
22	Westgaard & Wijst (2001)	Logit	22.7%	2.1%	97.3%	35287	35287	1995-1999	Norway	Different Industries
23	Yang, Platt & Platt (1999)	NN	50.0%	20.0%	74.0%	122	NA	1984-1989	US	Oil and Gas
24	Zavgren (1985)	Logit	NA	NA	82.0%	90	32	1972-1988	US	Different Industries
25	Charitou *et al*. (2004)	Logit NN	14.3% 9.5%	23.8% 23.8%	81.0% 83.3%	51	51	1988-1997	UK	Different Industries
26	Zhang *et al*. (1999)	NN Logit	18.2% 21.8%	23.9% 21.8%	80.5% 78.2%	176	44	1980-1991	UK	Different Industries
27	Brabazon & Keenan (2004)	NN	NA	NA	80.7%	128	50	1991-2000	UK	Different Industries
28	Low *et al*. (2001)	Logit	10.0%	0.0%	90.0%	68	10	1998	Malaysia	Different Industries
29	Vuran (2009)	NN	14.1%	17.6%	84.4%	122	NA	1999-2007	Turkey	Different Industries

Table 2. Variables used in previous studies

No.	Variable	Symbol	No. of used	References
1	Debt Ratio	debt_ratio	31	[2],[5],[6],[7],[8],[9],[11],[12],[14],[15],[18],[23],[24],[25],[26],[27],[29],[31],[32],[36],[40],[43],[45],[47],[48],[51],[52],[53],[54],[55],[56]
2	Currebt Ratio	current_ratio	27	[3],[4],[5],[7],[9],[11],[15],[16],[18],[21],[23],[27],[30],[36],[38],[39],[43],[44],[46],[47],[49],[50],[51],[52],[53],[54],[55]
3	Net Working Capital to Asset	nwc_ta	23	[1],[5],[7],[12],[15],[17],[23],[26],[28],[31],[36],[37],[39],[43],[44],[45],[49],[50],[51],[52],[54],[55],[56]
4	EBIT to Asset	ebit_ta	23	[1],[2],[4],[10],[11],[12],[17],[19],[21],[23],[28],[30],[31],[33],[37],[41],[43],[44],[48],[49],[50],[51],[55]
5	ROA	roa	22	[5],[7],[9],[12],[13],[16],[18],[20],[21],[23],[25],[26],[27],[29],[36],[38],[43],[45],[47],[53],[54],[56]
6	Quick Ratio	quick_ratio	19	[10],[11],[14],[15],[19],[21],[23],[24],[25],[29],[32],[36],[41],[43],[47],[48],[52],[53],[56]
7	Retained Earning to Asset	re_ta	17	[1],[4],[8],[11],[13],[17],[20],[23],[26],[28],[31],[32],[36],[43],[44],[54],[55]
8	Asset Turnover	sale_ta	16	[1],[6],[14],[17],[23],[28],[29],[35],[44],[45],[47],[51],[52],[53],[54],[56]
9	Size (Logarithm of Asset)	size	12	[4],[7],[8],[21],[23],[30],[36],[38],[39],[42],[47],[55]
10	Operational Cash Flow to Debt	ocf_td	12	[7],[8],[10],[11],[14],[16],[21],[25],[26],[38],[43],[45]
11	Current Asset to Total Asset	ca_ta	11	[12],[16],[19],[21],[23],[38],[42],[47],[48],[53],[54]
12	Current (or Long-term) Debt to Asset		11	[8],[15],[18],[23],[32],[34],[35],[36],[43],[47],[53]
13	Equity to Debt		9	[14],[36],[38],[41],[43],[49],[50],[54],[55]
14	EBIT to Sale	ebit_sale	9	[2],[23],[29],[43],[45],[49],[50],[54],[55]
15	ROE	roe	8	[13],[18],[23],[24],[27],[31],[32],[54]
16	Cash to Asset	cash_ta	7	[16],[23],[24],[32],[38],[41],[46]
17	Interest Coverage Ratio	int_coverage	6	[4],[8],[12],[30],[39],[45]
18	Fixed Asset to Total Asset	fa_ta	5	[23],[36],[37],[47],[54]
19	Equity to Fixed Asset	e_fa	5	[14],[18],[27],[47],[53]
20	Cash to Current Debt	cash_cd	4	[23],[26],[27],[56]
21	Net Working Capital to Total Debt	nwc_td	4	[2],[5],[8],[35]
22	Long-Term Debt to Equity	ld_e	4	[10],[14],[19],[54]
23	Gross Profit to Sale	gp_sale	4	[23],[24],[53],[54]
24	Inventory to Current Asset	inv_ca	4	[11],[18],[45],[53]
25	Gross Profit to Asset	gp_ta	4	[18],[31],[32],[36]
26	Quick Asset to Total Asset		3	[21],[33],[45]
27	Net Working Capital to Equity	nwc_e	3	[18],[27],[33]
28	Net Working Capital to Sale	nwc_sale	3	[20],[23],[43]
29	Current (or Long-Term Debt) to Total Debt		3	[20],[40],[52]
30	Interest Cost to Total Debt	int_td	3	[13],[52],[54]
31	Operational Cash Flow to Interest Cost	ocf_int	2	[47],[56]
32	Operational Cash Flow to Current Debt	ocf_cd	1	[42]
33	Operational Profit to Asset	op_ta	0	[Experts]
34	Operational Profit to Sale	op_sale	0	[Experts]

