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CREDIT–RISK ASSESSMENT USING SUPPORT VECTORS MACHINE AND MULTILAYER NEURAL NETWORK MODELS: A COMPARATIVE STUDY CASE OF A TUNISIAN BANK

Adel KARAA
University of Tunis, Tunisia

Aida KRICHENE[1]
University of Carthage, Tunisia

ABSTRACT

Credit risk evaluation or loan default risk evaluation is important to financial institutions which provide loans to businesses and individuals. Credit and loans have risk of being defaulted. To understand risk levels of credit users (corporations and individuals), credit providers (bankers) normally collect vast amount of information on borrowers. Statistical predictive analytic techniques can be used to analyze or to determine risk levels involved in loans. This study contributes to the credit risk evaluation literature in the Middle East and North Africa (MENA) region. We make a comparative analysis of two different statistical methods of classification (artificial neural network and Support Vector Machine). We use a multilayer neural network model and SVM methodology to predict if a particular applicant can be classified as solvent or bankrupt. We use a database of 1435 files of credits granted to industrial Tunisian companies by a Tunisian commercial bank in 2002, 2003, 2004, 2005 and 2006. The results show that the best prediction model is the multilayer neural network model and the best information set is the one combining accrual, cash-flow and collateral variables. The results show that Multilayers Neural Network models outperform the SVM models in terms of global good classification rates and of reduction of Error type I. In fact, the good classification rates are respectively 90.2% (NNM) and 70.13% (SVM) for the in-sample set and the error type I is of the order of 18.55% (NNM) and 29.91% (SVM).

Banking sector, Accounting data, Credit risk assessment, Default risk Prediction, Neural network, SVM, classification, training

[1] *Correspondence address*: Aida Krichène, University of Carthage (Tunisia), 1, Rue de la paix, Ain Zaghouane, 2046 Elaouina, Tunisia; phones: 00216.72.50.75, 00216.26.98.54.90, email address:aidakrichene@yahoo.fr or aida.krichene@iscae.rnu.tn

INTRODUCTION

Banks are faced with several types of risk such as: credit risk, liquidity risk, market risk, interest rate risk, earnings risk and solvency risk (Rose, 2002). Reference (Teker, 2006) grouped the different kinds of risks into three categories: credit risk, market risk and operational risk (Okan veli şafakli, 2007). According to (Okan veli şafakli, 2007) among these risks credit risk plays the major role since by far the largest asset item is *loans*, which generally account for half to almost three-quarters of the total value of all bank assets. The probability that some of a bank's assets, especially its loans, will decline in value and perhaps become worthless, is known as credit risk (Rose, 2002).

According to Basel Committee on Banking Supervision, credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical component of a comprehensive approach to risk management and essential to the long-term success of any banking organization (Bank of International Settlement, 1999, p. 4). Generally, credit risk is associated with the traditional lending activity of banks and it is simply described as the risk of a loan not being repaid partly or in full. However, credit risk can also derive from holding bonds and other securities (Casu *et al.*, 2006).

The financial crisis gave us a proof of the threat to find ways to work around regulation. By paying insurers such as American International Group AIG in order to avoid putting capital aside as required by regulation, banks succeeded in the short run to convert lower rated securities into AAA, but put the whole financial system in difficulty in the long run. Now and after the collapse of Lehman Brothers, there is a great appeal by politicians and economists for regulation. The field of credit risk and corporate bankruptcy prediction also gained considerable momentum (Bharath & Shumway, 2008, Davydenko, 2008, and Korteweg & Polson, 2008). In this paper, we show that we can apply regulation and save money.

Until recently, in developing countries, the credit decision used to be based on the traditional approach, which takes into account various quantitative as well as subjective factors, such as liquidity, leverage, earnings, reputation, etc. According to this information and by merely inspecting the application form details, the credit expert uses a judgmental approach to decide upon the credit worthiness of the applicant. But since June 2004, the Basel Committee on Banking Supervision issued a revised framework on International Convergence of Capital Measurement and Capital Standards. Following the "Internal Ratings-Based" (IRB) approach of Basel II, banking institutions will be allowed to use their own internal measures for key drivers of credit risk as primary inputs to their minimum regulatory capital calculation (McDonough ratio).

European countries started to calculate McDonough ratio since 2006. In Tunisia, the central bank issued a note in which it calls banks to introduce (IRB) approach [1]. In February 2006, the Basel Committee on Banking Supervision issued a consultative document for comment. This document was intended to provide banks and supervisors with guidance on sound credit risk assessment and valuation policies and practices for loans regardless of the accounting framework applied. The principle 3 states that "A bank's policies should appropriately address validation of any internal credit risk assessment models» [2]. In paragraph sixteen, it is stated that "Models may be used in various aspects of the credit risk assessment process including credit scoring, estimating or measuring credit risk at both the individual transaction and overall portfolio levels, portfolio administration, stress testing loans or portfolios and capital allocation".

The implementation of this principle turns out to be a daily decision based on a binary classification problem distinguishing good payers from bad payers. Certainly, assessing the insolvency plays an important role since a good estimate (related to a borrower) can help to decide whether granting the requested loans or not. The Basel Committee proposes a choice between two broad methodologies for calculating their capital requirements for credit risk, either external mapping approach or internal rating system. The collapse of many banks shows the inaccuracy of external mapping approach and suggests the use the internal rating, which is easy to implement since numerous methods have been proposed in the literature to develop credit-risk evaluation models. These models include traditional statistical methods (e.g., logistic regression, (Steenackers & Goovaerts, 1989), nonparametric statistical models (e.g., k-nearest neighbor, (Henley & Hand 1997), and classification trees, Davis *et al*,1992) and neural network (NNs) models (Desai *et al*,1996). NNs have served as versatile tools for data analysis in a variety of complex environments. In finance, they have been successfully applied to bankruptcy and loan-default prediction and credit evaluation (see West, 2000; Wu & Wang, 2000; Atiya, 2001; and Pang & Bai, 2002).

Our research question is how banks in the MENA region can develop fairly accurate quantitative prediction models that can serve as very early warning signals for counterparty defaults. Previous work looks at Business failure prediction from the mid-term and long-term prospects (failure versus non failure). In our paper, we look at the short-term prospect (payment versus non-payment of the short term credit at maturity). We also consider the case of a bank who wants to use prediction model to assess its credit risk [3].

Specifically, we use two kinds of prediction models (SVM models and artificial neural network) to help the credit–risk manager in explaining why a particular applicant is classified as either bad or good. We use a database of 1435 files of credits granted to industrial Tunisian companies by a commercial bank in 2003, 2004, 2005 and 2006. We choose to work with short-term commercial loans because they represent the largest part of loans and are subject to renewal every year. In order to assess the default likelihood of firms and determine which businesses will be safe and which will be not repaying, the database includes financial data. Commonly financial ratios and some other variables, such as debt covenant, firm size will be used.

The remainder of this paper is organized as follow. In sections 2 and 3, we provide the theoretical background supporting our research question and our research design respectively. In section 4, we describe data and methodology. In Section 5, we present our results and their interpretations. Finally, Section 6 concludes the paper and presents some limits.

1. CREDIT RISK EVALUATION OF BANKS: THEORY AND EMPIRICAL MODELING

To this date, credit risk remains a major concern for lenders worldwide. The more they know about the creditworthiness of a potential borrower, the greater the chance they can maximize profits, increase market share, minimize risk, and reduce the financial provision that must be made for bad debt. We present successively the theoretical foundation of the credit risk problem and the empirical modeling of its evaluation.

1.1. The Roots of the Credit Risk Problem: Agency Theory

The problem: One of the most fundamental applications of agency theory to the lender-borrower problem is the derivation of the optimal form of the lending contract. In debt market, the borrower usually has better information about the project to be financed and its potential returns and risk. The lender, however, doesn't have sufficient and reliable information concerning the project to be financed. This lack of information in quantity and quality creates problems before and after the transaction takes place. The presence of asymmetric information normally leads to moral hazard and adverse selection problems. This situation illustrates a classical principal-agent problem.

The principal-agent models of the agency theory may be divided into three classes according to the nature of information asymmetry. First, there are moral hazard models, where agent receives some private information after signing the contract.

Moral hazard refers to a situation in which the asymmetric information problem is created after the transaction occurs. Since the borrower has relevant information about the project the lender doesn't have, the lender runs the risk that the borrower will engage in activities that are undesirable from the lender's point of view because they make it less likely that the loan will be paid back. These models are qualified as models with ex-post asymmetric information.

Second, we find adverse selection models, where agent has private information already before signing the contract. Adverse Selection refers to a situation in which the borrower have relevant information that the lender lack (or vice versa) about the quality of the project before the transaction occurs. This happens when the potential borrowers who are the most likely to produce an undesirable (adverse) outcome (bad credit risks) are the ones who are most active to get a loan and are thus most likely to be selected. In the simplest case, lenders' price cannot discriminate between good and bad borrowers, because the riskiness of projects is unobservable. These models are known as models with ex-ante asymmetric information. Finally, signaling models, in which the informed agent may reveal his private information through the signal which he sends to the principal.

