Advances in Mathematical Finance
& Applications, 6(4), (2021), 717-732
DOI: 10.22034/AMFA.2020.1884838.1339

Published by IA University of Arak, Iran
Homepage: www.amfa.iau-arak.ac.ir

Presenting a New Bankruptcy Prediction Model Based on Adjusted Financial Ratios According to the General Price Index

Naimeh Jebelli[a] , *Iman Dadashi*[a,*] , *Mohammad Javad Zare Behnmiri*[b]

[a]*Department of Accounting, Babol Branch, Islamic Azad University, Babol, Iran*
[b]*Department of Accounting, University of Qom, Qom, Iran*

ARTICLE INFO

Article history:
Received 18 January 2019
Accepted 24 Augest 2019

Keywords:
Bankruptcy
General Price Index
Financial Ratio
LARS Algorithm

ABSTRACT

In a volatile economic environment, financial decision making is always associated with risk. Bankruptcy, as one of the most important risks, has a significant impact on the interests of the firm's stakeholders, so presenting appropriate bankruptcy forecasting patterns is of the utmost importance. In this study, after reviewing the theoretical literature and selecting the financial ratios used in previous bankruptcy prediction models as the variable input of the initial model, the financial ratios were adjusted based on the price index and then, using the LARS algorithm, the ratios that have the highest ability to differentiate between bankrupt and non-bankrupt firms were identified, and finally, using the SVM and Naive Bayesian algorithms, the final bankruptcy prediction model was developed. For this purpose, the data of 50 companies listed in Tehran Stock Exchange who had experienced bankruptcy for at least one year from 2008 to 2018 under Article 141 of the Commercial Code were used. The results show that the adjusted financial ratios based on the price index in the model presented by SVM algorithm can be a very good predictor for bankruptcy of companies with an accuracy of 99.4%.

1 Introduction

The growth of competition between businesses has limited access to resources increased and the likelihood of bankruptcy. Bankruptcy is an event that has a great impact on management, shareholders, customers, creditors, and other stakeholders. Previous research has shown that companies hide their bankruptcy and officially declare bankruptcy when it is too late to try to avoid bankruptcy. For this reason, the economic and social consequences of bankruptcy can be reduced or even avoided if information can be obtained before it occurs. Investors and creditors have long been provided with a more accurate understanding of the company's financial position by analyzing financial statements with different procedures and comparing companies with other competitors [14]. Corporate and business institutions and the complexity of economic and trade relations have changed dramatically since 1950s, and governments' emphasis on economic growth has further complicated the growth of companies and institutions. As financial decision making becomes more strategic, managers are forced to use advanced methods of analysis and forecasting to create long term visions, and adopt new models of control that are more comprehensive [21]. Changes in the economic environment of companies affect their financial situation and the risk of bankruptcy inflation can be mentioned as one of these changes therefore, in making models, both the financial ratios of companies and the variables that reflect changes in the economic environment must be considered [31]. As inflation rates soar in recent years, many accountants and users of financial statements are encouraged to think about the dynamics of financial statements

* Corresponding author. Tel.: *+989124400915*
E-mail address: *I.dadashi@gmail.com*

and to provide complementary information to illustrate the effects of inflation, prepare comparative statements and analyze them in terms of inflation accounting and historical expense in order to provide accurate reporting of financial events to domestic and foreign users.

Although many years have passed since the presentation of the aforementioned subject, In all internal research and major foreign research conducted in the field of predicting the financial performance of companies and in particular, bankruptcy, only to predict or compare the predictive power of models using historical information of financial statements, , but the main purpose of this study is to consider the effects of inflation on the input variables in the design of the bankruptcy prediction model. Thus, this research adjusts the financial statement items based on the price index using the information contained in the financial statements of listed companies in Tehran Stock Exchange and, through meta-heuristic approaches, designs an optimal model for predicting bankruptcy of companies in accordance with the conditions and economic system of the country. Given the above, the difference between the present study and other empirical studies predicting bankruptcy is rooted in four factors:

1- For the first time, this study has used various accounting indicators adjusted based on inflation rate in predicting bankruptcy, which is a new link between accounting and economics called macro accounting. Accurate and reliable financial information leads to useful economic decisions.
2- In this research, meta-heuristic models have been used in the optimization and training of neural networks. Artificial intelligence patterns reflect nonlinear effects and complex interactions between variables, unlike linear patterns, this has led to little time being spent calibrating the neural network parameters.
3- In this study, we tried to use all the financial ratios used in different models available in predicting financial bankruptcy to design a bankruptcy forecasting model.
4- Due to the multiplicity of financial ratios used in this study as input predictor variables, LARS algorithm was used to identify effective variables to introduce the key variables of bankruptcy prediction among the basic variables of financial statements and based on theoretical foundations.