After reviewing 56 papers (Table 3) in this field, we summarized variables in Table 2. Variables, used at least five times by authors, were selected for estimating. Also, we recognized two variables using Delphi method with experts in credit division of a commercial bank.

Table 3. List of previous studies for variables recognition

Reference Code	Author(s)	Reference Code	Author(s)	Reference Code	Author(s)
1	Altman (1968)	20	Foreman (2002)	39	Westgaard & Wijst (2001)
2	Altman (1984)	21	Frydman *et al* (1985)	40	Yang *et al* (1999)
3	Altman & Lavallee (1980)	22	Joe *et al* (1997)	41	Zavgren (1985)
4	Altman *et al* (1977)	23	Kahya & Theodossiou (1999)	42	Briggs & MacLennan (1983)
5	Beaver (1966)	24	Keasey and McGuinness (1990)	43	Charitou *et al* (2004)
6	Springate (1978)	25	Laitinen & Laitinen (1998)	44	Zhang *et al* (1999)
7	Ohlson (1980)	26	Lin and Piesse (2001)	45	Brabazon & Kennan (2004)
8	Fulmer *et al* (1984)	27	McKee and Lensberg (2002)	46	Low *et al* (2001)
9	Zmijewski (1984)	28	Moyer (1977)	47	Vuran (2009)
10	Houghton & Woodliff (1987)	29	Park & Han (2002)	48	Saeedi & Aghaie (2009)
11	Cielen *et al* (2004)	30	Piesse & Wood (1992)	49	Raei & Fallahpour (2004)
12	Permachandra *et al* (2009)	31	Pompe & Feelders (1997)	50	Raei & Fallahpour (2008)
13	Shirata (1998)	32	Shin & Lee (2002)	51	Soleimani Amiri (2002)
14	Back *et al* (1996)	33	Toffler (1982)	52	Fatheali & Haeri (2013)
15	Beynon & Peel (2001)	34	Toffler (1983)	53	Ebrahimi & Dayabor (2012)
16	Cazey & Bartczak (1984)	35	Toffler and Tisshaw (1977)	54	Arab Mazar & Safarzadeh (2010)
17	Coats & Fant (1993)	36	Theodossiou (1991)	55	Pourheydari & Haji (2010)
18	Dimitras *et al* (1999)	37	Theodossiou (1993)	56	Moradi *et al* (2012)
19	El Hennawy & Morris (1983)	38	Ward (1994)	-	-

Methodology

Models

Modeling techniques for failure prediction and credit scoring can generally be classified into two different groups: structural models and supervised learning. Parametric learning (linear or non-linear) and non-parametric learning (Density or Kernel machines) may also be classified under the latter methods. Supervised learning techniques learn from data to discriminate between good and bad counterparts. Based on financial ratios and other potentially relevant information, the credit-scoring model computes a score that is related to a default probability. The more powerful the scoring model discriminates between future defaults and non-defaults, the more the good counterparts receive high scores and the bad ones get low scores. In terms of default probability, this means that low scores and high scores correspond to increasingly higher and lower default rates with increasingly better discriminative power of the model. Because of the importance of credit scoring and classification problems in general, there is a wide variety of models (Gestel *et al*., 2005).