The solution: This problem is traditionally considered in the framework of costly state verification, introduced by (Townsend, 1979). The essence of the model is that the agent, who has no endowment, borrows money from the principal to run a one-shot investment project. The agent is faced with a moral hazard problem. Should he announce the true value or should he lower the outcome of the project? This situation describes ex-post moral hazard. We can also face a situation of ex-ante moral hazard, where the unobservable effort by agent during the project realization may influence the result of the project. Reference (Townsend, 1979) showed that the optimal contract which solves this problem is the so called standard (or simple) debt contract. This standard debt contract is characterized by its face value, which should be repaid by the agent when the project is finished. As another theoretical justification for simple debt contract was considered by (Diamond, 1984), where the costly state verification was replaced by a costly punishment. References (Hellwig, 2001), (Hellwig, 2000) showed that the two models are equivalent only under the risk neutrality assumption. However, when we consider the introduction of risk aversion, the costly state verification model still working, but the costly punishment model does not survive.

To overcome the asymmetric information problem and its consequences on credit risk assessment in the real world, banks use either collateral or bankruptcy prediction modeling or both. The next subsection will deal with this aspect.

1.2. Credit Risk Evaluation and bankruptcy prediction: Empirical Modeling

After the high number of profile bank failures in Asia, the research activity on credit risk took a step further. As a result, the regulators recognize the need and urge banks to utilize cutting edge technology to assess the credit risk in their portfolios. Measuring the credit risk accurately also allows banks to engineer future lending transactions, so as to achieve targeted return/risk characteristics. The assessment of credit risk requires the development of fairly accurate quantitative prediction models that can serve as very early warning signals for counterparty defaults [4].

There are two main approaches commonly addressed in the literature. In the first approach, the structural or market based models, the default probability derivation is based on modeling the underlying dynamics of interest rates and firm characteristics. This approach is based on the asset value model originally proposed by Merton (1974), where the default process is endogenous, and relates to the capital structure of the firm. Default occurs when the value of the firm's assets falls below some critical level. In the second approach, the empirical or accounting based models, instead of modeling the relationship of default with the characteristics of a firm, this relationship is learned from the data. Since the work of Beaver (1966) and Altman (1968), bankruptcy prediction has been studied actively by academics and practitioners. Many models have been proposed and tested empirically. Altman's popular Z-Score (Beaver, 1966) is an example based on linear discriminant analysis, and was used to predict the probability of default of firms. Ohlsons O-Score (Ohlson, 1980) is based on generalized linear models. Generalized linear models or multiple logistic regression models have been used either to identify the best determinants of bankruptcy and the predictive accuracy rate of their occurrence. Neural network models were adapted and used in bankruptcy prediction. Their high power of prediction makes them a popular alternative with the ability to incorporate a very large number of features in an adaptive nonlinear model (Kay*et al*, 2000).

The SVMs is also applied for bankruptcy prediction (Haardle *et al.*, 2003). Many researchers such as (Fan & Palaniswami, 2000) have compared the Support Vector Machine (SVM) with Neural Network (NN), Multivariate Discriminant Analysis (MDA) and Learning Vector Quantization (LVQ). The results show that SVM obtained the best results (70.35–70.90%), followed by NN (66.11–68.33%), followed by LVQ (62.50–63.33%), followed by MDA (59.79–63.68%). Van Gestel *et al.* (2003) used on their experiment the least squares SVMs (a modified version of SVMs). This method showed significantly better results in bankruptcy prediction when contrasted with the classical techniques. Kyung-Shik *et al.* (2005) showed that the classifier of SVM approach outperforms back-propagation neural network BPN to the problem of corporate bankruptcy prediction. Their experimentation results demonstrate that SVM has the highest level of accuracies and better generalization performance than BPN as the training set size is getting smaller sets.

To evaluate the prediction accuracy of SVM, Jae and Lee (2005) compared its performance with those of multiple discriminant analysis (MDA), logistic regression analysis (Logit), and three-layer fully connected back-propagation neural networks (BPNs). The experiment results show that SVM outperforms the other methods.

2. EMPIRICAL RESEARCH DESIGN: MULTILAYER NEURAL NETWORK AND SUPPORT VECTOR MACHINE

2.1. Multilayer Neural Network

The prediction of financial distress is an important studied topic since it can have significant impact on bank lending decisions and profitability. Several methods and techniques have been suggested in the literature to tackle these decisions. The early empirical approaches are those of Beaver (1966), Altman (1968) and Ohlson (1980). However, these approaches are either very simple (Beaver, 1966) or essentially linear models (Altman, 1968 or Ohlson, 1980). NNs approach started to be used for bankruptcy prediction in 1990 and they are still active now [5]. The reason why they received a lot of attention is their universal approximation property and their excellent ability to classify data (especially loan applications) [6]. Neural networks grew out of research in Artificial Intelligence; specifically, attempts to mimic the fault-tolerance and capacity to learn of biological neural systems by modelling the low-level structure of the brain (see Patterson, 1996) [7].

The majority of the NN approaches to default prediction use multilayer networks. ‘Feed-forward’ NNs are perhaps the most popular network architecture in use today, due originally to (Rumelhart *et al.*, 1986). They are sometimes also referred to as ‘back-propagation NNs’ or ‘multi-layer perceptrons (Ripley, 1996).

The feedforward network architecture is composed of an input layer, one or more hidden layers and an output layer. More precisely, feed-forward NNs have units with one-way connections, such that these units can always be arranged in layers so that connections go from one layer to another. This is best seen graphically, see Figure 1.

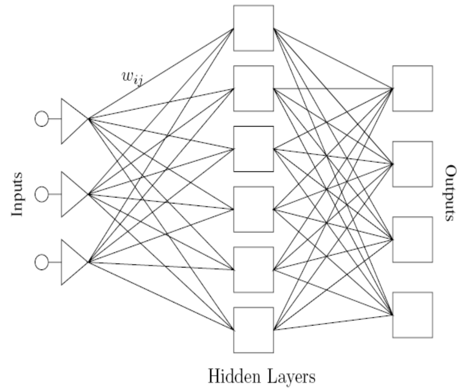


Figure 1. **A generic feed-forward network with a single hidden layer**
Source: Berg, 2005: 11

A network such as the one in Figure 1 represents a function from inputs to outputs (equation 1). Each unit sums its inputs and adds a constant (the 'bias') to form a total input x_j and applies a function f_j to x_j to give output y_j. The links have weights w_{ij} which multiply the signals traveling along them by that factor.

$$f_k(x) = f_0\left(\alpha_k + \sum_{i=1}^{N} u_{ik} x_i + \sum_{j=1}^{M} v_{jk} f_h\left(\beta_j + \sum_{i=1}^{N} w_{ij} x_i\right)\right), (1)$$

Here N, M and K are the number of input nodes (i.e. the number of explanatory variables), the number of nodes in the hidden layer (s) and the number of output nodes (i.e. the number of possible classes), respectively (Aas & Thune, 1999).

2.2 Support Vector Machine (SVM)

We briefly review the implementations of the binary classification using Support Vector Machines (SVMs), the so-called optimal separating hyper planes, through extremely non-linear mapping the input vectors into the high-dimensional feature space. SVM is a very well developed technique, this method constructs linear model to estimate the decision function using non-linear class boundaries based on support vectors. According to (Kyung-Shik *et al.*, 2005) , if the data is linearly separated, SVM trains linear machines for an optimal hyperplane that separates the data without error and into the maximum distance between the hyperplane and the closest training points. The training points that are closest to the optimal separating hyperplane are called support vectors. All other training examples are irrelevant for determining the binary class boundaries. In general cases where the data is not linearly separated, SVM uses non-linear machines to find a hyperplane that minimize the number of errors for the training set.

We present the following definitions of labeled training examples [xi, yi]:

an input

$x_i \in R^n$ is an input vector ,

$y_i \in \{-1,1\}$, i=1,.,l. is a class value

For the linearly separable case, the decision rules defined by an optimal hyperplane separating the binary decision classes is given as the following equation in terms of the support vectors.

$$Y= \text{Sign} \left(\sum y_i * \alpha_i(X*X_i) +b \right) \quad (2)$$

where

Y : is the outcome,

Y_i : is the class value of the training example xi, and represents the inner product.

The vector $X=(x_1,x_2,.,x_n)$ is an input

the vectors xi,I=1,.,N, are the support vectors.

In Eq. (2), b and α_i are parameters that determine the hyperplane.

For the non-linearly separable case, a high-dimensional version of Equation (2) is given as follows:

$$Y= \text{Sign} \left(\sum yi*\alpha i\ K(x,x_i)+b \right) \quad (3)$$

K(x,xi) : the kernel function for generating the inner products to construct machines with different types of non-linear decision surfaces in the input space.