2 Theoretical Foundations and Research Background

The rapid development of technology and the widespread environmental changes and expansion of capital markets, coupled with the attraction of large capitals, have given the economy an accelerating pace, while the growth of competition between businesses has limited profitability and increased the likelihood of bankruptcy. Therefore, understanding the causes of bankruptcy and, most importantly, predicting bankruptcy through financial statement information can have a significant impact on the efficiency of the capital market and the decisions of investors and creditors, and especially the organizations to predict bankruptcy before a failure occurs. Most investors expect that the operations of the investee companies will proceed according to their expected conditions and the returns they receive will be proportionate to the investment risk. From an economic point of view, bankruptcy is a natural phenomenon that should not be overlooked, as it is a social impact based on unemployment and purchasing power parity [24]. Decrease in product lifespan, increase of technology impact on corporate operations, expansion of global exchanges, and such factors have led to increased volatility in financial environments, which resulted in more focus on reducing risk and ensuring return on investment. In these situations, real and legal investors make a great effort to understand the status of investee companies in order to protect their capital, but this will be achievable only if reliable analytical methods are available

[33]. Survey about reasons for bankruptcy from financial point of view and recognition of financial basic and the most important thing evaluation of bankruptcy based on popular methods is very important. Bankruptcy level does by on time prediction of that we can have enough time to answer investors [36]. In recent years, many researchers have been predicting bankruptcy through different methods. In the area of bankruptcy forecasting, two sets of methodologies are discussed under the traditional and meta-heuristic models. In recent years, prior to the development of artificial intelligence methods, most researchers have used traditional methods such as logistic regression (LR) and Multiple Discriminant Analysis (MDA). Despite the ease and simplicity of traditional models in application, the use of statistical models in practice has some limitations, for example Beaver [3] refers to the assumption of linearity of the relationship between variables in univariate analysis models. Altman [2] refers to three limiting assumptions in multivariate analysis models. These include the normality of the distribution of variables, the assumption of the existence of a uniform distribution matrix, and the use of prior probabilities. Also Tamari [44] addresses to being unknown the relative importance and to be subjective of variables in the risk index model.

Assumptions about compliance to a particular statistical distribution (often, adherence to the normal distribution) in these methods, the mathematical accuracy of such methods may be ambiguous because real-world financial data does not necessarily follow the normal distribution. With the development of artificial intelligence, meta-heuristic models such as Artificial Neuron Network (ANN), Support Vector Machine (SVM), Genetic Algorithm (GA) and etc, have been used to predict bankruptcy. Artificial intelligence algorithms are ideal tools to predict because they do not have the limiting assumptions such as linearity, normality, and independence of input variables which limit the effectiveness and validity of the prediction then they learn by experience and do not come to a deadened. These algorithms, in addition to exploiting statistics, also consider mental aspects; therefore, they cover the weaknesses related to the necessity of adherence to the specific statistical distribution available in traditional methods [11]. Initially, Odom and Sharda [29] used neural networks to design bankruptcy forecast models. The findings of the study showed that the results of the neural networks methods are more accurate, precise, and more reliable than multivariate linear detection methods. Min et al. [27] developed a model for bankruptcy prediction using a Support Vector Machine and their research showed that their model performs better than traditional statistical models and in terms of generalizability and accuracy. Similar research has been done in Iran.

Research by Falahpour and Raei [34] has shown that the neural network model is significantly more accurate than the multivariate discriminant model in predicting bankruptcy. Findings of another study by Farajzadeh dehkordi [16] indicate that genetic planning can predict up to 90% of bankruptcies in the test sample, while multivariate discriminant analysis accounts for up to 73% of corporate bankruptcies. Therefore, it is expected that, as researches have shown, the meta-heuristic models of artificial intelligence have higher accuracy and predictive power than traditional models. Although researchers have presented different models for evaluating corporate financial status and performance, it seems that a method that uses more comprehensive criteria to create a relative predictive model of a firm's success or failure will help decision makers make the right decisions. In making appropriate economic decisions regarding a business entity, using the information contained in the financial statements without analyzing them may mislead users. Therefore, it is important to use information from financial statements analyzed by experts [9]. one of the financial statement analysis techniques is the expression of the relationship between the figures in a ratio. The simplicity of the ratios has made them to be widely recognized as a useful and acceptable tool [39]. Given that the single currency scale in accounting, which is the most efficient tool for measuring all financial events and information processing of a business unit,