It is more difficult to validate these kinds of models. According to Aziz and Dar (2006), one of the most accurate linear models is Logit model. Also, they claim that Neural Networks are accurate in non-linear category. As a result, we choose these models for presenting a new hybrid model. But first, we would review the basic models.

Logistic Regression Model

Logistic Regression (LR) is a predictive model widely used in classification of two groups using a set of predictor variables (Akkoc, 2012). According to Thomas (2000), LR is a linear regression in which the target variable is a non-linear function of the probability of being good. In addition, he stressed that the classification results of LR model are sensitive to correlations between the independent variables. Therefore, variables used in developing the model should not be strongly correlated. Yap, Ong and Husain (2011) stressed that LR credit scoring model aims to determine the conditional probability of each application belonging to one class, i.e. good or bad, given the values of the explanatory variables of the credit applicant. Lee and Chen (2005) supported this view by stressing that each application will be assigned only to one class of the dependent variables. However, the logistic regression model limits the generation of the predicted values of the dependent variable to have a value between zero and one. The LR model is represented as in Eq. (1).

$$\ln\left(\frac{\mathrm{Pj}}{1-\mathrm{Pj}}\right) = \beta_\circ + \sum_{\mathrm{i}=1}^{\mathrm{n}} \beta\mathrm{i}.\mathrm{xi} + \varepsilon \qquad (1)$$

Pi is the probability of being good for a particular customer, i, which is also a function of the predictor variables, xi are attributes that represent the applicant's characteristics. $\beta_\circ$ is the intercept, βi (i= 1, … , n) are the coefficients associated with the corresponding predictor xi (i= 1, … , n); Pj is the probability of default (PD), (ln(Pj/1 − Pj)) represents the credit decision (CD), and ε is errors' terms.

In this paper, first we used Logit model for estimating the primary model and errors of this model were fed to the secondary model.

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are fruitful non-linear modeling tools. ANNs have a biologically inspired capability that mimics processing capabilities of the human brain (Cao & Parry, 2009). Artificial Neural Networks (ANNs) have been used in many business applications and in classification, pattern recognition, forecasting, optimization, and clustering problems. ANNs are distributed information processing systems composed of many simple interconnected nodes inspired biologically by the human brain (Eletter, 2012). In fact, a Neural Network model is composed of a number of processing units called neurons cooperating across different layers (Akkoc, 2012) and connected through several connections or weights. Paliwal and Kumar (2009) asserted that ANNs have been applied widely in research works focused on prediction and classification in a combination of fields' applications. They viewed Neural Networks and traditional statistical techniques as competing model building tools. Angelini, Tollo and Roli (2008) pointed out that ANNs have emerged effectively in credit scoring because of their ability to model the non-linear relationship between a set of inputs and a set of outputs. In other words, ANN, developed by simulating working principles of the human brain, is a flexible non-linear modeling tool and has the ability to learn from examples (Bekhet & Eletter, 2014).

ANN is composed of a number of processing elements which come together within the frame of particular rules called neurons or nodes (Haykin, 1999; Zhang, Patuwo & Hu, 1998). An ANN is generally consisted of three layers of interconnected neurons. A three layer ANN is shown in Figure 1. The first layer is called the input layer where the external information, corresponding to independent variables in statistics, is received. Each neuron in the input layer sends signals to the hidden layer. Information received from the input layer is processed in the hidden layer. The output layer transmits the information outside of the network that corresponds to a dependent variable in statistics.