Three common types of SVM are used to construct decision rules namely :

- A polynomial machine with kernel function

$$k(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j} + 1)^d$$

- A Radial basis function with kernel function

$k(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma \|\mathbf{x_i} - \mathbf{x_j}\|^2)$, for $\gamma > 0$. Sometimes parameterized using $\gamma = 1/2\sigma^2$

- A two-layer Neural Network machine with Kernel function

$k(\mathbf{x_i}, \mathbf{x_j}) =$ S[(x*xi)]=1/[1+exp{v(x*xi)-c}]

v and c : pa

S[(x*xi)] satisfying the inequality $c \geq v$

According to (Kyung-Shik *et al.*, 2005) "To construct decision functions of SVM the learning process is represented by the structure of only two layers, which seems to be similar with Neural Network. However, learning algorithm is different in that SVM is trained with optimization theory that minimizes misclassification based on statistical learning theory. The first layer selects the basis K (x,xi), i= 1,.,N and the number of support vectors from given set of bases defined be the kernel. The second layer constructs the optimal hyperplane in the corresponding feature space (Vapnik, 1998)."

The scheme of SVM is shown in Figure 2:

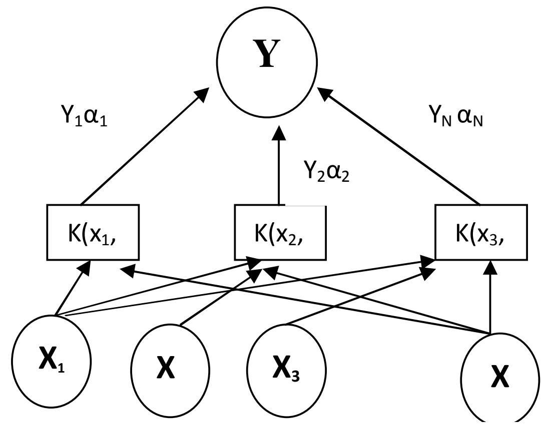


Figure 2. **The scheme of SVM**
(**adapted from Vapnik,1995**). Source: Kyung-Shik et al, 2005: 130)

3. SAMPLE AND DATA

When lenders want to know about company's ability to pay debts on time, they assess its credit risk. To understand credit risk levels of users, financial institutions normally collect large amount of information on borrowers. The basic part of this information relies on the lessons of the traditional financial analysis. Financial analysis of a potential borrower begins with an understanding of the firm, its business, its key risks and success factors. Then, commonly financial ratios and some qualitative variables are calculated from available data. Statistical methods based on data mining techniques are used to analyze or to determine risk levels involved in credits and loans, i.e., default risk levels.

We start by presenting our sample and the nature and sources of our primary data. Then, we explain how our variables are justified and measured.

Table 1. **Sample subsets characteristics**

	2003		2004		2005		2006	
	No. of firms	**%**	**No. of firms**	**%**	**No. of firms**	**%**	**No. of firms**	**%**
HEALTHY FIRMS	176	47.4	206	52.6	195	51.5	150	50.8
RISKY FIRMS	195	52.56	185	47.32	183	48.42	145	49.15
TOTAL	**371**	**100**	**391**	**100**	**378**	**100**	**295**	**100**

3.1. Variables measurement

3.1.1. *Dependent Variable*

Our dependent variable is the probability of default. We use dummy variable, which equals 0 if the classified as healthy and 1 otherwise. Hence:

Y = 0 if no delay of payment

Y = 1 if more there is more than 3 month delay

3.1.2. *Independent Variables*

Default risk prediction relies in general on a good appraisal of the couple risk-return of a company. Financial ratios drawn from financial statements (balance sheet, income and cash flow statement) are usually used. Financial ratio analysis groups the ratios into categories which tell us about different facets of a company's finances and operations (liquidity, activity or operational, leverage and profitability).

In our experiment we retain 24 financial indicators. The financial indicators are inspired from Altman's popular Z-Score and recommended textbooks in financial statement analysis and valuation (Berstein &Wild, 1998; Revsine *et al.*, 1999; Palepu *et al.*, 2000). The object of this subsection is to discuss why such particular indicators have been chosen and how they were measured.

3.1.3. *Liquidity ratios*

These ratios give a picture of a company's short term financial situation or solvency. Liquidity refers to the ability of company resources to meet short term cash requirements. A lack of liquidity may indicate the inability of a company to take advantage of favorable discount or profitable opportunities. A company's short term liquidity risk is affected by the timing of cash inflows and outflows along with its prospects for future performance. Short term is conventionally viewed as a period up to one year, though it is identified with the normal operating cycle of a company (the time period encompassing the buying-producing-selling-collecting cycle). A company's customers and suppliers of products and services are affected by short term liquidity problems. Implications include a company's inability to execute contracts and damage to important customer and supplier relationships [8]. When a company's owners possess unlimited liability (proprietorship and certain partnership), a lack of liquidity endangers their personal assets. To creditor of a company, a lack of liquidity can yield delays in collecting interest and principal payments or the loss of amounts due to them. In brief, when a company fails to meet its current obligations, its continued existence is doubtful.

Working capital is widely used to measure short term liquidity. Working capital is defined as the excess of current assets over current liabilities. When current liabilities exceed current assets, the firm has a working capital deficiency. WC is important as a measure of liquid assets because it provides a safety cushion to creditors. It is also a liquid reserve a company may use to face contingencies and uncertainties surrounding balance of cash inflows and outflows. When it is too negative, the company might default on some payments.

Operating activity is also an important measure of liquidity. This can be seen by decomposing WC in account receivable and inventory. For most companies selling on credit, account and notes receivable are an important part of WC. In assessing liquidity, it is necessary to measure the quality and liquidity of receivables. Liquidity refers to the speed in converting account receivables to cash. Another component to watch is the relation between the provision for doubtful accounts and gross accounts receivable. Increases in such component suggest a decline in the collection of receivables and conversely.
Furthermore, an increase in inventory means a drop in sales. Such situation may create a liquidity problem since loans repayment usually comes from the routine conversion of these current assets into cash.

Cash flows: The static nature of the current ratio and its inability to recognize the importance of cash flows in meeting maturing obligations has led to a search for a dynamic measure of liquidity. Since liabilities are paid with cash, a ratio comparing operating cash flow to current liabilities overcomes the static nature of the current ratio, which could give a better insight of liquidity risk.

The ratios R1 to R7 (table 2) capture the liquidity risk of a firm according to the approaches developed above. While R1 to R6 should have a positive impact on healthiness, R3 (provision for doubtful accounts) will impact negatively the healthiness of a company.

3.1.4. *Leverage ratios and long term solvency*

Beyond advantages of excess return to financial leverage and the tax deductibility of interest, a long term debt position can yield other benefits to equity holders (avoidance of earnings dilution for growth companies). However, the fundamental risk with leverage is the risk of inadequate cash under conditions of adversity. While certain fixed charges can be postponed in times of cash shortages, the fixed charges related to debt (interest and principal repayments) cannot without adverse effect. An excess of leverage runs a risk from loss of financing flexibility, which compromises the company's ability to raise funds, especially in periods of adverse market conditions.

Capital structure measures serve as screening devices. The relation between liabilities and equity capital is an important factor in assessing long term solvency. The higher the proportion of debt, the larger the fixed charges of interest and principal, and the greater the likelihood of insolvency during periods of earnings decline or hardship.

There are several variations in debt ratios. R_8 to R_{14} (table 1) are those retained in our analysis. While R_8 (debt coverage by cash flow) should have a negative impact on the probability of failure, this probability of failure should be positively associated with ratios R_9 to R_{14}.

Nevertheless, even if debt ratios are useful for understanding the financial structure of a company, they provide no information about its ability to generate a stream of inflows sufficient to make principal and interest payments. That's the assessment of insolvency is completed by other indicators involving flows (like operating income, operating cash-flow, interest and principal repayment). Without a doubt, creditors are primarily concerned with assessing a firm's ability to meet its debt obligations through timely payment of principal and interest. Commercial banks and other financial institutions form opinions about a company's credit risk by comparing current and future debt-service requirements to estimate of the company's current and expected future cash flows.

There are a number of ratios which help the analyst in this area (R_{15} to R_{17} in Table 1). The probability of failure should be negatively associated with these ratios.

3.1.5. *Profitability ratios*

A company performance can be analyzed in several ways. Revenue, gross profit and net income are performance measures in common use. However, none of these measures alone are comprehensive proxy for performance because of the interdependency of business activities.

Profitability ratios use margin analysis and show the return on sales and capital employed. Profit margins reflect the firm's ability to produce a product or a service at a low cost or a high price. Nevertheless, profit margins are not direct measures of profitability because they are based on total operating revenue, not on the investment made in assets by the firm or the equity investors. To complete the profitability analysis, it is recommended to use indicators based on the firm's earnings. Another related indicator, widely used, and less prone to management manipulation is the cash flow.

Among profitability indicators, Return On Invested capital (ROI) is probably the most widely recognized measure of firm performance. It is a good indicator of a company's long-term financial strength. It uses key summary measures from both income statement and the balance sheet to assess profitability. Other measures of performance are not of lower interest. They enable us to better estimate both the return and risk of a company. They allow us to distinguish between performance attributed to management (operating decision) and those less tied to management (taxes and selling prices).

Ratios R_{15} to R_{19} (Table2) have been used in our study to gauge the perspective of borrowers. There should a negative link between these variables and the probability of default.