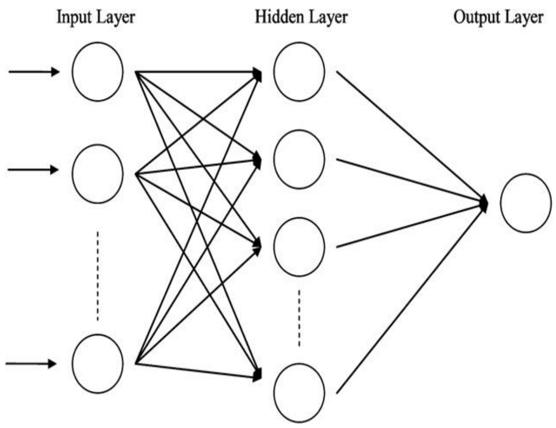

Fig. 1. A neural network sample

Since 1990s, ANNs have been widely used in financial prediction studies, especially in bankruptcy prediction. The majority of these studies report that prediction accuracies of ANNs are higher than conventional statistical techniques. Although ANN can be applied successfully in many fields, it has some disadvantages. ANN requires a long training process in developing the optimal model. ANN has also been criticized for its lack of theory. There is no opportunity to explain the results produced by ANN, in other words, the model acts as a black box (Chen & Huang, 2003; Piramuthu, 1999; Trippi & Turban, 1996; West, 2000).

A hybrid model

Techniques such as Neural Networks are often seen as black box techniques, i.e. the model obtained is not understandable in terms of physical parameters. This is an obvious issue applying these techniques to a credit risk-modeling scenario, where physical parameters are required. To solve this issue, hybrid models are developed. They are formed using at least two models and can eradicate these disadvantages and produce promising results. So, if we have a hybrid model based on linear and non-linear models, we can benefit from advantages of both types, while each model brings its own strengths.

So, in this paper, we propose using a two-stage approach to combine the good comprehensibility of Logit with the predictive power of non-linear techniques like NN (Gestel *et al*., 2005).

In the first stage, a logistic regression is built:

$$\ln\left(\frac{P_{it}}{1-P_{it}}\right) = \beta_\circ + \sum_{i=1}^{n} \beta_i X_{it} + \varepsilon \qquad (1)$$

In the second stage,

$$e_{it} = f(X_{it}) + e_{it}^{*} \qquad (2)$$

where i = 1, …, n are companies (sample) and t = 1, …, 6 is period of sample (2008-2014).

The residuals of this linear model are estimated with Neural Network ($f(X_{it})$) in order to improve the predictive ability of the model.

Doing so, the model takes the following form:

$$Y = \ln\left(\frac{P_{it}}{1-P_{it}}\right) + f(X_{it}) + \varepsilon^{*} \qquad (3)$$

$$Y = \beta_\circ + \sum_{i=1}^{n} \beta_i X_{it} + f(X_{it}) + \varepsilon^{*} \qquad (4)$$

where ε^* are the new residuals of estimating ε.

In this hybrid model, statistically we expect ε^* to be less than ε and the accuracy of the hybrid model is expected to be more than either Logit or Neural Network model.

Variable Selection

A common problem is that there is a large set of candidate predictor variables, therefore, we need to choose a small subset from the larger set so that the resulting regression model is simple, yet having good predictive ability.

In statistics, stepwise regression includes regression models, in which the choice of predictive variables is carried out by an automatic procedure (Hocking, 1976). Efroymson (1960) first proposed this widely used algorithm. This is an automatic procedure for statistical model selection in case there are a large number of potential explanatory variables, and no underlying theory is available, on which the model selection could be based. The procedure is used primarily in regression analysis, though the basic approach is applicable in many forms of model selection. Usually, this takes the form of a sequence of F-tests or t-tests. The main approaches are:

- Forward selection, which involves starting with no variables in the model, testing the addition of each variable using a chosen model comparison criterion, adding the variable (if any) that improves the model the most, and repeating the process until no more improvement occurs.
- Backward elimination, which involves starting with all candidate variables, testing the deletion of each variable using a chosen model comparison criterion, deleting the variable (if any) that improves the model the most by being deleted, and repeating this process until no further improvement is possible.

Because there are relations between some variables (as shown below), and it may cause multi-collinearity among the variables, we eliminate variables no. 12, 13, 26, and 29. The relation between variable has been shown below.

$$\mathrm{Var}(12) \times \mathrm{Var}(2) = \mathrm{Var}(11); \qquad (5)$$

$$\mathrm{Var}(1) = \frac{1}{1+\mathrm{Var}(13)};$$

$$\mathrm{Var}(21) \times \mathrm{Var}(1) = \mathrm{Var}(3)\ ;$$
$$\mathrm{Var}(29) \times \mathrm{Var}(2) \times \mathrm{Var}(1) = \mathrm{Var}(11);$$

So, we use 30 variables for modeling.