In order to improve the quality and the performance of our prediction model, we retain in our analysis other ratios used by the bank to assess its credit decision (R_{19} to R_{22} in Table 2). The ratios R_{19} (net fixed assets over total debt) and R_{22} (fixed asset turnover) will be negatively associated to the probability of default. However, Ratios R_{20} (short term debt to sales) and R_{21} (financial expenses to revenue) should be positively associated to failure probability.

3.1.6. *Other variables*

Besides, commonly financial ratios, some other variables are either suggested by the theory (collateral) or suggested by the banking credit context. We choose three for our investigation: collateral, firm size.

Collateral: Collateral plays an important role in bank behavior. In effect, debt holders impose covenants on the firm, restricting the firm's operating, investment and financing decisions. Many models were designed to show the impact of collateral on the borrower- lender relation. Bester (1985) and Besanko & Thakor (1987) build on the ex-ante screening model of Stiglitz & Weiss (1981) to infer the signaling role of collateral to solve the adverse selection problem inherent in debt financing under asymmetric information. In a model with two types of projects (high and low risk) and two agents, it was shown that each agent finds it optimal to choose the contract designed for him. Low-risk borrowers choose contracts with collateral. High-risk borrowers, in contrast, prefer loans with no collateral. Thus, the equilibrium solution is given by two separating contracts, and as long as these optimal contracts for different types of agents are different, we are in the case of a separating equilibrium [9]. Hence, the signaling models predict a negative correlation between loan risk and collateral. As we can see, the signaling model is concerned with the pre-contractual stage. Once the contract has been concluded, the informational problem is resolved.

A second class of models focuses on the ex post monitoring function of banks (Bester, 1994) develops a model of debt renegotiation that predicts a positive correlation between expected default risk and collateralization. In this model, a creditor cannot distinguish between strategic default (borrower is cheating), and default due to bad state of nature. The provision of outside collateral will reduce, in that case, the debtor's incentive for strategic default. Rajan and Winton (1995) model the situation where the collateralization decision of an inside bank is observed by less informed agents (thereby transforming private information on borrower quality into public information). Thus, the inside bank is compensated for this externality by a more senior debt position. Since in equilibrium the informed lender tends to collateralize loans with high risk borrowers, there should be a positive association between risk and collateral implied.

In bankruptcy prediction, this positive correlation between project risk and collateral corresponds to conventional wisdom in banking, which views collateral as a means to lower the risk exposure of a bank (see e.g. Berger & Udell, 1990)). We should observe a positive relation between collateral and default risk. In our study this indicator is measured by LOG (Guarantee).

Firm Size: A company's total assets give some indication on the size of the firm and can be used to have an idea about the solidity of a company. Therefore, it is frequently used as a normalizing factor. However, in the case of this study the size of firms is measured by LOG (total assets).

Table 2. **Variables definition and measurement**

RISK FACET	CODE	VARIABLE DEFINITION	VARIABLE MEASURE
Liquidity indicators	R_1	Long term financing of Working capital	(Shareholders' equity+ non current liabilities)-non current assets
	R_2	Working capital requirement	Working capital/ shareholders' equity +non current liabilities)-non current assets
	R_3	Account receivable liquidity	Provision for doubtful accounts /Gross account receivables
	R_4	Current ratio	Current assets / Current liabilities
	R_5	Quick ratio	Current assets – inventories / Current liabilities
	R6	Cash flow ratio	$\frac{\text{Operating cash flow}}{\text{Current liabilities}}$
	R7	Inventory turnover	Sales / inventories
Leverage and solvency indicators	R8	Debt Cash Flow Coverage Ratio	Cash flow /Total debts
	R9	Liabilities to equity ratio	Total liabilities / shareholders' equity
	R10	Net debt to equity ratio	Short term debt +long term debt-cash and marketable securities / shareholders' equity

RISK FACET	CODE	VARIABLE DEFINITION	VARIABLE MEASURE
	R11	Debt to capital ratio	Short term debt +long term debt / short term debt +long term debt +shareholders' equity
	R12	Long term debt to assets	Long term Debt / Total Assets
	R13	Long term debt to tangible assets	Long term debt / Total tangible assets
	R14	Interest coverage ratio	Operating income before taxes and interest/interest expense
Profitability indicators	R15	Net profit margin	Net income / Total operating revenue
	R16	Gross profit margin	Earnings before interest and taxes/Total operating revenue
	R17	Return on invested capital	Net income/Total assets
	R18	Return On Equity (ROE)	Net income / Stockholders equity
Ratios used by the bank	R19	Fixed asset to debt ratio	Net fixed assets/ Total debt
	R20	Short term debt to sales ratio	Short term debt /Total sales
	R21	Financial expenses to revenue ratio	Financial expenses / Total revenues
	R22	Fixed asset turnover	Sales /Fixed assets
Other variables	V01	collateral	LOG(GUARANTEE)
	V02	Firm size	LOG(TOTAL ASSETS)

4. EMPIRICAL RESULTS

To get a better idea about our data before running the SVM model, we will perform a test of mean differences between the two risks classes defined above (Table 3).

In order to test the prediction capacity of model, we split our sample of the bank credit files into two sub samples. The first sub-sample is composed of 924 files of short term loan granted to 231 industrial Tunisian companies in 2003 and 2004, 2005 and 2006. The data of this sub-sample are used as a training set (the in-sample set) to construct the prediction models. The second one is composed of 510 files and is used for validation (the out-of sample set).

Table 3. **Summary statistics: mean differences**

Ratios	Code	Mean	Std. Deviation
R2:	,00	***16,8191***	58,85241
	1,00	***8,5990***	15,69326
R3:	,00	,0471	,13891
	1,00	,0568	,14135
R4:	,00	***2,9623***	7,05638
	1,00	***3,2328***	8,05572
R6:	,00	***2,0391***	22,41881
	1,00	***-,6450***	38,61664
R7:	,00	,0439	,10179
	1,00	,0757	,14164
R8:	,00	***1,4900***	2,00318
	1,00	***1,0742***	,91636
R10:	,00	,0452	,33929
	1,00	,0347	,16519
R11:	,00	***,0569***	,15137
	1,00	***,0166***	,10049
R12 :	,00	***,4993***	2,33091
	1,00	***,2348***	1,14838
R13:	,00	,7708	,97464
	1,00	,7151	,58013
R14:	,00	***,2274***	1,06959
	1,00	***,0588***	,74966
R15:	,00	***5,0372***	55,16137
	1,00	***13,4255***	16,99936
R18:	,00	***,6227***	2,93441
	1,00	***7,4529***	54,44136
R19:	,00	1,8072	2,80796
	1,00	1,7822	3,89486
R20:	,00	1,1982	2,38237
	1,00	1,1215	3,14473
R21:	,00	***,0634***	,30944
	1,00	***,2492***	2,91846
R22:	,00	***,0115***	,43979
	1,00	***-,0284***	,25000

a - 00: corresponds to healthy group
b - 01: corresponds to risky group

The summary statistics and the mean differences can be seen as an analysis similar to Beaver (1966). Table 3 presents the descriptive statistics of our data. When we run mean differences analysis between the two risks classes (healthy and risky groups), this analysis can give us a flavour of our data, since such analysis allows us to verify if there a difference between the two classes in terms of financial ratios. In Table 3 we recalculate some summary statistics for the two risks classes.

Table 3 shows significant mean differences between the two groups for some ratios (R_2; R_4;R_6 ;R_8 $R_{11;}$ R_{12} ;$R_{14;}$ $R_{15;}$ R_{18} ;$R_{21}$and R_{22}) and no significant differences for others ($R_{1;}$ $R_{3;}$ $R_{5;}$ R_7 ;$R_{9;}$ R_{10} ;$R_{11;}$ $R_{13;}$ $R_{16;}$ $R_{17;}$ R_{19} and R_{20}). Globally, they tell us that the liquidity risk does not differentiate the two groups. The leverage and solvency ratios do better in differentiating the two groups. For others indicators (coverage and profitability), the results are mitigated. For example, while return on equity (R_{18}) shows a significant difference gross profit margin (R_{16}) and return on invested capital (R_{17}) are not.

When we look at the relevance of mean differences, we realise that globally the good indicators are superior in the healthy group, while the bad indicators are higher in the risky group. For example the mean of cash flow ratios (R_6), Working capital requirement (R_2), leverage and solvency ratios (R_{11}, R_{12}, R_{14} and R_8) is bigger in health group. Current ratio (R_4), profitability ratios (R_{18} and R_{15}), have a higher mean in the risky group.

Let’s see now if NN models and SVM models do better job in predicting default risk.

4.1. Results of Neural Network Models: the in-sample set

Panels 1, 2 and 3 of Table 4 show the results for the type one and two NN models (without and with cash flow ratios). Figures 3, 4 and 5 display the curves of the Mean Square Error MSE (training) for the three types of NN models retained. These figures show the power curves of the three best networks.

Table 4: **Results for Non cash-flow and cash-flow NNs models (In and out-of-sample)**

Panel 1. Non cash-flow NNs models

Architecture	(In-sample training)			(Out-of-sample validation)		
	MSE (%)	1-MSE	Good classification rate	MSE	1-MSE	Good classification rate
Net_00 [21 2]	13.38	86.62	81.5	14.56	85.44	71.8
Net_01 [21 10 2]	12.73	87.27	84	13.35	86.65	73.38
Net_02[21 12 12 2]	2.9	97.1	97	2.7	97.3	73
Net_03 [21 15 15 15 2]	5.2	94.8	95.5	5.3	94.7	81
Net_03 [21 14 14 8 2]	2.7	97.3	97.5	2.65	97.35	84.9
Net_03 [21 10 10 8 2]	3.4	96.6	96.7	3.90	96.1	81.9
Net_03 [21 12 12 10 2]	7.9	92.1	91.55	8	92	81.8
Net_03 [21 10 10 10 2]	5	95	95.4	4.8	95.2	83.75
Net_03 [21 13 13 13 2]	**2.3**	**97.7**	**97.8**	**2.26**	**97.74**	**85.9**

Panel 2. Cash-flow NNs models

Architecture	(In-sample training)			(Out-of-sample validation)		
	MSE	1-MSE	Good classification rate	MSE	1-MSE	Good classification rate
Net_00 ǀ23 2]	11.64	88.36	85.38	12.75	87.25	83
Net_01 [23.8 2]	2.11	97.89	98	3.2	96.8	71.4
Net_02 [23 10 8 2]	1.3	98.7	96	1.35	98.65	79.84
Net_02 [23 15 15 2]	1.8	98.2	96	2.03	97.97	82.38
Net_02 [23 15 10 2]	2.8	97.2	97	3.24	96.76	83.36
Net_02 [23 12 12 2]	2	98	98	2.14	97.86	84.34
Net_03[23 15 15 15 2]	**1**	**99**	**99**	**1.10**	**98.9**	**88.45**
Net_03 [23 12 12 12 2]	1	99	99	1.30	98.7	87.08

Panel 3. Full information Neural Network models

Architecture	(In-sample training)			(Out-of-sample validation)		
	MSE	1-MSE	Good classification rate	MSE	1-MSE	Good classification rate
Net_00 [24 2]	9.6	90.4	89.9	20.6	79.4	74.5
Net_01 [24 12 2]	3.7	96.3	96.4	4.54	95.46	82.5
Net_02 [24 12 10 2]	1	99	95.35	2.64	97.36	86.8
Net_02 [24 15 15 2]	0.3	99.7	96.8	2.6	97.4	82.1
Net_02 [24 12 12 2]	1	99	97.6	2	98	79.6
Net_03 [24 21 15 10 2]	**0.5**	99.5	**97**	**0.9**	**99.1**	**90.2**
Net_03[24 12 12 12 2]	1.5	98.5	95.5	2.8	97.2	80.6
Net_03 [24 15 15 15 2]	0.6	99.4	97	1.38	98.62	87.7

We can see from these results (panel 1) that the introduction of hidden layers improves the performance of the model. The MSE drops from 13.38% (Net 00) to 2.3% for the best three hidden layers NN (Net_03 [21 13 13 13 2]). The classification rate is improved from 81.5% to 97.8%. The introduction of cash-flow variables (panel 2) improves the performance since the type 2 model gives a better MSE (11.64 % for the no hidden layer and 1% for the three hidden layers)[2]. The classification rate is improved from 85.38% to 99% Panel 3 of table 4 shows that the type three outperforms the two previous models since the MSE is lower and the classification is higher for all versions (without and with hidden layers). The collateral variable has the best contribution. The best version (Net 03 [24 21 15 10 2]) has the lowest mean square error (0.5%) and allow us the classification rate of 97%[3].

Figure 3. **Curve of the MSE for the non Cash-flow NNs models**

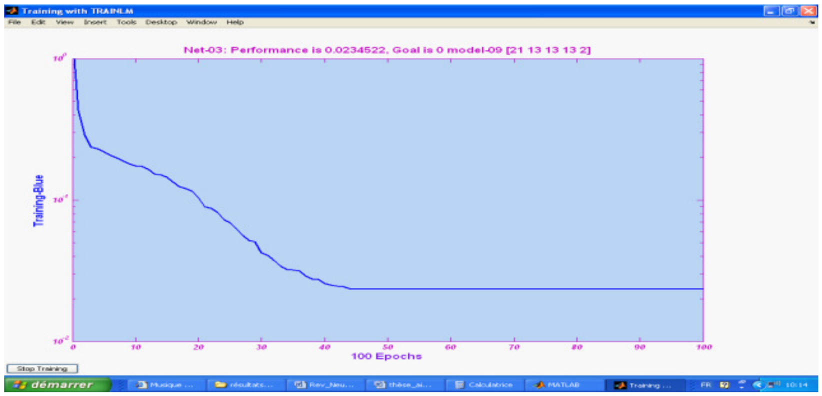
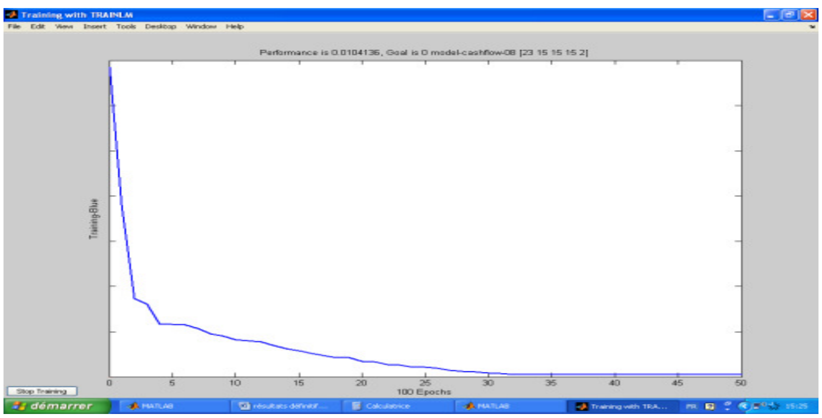


Figure 4. **Curve of the MSE for the Cash-flow NNs models**



[2] We note that until now Tunisian bankers do not use cash-flow measures in their analysis.

[3] This network is dominated by the two hidden layers network (Net_02 [24 15 15 2]) in term of MSE. In spite of performance improvement of this network, the global classification rate has decreased. This can be explained by the over-fitting problem. This problem usually occurs when we have a good performance in the training step in term of MSE, but the model doesn't have a good discrimination power

Figure 5. **Curve of the M S E for the Full information NN models**

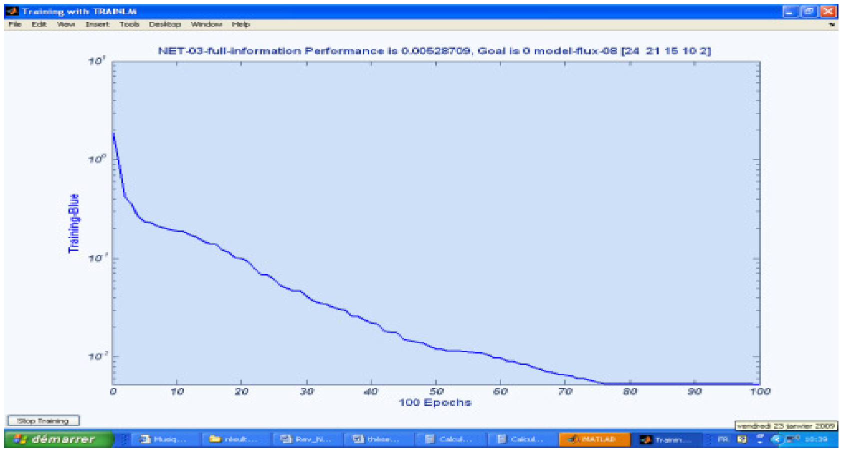


Table 5 shows the evolution of the error type I for the three models.

Table 5. **The evolution of the error type I of the three models**

	Non cash flow NNs	Cash-flow NNs models	Full information NN
ERROR TYPE I	50.91%: 220/458	26.66%:122/458	18.55%:85/458

We can see from the table 5 that the error has decreased significantly from 50.91% to 18.55% when we introduce all information. This reduction can be explained by the importance of cash flow, guarantee and firm size indicators in predicting credit risk.

4.2. Out-of- sample validation

Table 4 presents the results of the validation test for the three types of NN models obtained from the training set. We can see form panel 1 that the best model in training gives also the best performance (with a MSE of 2.26%) in the out-of-sample. The corresponding classification rate is 85.9%. The introduction of cash-flow indicators (panel 2) improves the performance of the model in term of classification rate (with a 88.45% of good classification rate). The classification rate jumped to 90.2% (panel 3) when we introduced the whole set of indicators. We can notice here that the best network (Net 03 [24 21 15 10 2]) in the training sample is also the best one in the validation with the lowest MSE.

4.3. Results of SVM models

The SVM node offers a choice of kernel functions for performing its processing. As there's no easy way of knowing which function performs best with any given dataset, we'll choose different functions in turn and compare the results.

The model has created two extra fields:

- $S-Risk: Value for "Risk" predicted by the model.
- $SP-Risk : Propensity score for this prediction (the likelihood of this prediction being true, a value from 0.0 to 1.0).