Sample and Data

In recent years, the panel approach is widely used. Panel data approach uses additional information from cross sectional dimension to improve estimations. In panel data approach, there are less heteroscedasticity and multi-collinearity among the variables. Therefore, we use panel data in this paper. Data from 175 companies, listed in Tehran stock exchange, was collected from Comprehensive Database of Listed Companies (Codal.ir) and dependent variable was collected from Iranian Credit Rating Institution for a period of 6 years (2008-2013). A set of 125 samples was used for model estimation and 50 were used as out of sample for testing the models.

For independent variable definition, according to Central Bank of Iran (CBI) regulation, the non-performing loans divided into 3 categories:

- **Past Due:** loans that the last payment was maximum 6 months ago.
- **Delayed:** loans that the last payment was 6 – 18 months ago.
- **Doubtful:** loans that the last payment was at least 18 months ago.

Also, according to CBI and Accepted Accounting Principles, because delayed and doubtful loans are in default or close to being in default, interest of loans could not be recognized as interest income, so we define independent variable (probability of default) as 1 if the cases have a default in year t (delayed or doubtful) or 0 if don’t have.

Empirical results

For model estimation and forecasting, we use E-Views 8 and MATLAB 2009.

Before analysis and modeling, we need to know if the model should run with the pooled or panel data.

Estimation with Pooled or Panel data

F-limer test is also known in some sources as Chow test. F-Limer test has been used for choosing between pooled and panel data method.

Table 4. Output of F-limer test

Redundant Fixed Effects Tests
Equation: SWAP04LS
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	2.912225	(124,621)	0.0000
Cross-section Chi-square	343.783652	124	0.0000

As the results show, F-limer test indicates that panel data should be used for estimation. In the next step, Hausman test is used for selecting between fixed effects method and random effects method.

Table 5. Output of Hausman test

Correlated Random Effects - Hausman Test
Equation: SWAP04LS
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	1.601723	4	0.8085

According to the results, the hypothesis of random effect is not rejected.

Estimation results

Stepwise Least Square (Forward and Backward approach) and Swapwise methods were used for estimating LS models up to 17 variables to determine the best explaining variables. Then, 19 Logit models were estimated and the accuracy of these models was calculated by the out of sample data. The results show that the best Logit model is Logit_Swap04 model with variables as follows: gross profit to sale, retained earnings to total asset, fixed asset to total asset, and interest to total debt (Table 6).

Table 6. Output of Logit_Swap04 model

Dependent Variable: Y
Method: ML - Binary Logit (Quadratic hill climbing)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.250555	0.323213	0.775202	0.4382
GP_SALE	-6.876968	0.989833	-6.947602	0.0000
RE_TA	-1.898408	0.586753	-3.235444	0.0012
FA_TA	-3.007578	0.784341	-3.834528	0.0001
INT_TD	11.94440	2.889403	4.133862	0.0000
McFadden R-squared	0.254831	Mean dependent var		0.192000
S.D. dependent var	0.394136	S.E. of regression		0.335773
Akaike info criterion	0.742273	Sum squared resid		83.99402
Schwarz criterion	0.773073	Log likelihood		-273.3523
Hannan-Quinn criter.	0.754141	Deviance		546.7045
Restr. deviance	733.6650	Restr. log likelihood		-366.8325
LR statistic	186.9605	Avg. log likelihood		-0.364470
Prob(LR statistic)	0.000000			
Obs with Dep=0	606	Total obs		750
Obs with Dep=1	144			

Table 7 shows the variables and accuracy of Logit models.

For NN modeling, we developed a feed-forward back prop NN with 3 Layers. In each layer, we had 10 neurons and training function was TRAINLM. Adoption learning function was LEARNGDM and the performance criteria for choosing the best NN is MSE (Mean Squared Error). Also, Transfer function between layers is TANSIG.

This Neural Network was created based on forecast errors and the results show that accuracy of the best Neural Networks is better than the best Logit model in Type I error, while it is worse in type II error. Yet the best Logit model outperformed Neural Network in overall accuracy.