Just by looking at the table, we can see that the propensity scores in the $SP-Risk column are high for most of the records. However there are some significant exceptions where the values are low. Also, comparing Risk with $S-Risk, it's clear that this model has made a number of incorrect predictions.

Panel 1, 2 and 3 of Table 6 show the results for the first , second and third SVM models.

Table 6. **Results for Non cash-flow and cash-flow NNs and full information models**

Panel 1. Non cash-flow SVM model (cf. appendix panel 1)

	Kernel function : RBF		**Kernel function Sigmoid**		Kernel function: polynomial	
	Healthy	Risky	**Healthy**	**Risky**	**Healthy**	Risky
Healthy firms	351	116	**350**	**116**	350	116
Risky firms	253	205	**247**	**211**	247	205
% Total Good and Bad Classification						
Good classification	60.17% (351+205/924)		**60.71% (350+211/924)**		60.52% (350+205/917)	
Bad classification	39.83% (116+253/924)		39.29% (116+247/924))		39.48% (116+247/917)	

Panel 2. Cash-flow SVM model (cf. appendix panel 2)

	Kernel function : RBF		**Kernel function Sigmoid**		**Kernel function: polynomial**	
	Healthy	**Risky**	**Healthy**	**Risky**	**Healthy**	**Risky**
Healthy companies	**354**	**112**	312	154	354	112
Risky companies	**175**	**283**	238	220	181	277
% Total Good and Bad Classification						
Good classification	**68.94% (354+283/924)**		57.58% (312+220/924)		68.29% (354+277/924)	
Bad classification	31.06% (112+175/924)		42.42% (154+238/924)		31.71% (112+181/924)	

Panel 3. Full information SVM models (cf. appendix panel 3)						
	Kernel function : RBF		Kernel function Sigmoid		**Kernel function: polynomial**	
	Healthy	Risky	Healthy	Risky	**Healthy**	**Risky**
Healthy companies	318	148	322	144	**327**	**139**
Risky companies	154	304	169	289	**137**	**321**
% Total Good and Bad Classification						
Good classification	67.32% (318+304/924)		66.13% (322+289/924)		**70.13% (327+321/924)**	
Bad classification	32.68% (154+304/924)		33.87% (144+169/924)		29.87% (139+137/924)	

We can see from these results (panel 1, 2 and 3) that the global good classification rate is getting better when we introduce indicators relating to cash flow, firms size and guarantee. In fact, the best good classification rates are of the order of 60.71%, 68.94% and 70.13% respectively for the three models (non cash flow, cash flow and full information).

We can also see from the panel that the best Kernel function is the sigmoid for the first model (without cash flow information), then the RBF for the second model (with cash flow information) and the polynomial function for the third model (with all indicators).

Concerning Panel 1 we can remark that there is not significant differences between the three Kernel functions (sigmoid, polynomial and RBF). In fact, the good classification rates are in order of 60.17%, 60.52% and 60.71% respectively for RBF, Polynomial and sigmoid kernel functions. These rates are relatively low comparing to Neural networks models.
Moreover, the error type I is very high for three functions:

Table 7. **Error I type of panel 1**

Kernel function	Error		
RBF	TYPE I	55.24%	253/458
POLYNOMIAL	**TYPE I**	**53.93%**	**247/458**
SIGMOID	TYPE I	55.93%	247/458

The introduction of cash flow variables (panel 2) has improved the results. The good classification rate is getting better with RBF function. In addition the model based on the RBF function has reduced the error type I to 38.20% (cf. Table8).

Table 8. **Error I type of panel 2**

Kernel function	Error		
RBF	**TYPE I**	**38.20%**	**175/458**
POLYNOMIAL	TYPE I	38.52%	181/458
SIGMOID	TYPE I	51.96%	238/458

Concerning the full information model, the best kernel function is the polynomial: it allows us to improve the good classification rate and to reduce the error type I to 29.91%.

Table 9. **Error I type of panel 3**

Kernel function	Error		
RBF	TYPE I	33.62%	154/458
POLYNOMIAL	**TYPE I**	**29.91%**	**137/458**
SIGMOID	TYPE I	36.86%	169/458

In conclusion we can see that the neural network models outperform the SVM models in term of global good classification rate and error type I. These results don't corroborate with those found by Kyung-Shik *et al.* (2005) and Jae & Lee (2005).

4.4. Out-of- sample validation

Table10. **Results of the validation test**

	In –of- sample	Out-of-sample
Panel 1: Sigmoid	**60.71%**	**58.51%**
Panel 2: RBF	**68.94%**	**65.16%**
Panel 3: polynomial	**70.13%**	**70.05%**

Table10 presents the results of the validation test for the three SVM models with the best kernel function obtained from the training set. We can see form panel 1table 6 that the best model in training gives a performance of 60.71% in term of good classification rate and 58.51% in the out-of-sample. The introduction of cash-flow indicators (panel 2) improves the performance of the model in term of classification rate (with a 65.16% of good classification rate). The classification rate jumped to 70.05 % (panel 3) when we introduced the whole set of indicators. We can notice here that the best SVM model in the training sample is also the best one in the validation with the best good classification rate.

CONCLUSION AND LIMITS

In recent years, credit risk evaluation and credit default prediction have attracted a great deal of interests from practitioners, theorists and regulators in the financial industry. According to Basel Committee on Banking Supervision, credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms (Okan veli şafakli, 2007).

Until recently, in developing countries, the credit decision used to be based on the traditional approach, which takes into account various quantitative as well as subjective factors, such as liquidity, leverage, earnings, reputation etc. According to this information and by merely inspecting the application form details, the credit expert uses a judgmental approach to decide upon the credit worthiness of the applicant.

The Basel Committee on Banking Supervision reviewed progress and recent initiatives to achieve its strategic objectives of implementation of Basel II. It is stated that areas of potential emphasis include: new measurement approaches for credit risk, the treatment of diversification effects, the assessment of complex counterparty credit risks, the treatment of interest rate risk, and firms' approaches to validation of internal capital assessments. In fact, Basel II was introduced to reflect improved risk measurement and management techniques. It streamlines the minimum capital held against credit risk, and assigns capital against credit and operational risk for the first time, mitigating even further the credit and operational banking risks.

In this paper we tried to assess the credit risk for a Tunisian bank through modeling the default risk of its commercial loans. We used a data base of 1435 credit files during 2003 and 2004, 2005 and 2006. In order to apply an artificial neural network methodology we split our sample into two sub-samples. The first corresponds to the training data (in-sample set) and contains 924 credit files (from 2003 to 2006). The second sub-sample contains 510 credit files (from 2003 to 2006) and contains the validation data (out-sample set).

Inputs variables were classified in three categories: non cash-flow ratios, cash-flow ratios and non financial variables. The main results can be summarized as follow:

1. Non cash-flow variables have a good prediction capacity of 97.8% for the Neural Network Models in the training set and 60.71% for the SVM models.
2. The introduction of cash-flow variables improves the prediction quality, and the classification rates passed to 97 % and 68.94% respectively in Neural Network and SVM models in the training set.

3. Collateral played an important role in default risk prediction. Its introduction in the model improves substantially the prediction capacity to 99% and 70.13% respectively in Neural Network and SVM models.

These findings are encouraging and militate in favor of a quick adoption of IRB in Tunisia and abroad. Our study can be helpful either for banks or authority regulation. It may help banks to identify the best financial predictor for default risk. It may also help authorities to implement an internal based risk method for assessment of credit risk evaluation.

Our study confirms the superiority of NN models to SVM models. The prediction performances of the neural network models (all versions) outperform the SVM model by more of 20% for the in-sample (model with full information). By the way, using the same data, we obtained a classification rate of only 75% from a discriminant analysis and 86.58% from a logistic regression with panel data. Hence, our study confirms the superiority of NN models to other techniques in the prediction of default and the assessment of credit risk evaluation (Matoussi & Krichène, 2010).

Finally, even if the Tunisian banking system may suffer from the absence of reliable data, our findings should give them incentive to build up strong and reliable databases, which will help them to meet the strict requirements of the new Basel Accord.
For further study, we can probably improve the results of the SVM models by establishing others models and choosing optimal values of the upper bound *C* and the kernel parameter *g* that are most important in SVM model selection.

According to (Jae & Lee, 2005) « Selecting the optimal parameter values through the grid-search, we could build a bankruptcy prediction model with high stability and prediction power ». In other words, it is interesting to derive judicious procedures to select proper kernel functions and the corresponding parameter values according to the types of classification problems.