Then, for hybrid modeling, we first chose Logit_Swap04 model as the primary model and the errors of this model were fed to a Neural Network and based on the out of sample forecast errors a secondary model was developed. Combining these two models (Logit_Swap04 and NN), the hybrid model was introduced. The result shows that the overall accuracy of hybrid model is better than either Logit or NN models. Table 7 describes the errors and accuracy of models. Also, Figure 2 illustrates the prediction output of 3 models (Logit_SWAP04, NN and Hybrid).

Table 7. Accuracy and variables of Logit models

Model Name	Method used for variable selection	No. Ind. Var.	McFadden R-squared	Threshold	Overall Accuracy	Errors: Error of Model	Errors: Type I Error	Errors: Type II Error	C	GP_SALE	RE_TA	FA_TA	INT_TD	GP_TA	OP_SALE	EBIT_SALE	CASH_TA	E_FA	LD_E	INT_COVERAGE	NWC_SALE	OCF_TD	CASH_CD	OP_TA	OCF_TD	CURRENT_RATIO	CA_TA	QA_TA	OCF_INT	QUICK_RATIO
Logit_backward	Stepwise (Backward)	11	0.318824	0.3	90.67%	9.33%	24.10%	3.69%	0.817553			-2.971265	12.64011	-4.856394	-4.834263	-0.340173	-6.307417	-1.33823	-0.012391	-8.86E-08	0.05704	-0.040401								
									0.0291			0.0002	0.0001	0.0001	0.0000	0.0003	0.0204	0.0167	0.4459	0.7893	0.433	0.5800								
Logit_Forward	Stepwise (Forward)	10	0.311326	0.305	90.33%	9.67%	25.30%	3.69%	0.509949		-0.481344	-3.199734	13.22019	-4.542764	-5.239458	-0.381658	-7.082462		-0.012569	-7.31E-08		-0.051617								
									0.1469		0.2494	0.0000	0.0000	0.0003	0.0000	0.0000	0.0109		.4090	0.8128		0.4750								
Logit_Swap01	Swapwise (m=1)	1	0.161292	0.26	81.67%	18.33%	18.07%	18.43%	0.326306	-7.315351																				
									0.0940	0.0000																				
Logit_Swap02	Swapwise (m=2)	2	0.19954	0.315	84.67%	15.33%	32.53%	8.76%	0.244423	-6.067522	-2.281181																			
									0.2259	0.0000	0.0001																			
Logit_Swap03	Swapwise (m=3)	3	0.230676	0.325	88.33%	11.67%	34.94%	2.76%	0.992941	-6.207236	-2.370927	-3.405769																		
									0.0003	0.0000	0.0001	0.0000																		
Logit_Swap04	Swapwise (m=4)	4	0.254831	0.265	94.33%	5.67%	14.46%	2.30%	0.250555	-6.876968	-1.898408	-3.007578	11.94440																	
									0.4382	0.0000	0.0012	0.0001	0.0000																	
Logit_Swap05	Swapwise (m=5)	5	0.277078	0.36	92.00%	8.00%	25.30%	1.38%	0.596897	-4.846090	-1.229911	-2.894794	12.45654	-5.000041																
									0.0726	0.0000	0.0182	0.0001	0.0000	0.0001																
Logit_Swap06	Swapwise (m=6)	6	0.281674	0.35	92.33%	7.67%	24.10%	1.38%	0.583341	-4.829420	-1.184603	-2.860693	12.26792	-4.978267					-0.012646											
									0.0795	0.0000	0.0211	0.0002	0.0000	0.0001					0.3568											
Logit_Swap07	Swapwise (m=7)	7	0.296335	0.3	92.00%	8.00%	21.69%	2.76%	0.611127			-2.831005	11.58930	-4.897352	-4.581171	-0.329379		-1.52087		-1.65E-07										
									0.0864			0.0002	0.0001	0.0000	0.0000	0.0000		0.0036		0.5796										
Logit_Swap08	Swapwise (m=8)	8	0.30078	0.3	92.00%	8.00%	21.69%	2.76%	0.578286			-2.799866	11.41982	-4.837810	-4.589506	-0.329062		-1.451288	-0.012917	-1.65E-07										