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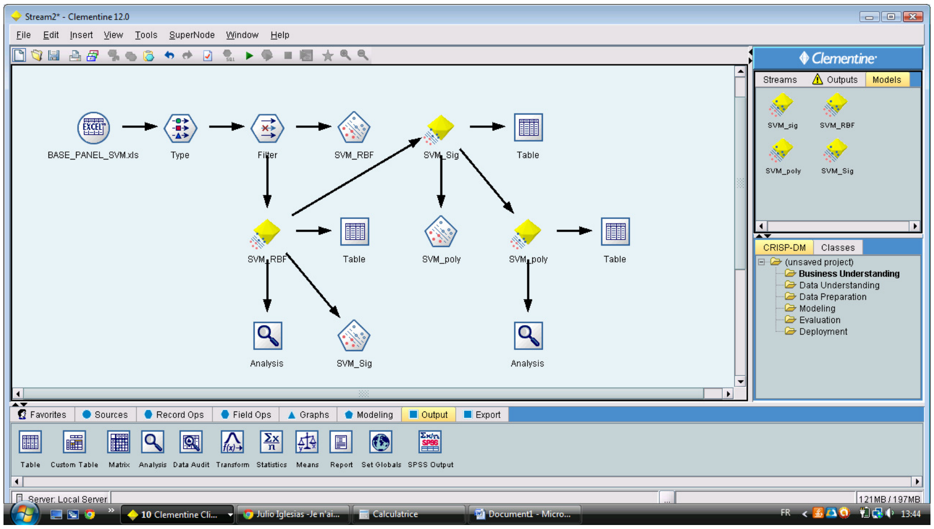
Appendix. Results of SVM models

Panel 1: non cash flow information



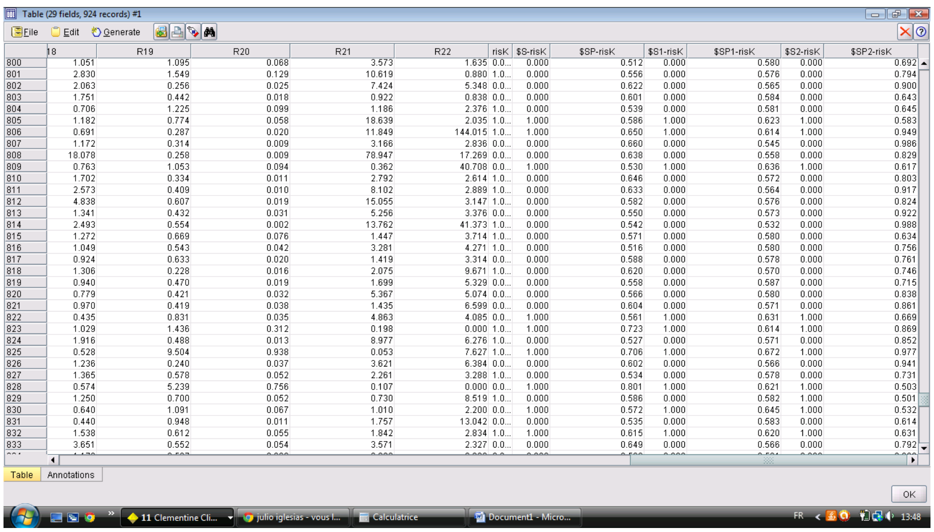
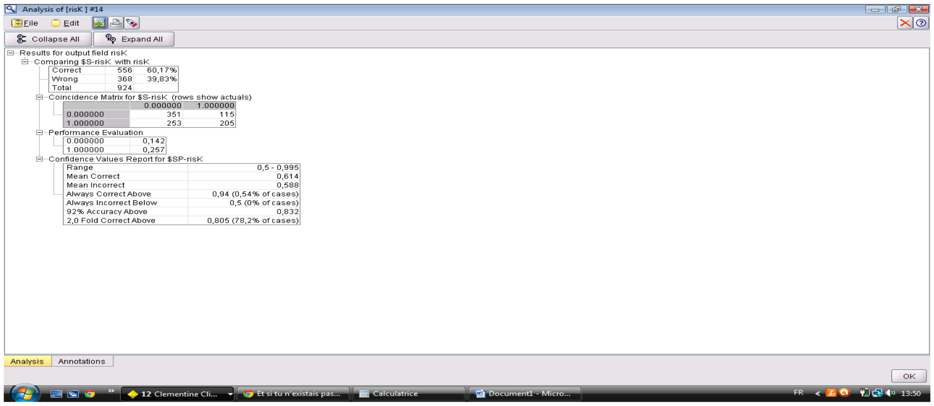


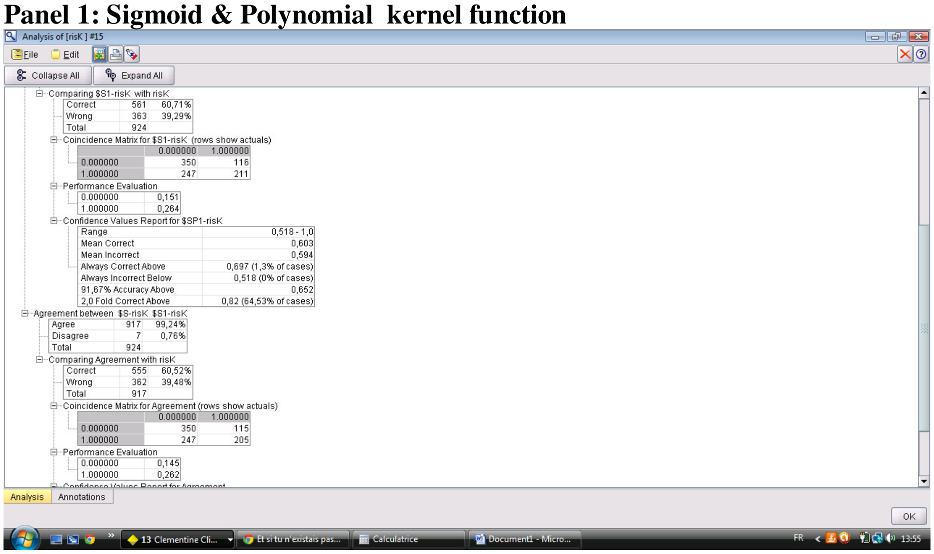
Table (29 fields, 924 records) #1

	18	R19	R20	R21	R22	risK	$S-risK	$SP-risK	$S1-risK	$SP1-risK	$S2-risK	$SP2-risK
800	1.051	1.095	0.068	3.573	1.635	0.0...	0.000	0.512	0.000	0.580	0.000	0.692
801	2.830	1.549	0.129	10.619	0.880	1.0...	0.000	0.556	0.000	0.576	0.000	0.794
802	2.063	0.256	0.025	7.424	5.348	0.0...	0.000	0.622	0.000	0.565	0.000	0.900
803	1.751	0.442	0.018	0.922	0.838	0.0...	0.000	0.601	0.000	0.584	0.000	0.643
804	0.706	1.225	0.099	1.186	2.376	1.0...	0.000	0.539	0.000	0.581	0.000	0.645
805	1.182	0.774	0.058	18.639	2.035	1.0...	1.000	0.586	1.000	0.623	1.000	0.583
806	0.691	0.287	0.020	11.849	144.015	1.0...	1.000	0.650	1.000	0.614	1.000	0.949
807	1.172	0.314	0.009	3.166	2.836	0.0...	0.000	0.660	0.000	0.545	0.000	0.986
808	18.078	0.258	0.009	78.947	17.269	0.0...	0.000	0.638	0.000	0.558	0.000	0.829
809	0.763	1.053	0.094	0.362	40.708	0.0...	1.000	0.530	1.000	0.636	1.000	0.617
810	1.702	0.334	0.011	2.792	2.614	1.0...	0.000	0.646	0.000	0.572	0.000	0.803
811	2.573	0.409	0.010	8.102	2.889	1.0...	0.000	0.633	0.000	0.564	0.000	0.917
812	4.838	0.607	0.019	15.055	3.147	1.0...	0.000	0.582	0.000	0.576	0.000	0.824
813	1.341	0.432	0.031	5.256	3.376	0.0...	0.000	0.550	0.000	0.573	0.000	0.922
814	2.493	0.554	0.002	13.762	41.373	1.0...	0.000	0.542	0.000	0.532	0.000	0.988
815	1.272	0.669	0.076	1.447	3.714	1.0...	0.000	0.571	0.000	0.580	0.000	0.634
816	1.049	0.543	0.042	3.281	4.271	1.0...	0.000	0.516	0.000	0.580	0.000	0.756
817	0.924	0.633	0.020	1.419	3.314	0.0...	0.000	0.588	0.000	0.578	0.000	0.761
818	1.306	0.228	0.016	2.075	9.671	1.0...	0.000	0.620	0.000	0.570	0.000	0.746
819	0.940	0.470	0.019	1.699	5.329	0.0...	0.000	0.558	0.000	0.587	0.000	0.715
820	0.779	0.421	0.032	5.367	5.074	0.0...	0.000	0.566	0.000	0.580	0.000	0.838
821	0.970	0.419	0.038	1.435	6.599	0.0...	0.000	0.604	0.000	0.571	0.000	0.861
822	0.435	0.831	0.035	4.863	4.085	0.0...	1.000	0.561	1.000	0.631	1.000	0.669
823	1.029	1.436	0.312	0.198	0.000	1.0...	1.000	0.723	1.000	0.614	1.000	0.869
824	1.916	0.488	0.013	8.977	6.276	1.0...	0.000	0.527	0.000	0.571	0.000	0.852
825	0.528	9.504	0.938	0.053	7.627	1.0...	1.000	0.706	1.000	0.672	1.000	0.977
826	1.236	0.240	0.037	3.621	6.384	0.0...	0.000	0.602	0.000	0.566	0.000	0.941
827	1.365	0.578	0.052	2.261	3.288	1.0...	0.000	0.534	0.000	0.578	0.000	0.731
828	0.574	5.239	0.756	0.107	0.000	0.0...	1.000	0.801	1.000	0.621	1.000	0.503
829	1.250	0.700	0.052	0.730	8.519	1.0...	0.000	0.586	0.000	0.582	1.000	0.501
830	0.640	1.091	0.067	1.010	2.200	0.0...	1.000	0.572	1.000	0.645	1.000	0.532
831	0.440	0.948	0.011	1.757	13.042	0.0...	0.000	0.535	0.000	0.583	0.000	0.614
832	1.538	0.612	0.055	1.842	2.834	1.0...	1.000	0.615	1.000	0.620	1.000	0.631
833	3.651	0.552	0.054	3.571	2.327	0.0...	0.000	0.649	0.000	0.566	0.000	0.792