									0.1050			0.0003	0.0001	0.0001	0.0000	0.0000		0.0051	0.4092	.5766										
Logit_Swap09	Swapwise (m=9)	9	0.313493	0.31	91.33%	8.67%	22.89%	3.23%	0.707695			-3.042760	12.65222	-4.868971	-4.823821	-0.351721	3.607485	-1.002098		-8.07E-08			-5.238925							
									0.0619			0.0001	0.0000	0.0001	0.0000	0.0000	.6682	0.0786		0.8076			0.2997							
Logit_Swap10	Swapwise (m=10)	10	0.318491	0.305	91.00%	9.00%	22.89%	3.69%	0.713276			-3.036094	12.52149	-4.779736	-4.888543	-0.355301	1.175503	-0.983148	-0.012471	-8.09E-08			-4.106207							
									0.0610			0.0001	0.0001	0.0001	0.0000	0.0000	.8903	0.0812	0.4296	0.8076			.4109							
Logit_Swap11	Swapwise (m=11)	11	0.319535	0.31	91.33%	8.67%	22.89%	3.23%	0.724942			-2.938384	12.62929	-4.929556	-4.712791	-0.330443	1.103431	-1.126312	-0.012524	-7.94E-08	0.060061		-4.057010							
									0.0576			0.0002	0.0001	0.0001	0.0000	0.0004	0.8969	0.0605	0.4336	0.8115	0.4099		0.4157							
Logit_Swap12	Swapwise (m=12)	12	0.320351	0.31	91.67%	8.33%	22.89%	2.76%	0.791360			-2.935339	12.42548	-5.834927	-5.290089	-0.364304	1.105916	-1.160547	-0.012551	-9.98E-08	0.054464		-4.059886	1.753285						
									0.0436			0.0002	0.0001	0.0008	0.0000	0.0004	0.8972	0.0566	0.4322	0.7677	0.4564		0.4179	0.4378						
Logit_Swap13	Swapwise (m=13)	13	0.321517	0.29	91.33%	8.67%	22.89%	3.23%	-0.100281			-2.132200	12.94790	-5.472497	-4.544513	-0.323843	-6.647400	-0.909419	-0.012883	-8.57E-08	0.040975				-0.043379	-0.298260	1.483223			
									0.9060			0.0452	0.0000	0.0001	0.0000	0.0004	0.0169	0.1977	0.4174	0.7986	0.5793				0.5579	0.5241	0.1604			
Logit_Swap14	Swapwise (m=14)	14	0.322055	0.28	92.00%	8.00%	20.48%	3.23%	0.033340			-2.203243	12.73250	-6.156412	-5.043712	-0.352844	-6.646845	-0.929162	-0.012874	-1.03E-07	0.038537			1.447181	-0.045825	-0.310851	1.401777			
									0.9697			0.0403	0.0001	0.0005	0.0001	0.0005	0.0171	.1942	0.4174	0.7618	0.6044			0.5297	0.5336	0.5116	0.1899			
Logit_Swap15	Swapwise (m=15)	15	0.322323	0.28	92.00%	8.00%	20.48%	3.23%	-0.015672			-2.142622	12.82700	-6.175804	-5.130932	-0.360416	-6.554037	-0.950485	-0.012882	-1.18E-07	0.036281	-0.042598		1.582885		-0.283925	1.180054	0.381858		
									0.9859			0.0485	0.0001	0.0005	0.0001	0.0005	0.0184	0.1862	0.4196	0.7356	0.6270	0.5637		0.4957		0.5509	0.3179	0.6579		
Logit_Swap16	Swapwise (m=16)	16	0.32233	0.28	91.33%	8.67%	21.69%	3.69%	-0.015254			-2.140221	12.81639	-6.174217	-5.130140	-0.360348	-6.549539	-0.950764	-0.012880	-9.53E-08	0.036337			1.579927	-0.042528	-0.284770	1.180534	0.383212	-2.96E-08	
									0.9863			0.0488	0.0001	0.0005	0.0001	0.0005	0.0185	0.1861	0.4196	0.8281	0.6265			0.4965	0.5644	0.5499	0.3177	0.6568	0.9438	
Logit_Swap17	Swapwise (m=17)	17	0.346469	0.31	92.00%	8.00%	15.66%	5.07%	0.827497	-3.559015		-2.586425	16.03342	-4.627275	-3.443405	-0.180318	-6.982237	-0.920442	-0.012096	-8.04E-08	0.097968				-0.055067	3.057883	-5.433663	10.48425	-1.51E-07	-5.8897
									0.3727	0.0103		0.0217	0.0000	0.0021	0.0014	0.0690	0.0163	0.2311	0.4384	0.8575	0.2846				0.4513	0.0029	0.00112	0.0006	0.7496	0.0007

Table 8. Accuracy of 3 models (Logit_SWAP04, NN and Hybrid)

Model Name	Method used for variable selection	No. Ind. Var.	McFadden R-squared	Threshold	Overall Accuracy	Errors		
						Error of Model	Type I Error	Type II Error
Logit_Swap04	Swapwise (m=4)	4	0.254831	0.265	94.33%	5.67%	14.46%	2.30%
	Neural Network			0.45	94.00%	6.00%	12.05%	3.69%
	Hybrid Model			0.975	95.33%	4.67%	13.25%	1.38%

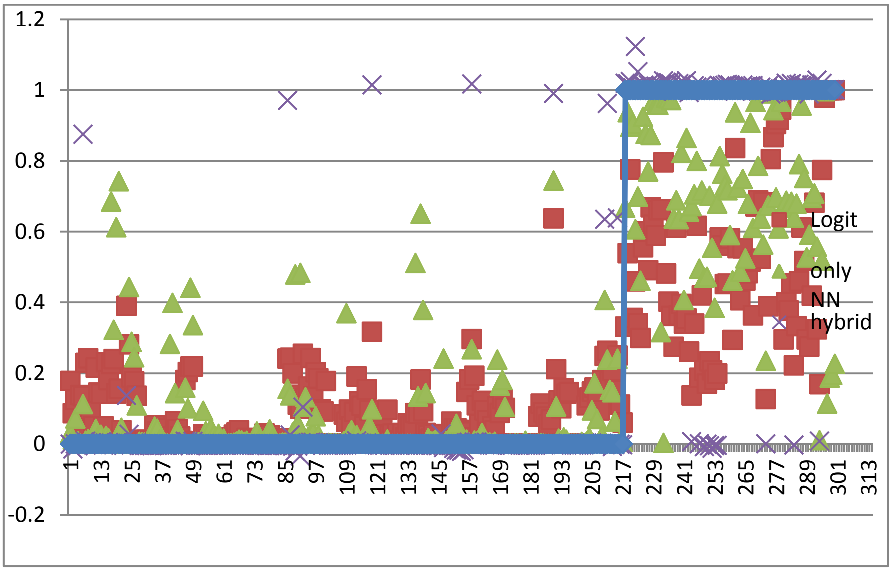

Fig. 2. Actual and prediction output of models

Conclusions

In this paper, we aimed to develop a new hybrid model combining Logit model (as the linear model) and Neural Network (as the non-linear model) to reach a superior estimation. The results show that the overall accuracy of hybrid model outperformed both base models. Combining linear and non-linear models to benefit from advantages of both models, as used in this paper, could be done with different models, e.g. Least Square (LS) and Probit (as linear) and Support Vector Machine (SVM) and Genetic Algorithm (GA) (as non-linear) to have a superior hybrid model. So, we recommend other kinds of combinations in modeling future research works.

Also, these models could be used for predicting prices, indexes, and probabilities in other aspects. So, we recommend investigating the superiority of hybrid models in different fields.

The results of Logit model show us that the most important explaining variables are gross profit to sale, retained earnings to total asset, fixed asset to total asset, and interest to total debt. Gross profit to sale ratio has been used by 4 authors, retained earnings to total asset by 17 authors, fixed asset to total asset by 5 authors, and interest to total debt only by 3 authors (as mentioned in Tables 2 and 3). But the results show that the most used ratios by previous authors like debt ratio (31 authors), net working capital to asset (23 authors), EBIT to asset (23 authors), ROA (22 authors) were insignificant in Logit models. Also, current ratio (27 authors) and quick ratio (19 authors) were significant only in Logit_Swap17 model. Reviewing the literature showed that the significant variables in Logit models were as follows: gross profit to sale, retained earnings to total asset, fixed asset to total asset and interest to total debt, gross profit to asset, operational profit to sale, and EBIT to sale.

Due to the importance of credit risk in banks and impact of accurate default estimation on profitability of a bank, it is recommended to use introduced hybrid model for estimating the probability of default of corporate customers.

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