Panel 1: RBF kernel function

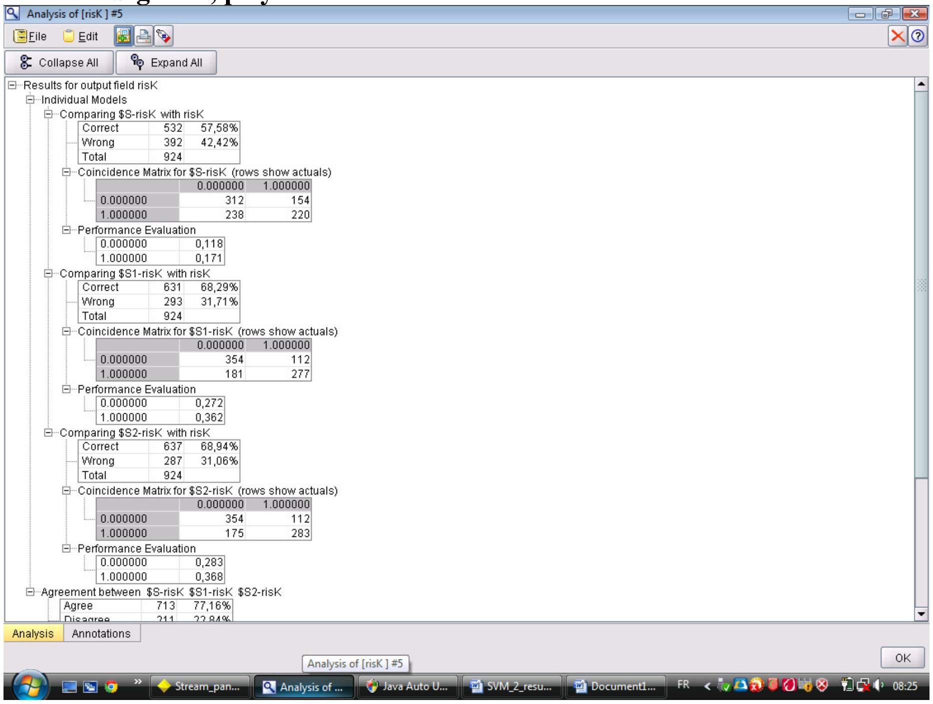


Panel 1: Sigmoid & Polynomial kernel function



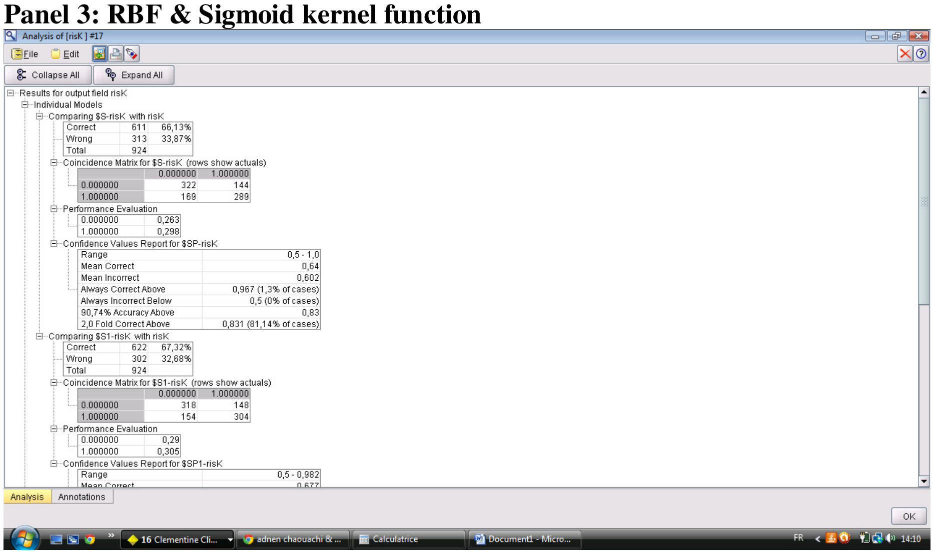
Panel 2 : Cash Flow Models

Panel 2: Sigmoid, polynomial and RBF kernel functions

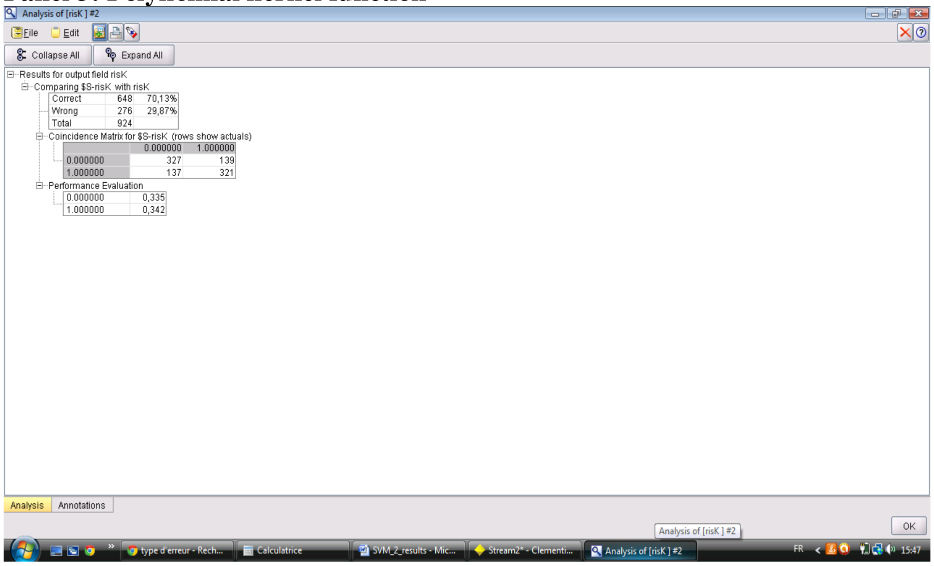


Panel 3: Full information models

Panel 3: RBF & Sigmoid kernel function



Panel 3: Polynomial kernel function



Note

[1] Circulaire aux établissements de crédits N° 2006-19 portant sur le contrôle interne.

[2] "Sound Credit Risk Assessment and Valuation for Loans », Consultative Document, Bank for International Settlements Press & Communications, Basel (November 2005).

[3] See failure prediction in Tunisia by Matoussi *et al.* (1999), financial distress prediction using Neural Networks by Abid & Zouari (2000), financial distress in Egypt by El-Shazly (2002), credit scoring model for Turkey's micro & small enterprises by Davutyan & Özar (2006).

[4] "To get an idea about the potential impact of the bankruptcy prediction problem, we note that the volume of outstanding debt to corporations in the United States is about $5 trillion. An improvement in default prediction accuracy of just a few percentage points can lead to savings of tens of billions of dollars" (Atiya, 2001).

[5] The use of artificial neural networks began in the 40's, but their applications in finance are more recent. According to the bibliography research by (Wong *et al.*, 1995), the early experimentations started in 1988 and the first paper on bankruptcy prediction was published in 1990.

[6] "NNs have generally outperformed the other existing methods. Currently, several of the major commercial loan default prediction products are based on NNs. For example, Moody's *Public Firm Risk Model* is based on NNs as the

main technology. Many banks have also developed and are using proprietary NN default prediction models" (Atiya, 2001).

[7] Neural networks are applicable in virtually every situation in which a relationship between the predictor variables (independents, inputs) and predicted variables (dependents, outputs) exists, even when that relationship is very complex and not easy to articulate in the usual terms of "correlations" or "differences between groups."

[8] "The reasons for the current ratio's widespread use as a measure of liquidity include its ability to measure:

- *Current liability coverage*: the higher the amount of current assets to current liabilities, the greater assurance we have in current liabilities being paid.
- *Buffer against losses*: the larger the buffer, the lower the risk. The current ratio shows the margin of safety available to cover shrinkage in noncash current asset values when ultimately disposing or liquidating them.

Reserve of liquid funds: the current ratio is relevant as a measure of the margin of safety against uncertainties and random shocks to a company's cash flows. Uncertainties and shocks, such as strikes and extraordinary losses, can temporarily and unexpectedly impair cash flows." (Berstein, & Wild, 1998).

[9] However, if all the types prefer to receive the same contract, we are in case of the pooling equilibrium. See (Capra *et al.*, 2001).