is not constant over time, unlike physical scales, and is fluctuating simultaneously with recession and inflation, and with the rise of inflation in recent years accountants have been encouraged to provide complementary information to illustrate the effects of inflation and most financial statement users, economic decision makers and especially managers believe that efforts must be made to prepare adjusted financial statements in order to provide relevant, reliable, timely, complete and accurate information on financial events to both internal and external users with the lowest possible cost [22].
Due to the importance of the subject, a number of researchers also predicted bankruptcy in their research using a combination of accounting and market information, for example, Shumway [42], Campbell et al. [6], and Christidis and Gregory [7]. Also the results of the research by Charalambakis et al. [8] showed that in predicting financial crisis, a model that combines accounting information and market information performs better. Hernández Tinoco & Wilson [45] used accounting, market and macroeconomic variables to investigate financial distress and bankruptcy predictions and found that combining the accounting, market, and macroeconomic variables lead to a very accurate prediction of bankruptcy risk. Pawełek & Baryła [31] developed a bankruptcy forecasting model using financial ratios and indicators of economic growth, inflation, labor market, economic status and inflation and it was confirmed that the change in the economic environment of companies affects their financial situation and the risk of bankruptcy. Also in domestic researches, Royayi [37] and Zand Raeisi [49] investigated the status of corporate financial statements in inflationary conditions as well as how investors decide to deal with inflation and presented the results of their research on inflation accounting, suggesting that adjusting accounting items and financial statements has benefits which can influence the economic decisions of corporations and firms. Sadeghi et al. [38], concluded that the role of macroeconomic factors in corporate health and financial distress is far greater than that of strategic system factors.

3 Research Method

This study seeks to answer the fundamental question of which of the two SVM and Naive Bayesian algorithms is more accurate in designing a corporate bankruptcy prediction model using financial ratios adjusted based on price indexes?
Because the results of this study can be used in the decision-making process, this research is applied in terms of purpose, and it is also descriptive-correlation in nature. Research is done in the context of deductive-inductive reasoning. In this study, library research or organizational documents were used to collect the required information. Preliminary studies, research backgrounds, and theoretical frameworks of research have been collected using library resources including books, journals, thesis, research articles, and websites. The research data were collected through the RAHAVARD software and the stock exchange databases. In this study and in the descriptive statistics section, data analysis was performed using central indexes such as mean, median, and standard deviation and Excel and MATLAB software were used in order to analyze the data and extract the research results.

3.1 Statistical Population and Research Sample

The statistical population of the present study is the listed companies in Tehran Stock Exchange. The research period is between 2007 and 2016. It should be noted that for calculating some ratios such as the average inventory of goods, the financial information of 2006 is required, therefore some items of 2006 financial statements have been adjusted. The systematic elimination method was used to select the sample in this study and the criteria applied are as follows:

1- Large and active production companies other than credit and insurance companies.

2- Membership in the Iranian Stock Exchange during the years under study.

3- The date of the end of the fiscal year of the companies should be 12/29.

4- The financial information needed to calculate the research variables for those companies must be available during the research period.

5- In joint stock companies with subsidiaries, the financial statements of the main or parent company were used in the research.

6- Sample companies must have been recognized the research period for at least one year by applying the theoretical concepts stated in the bankruptcy literature in accordance with Article 141 of the Bankruptcy Law. Given the above limitations, the number of firms in a homogenized community is 50. In this research, we have tried to consider all stock exchange companies that were bankrupt for at least one year for the period between 2008 to 2018 as a sample of the research, which tested a total of 545 (year-company) samples, so it should be considered as a limitation of this study stated.

3.2 Research Steps

3.2.1 Review of Theoretical Foundations and Research Background

The history of using financial ratios goes back to 1870 [9]. It was at that time when analysts developed and promoted financial ratios, therefore today, ratios analysis is a powerful technique and a useful tool for users to evaluate the performance of past, present and future, and to this day, due to the expansion of science and knowledge as well as the technology advances in computing and information, there have been many advances in the use of financial ratios [22]. Financial ratios have been used in many researches for analysis in the field of bankruptcy prediction and as a result, a background of all the financial ratios used in all of the available bankruptcy models has been presented and classified as Table 1, and ultimately 40 financial ratios have been considered as the independent research variables.

Table 1: Background of Financial Ratios Explaining Bankruptcy

Symbol	Financial Ratio	Researchers
x_1	Ratio of accumulated profits to total assets	Altman [1], Fulmer [17], Philosophov [32], Iranian Kurdestani Modified Altman Model [23]
x_2	Ratio of working capital to total assets	Altman [1], Beaver [4], Springate [43], Ohlson [30], Falmer [17], Grice [18], Wallace [47], Iranian Kurdestani Modified Altman Model[23]
x_3	Ratio of Earnings before Interest and taxes to total assets	Altman [1], Springate [43], CA_Score [26], Grice [18], Philosophov [32], Iranian Kurdestani Modified Altman Model [23]
x_4	Ratio of the company shares book value to the total debt book value	Altman [1], Thai DA [5]
x_5	Ratio of sales to total assets	Altman [1], Springate [43], Falmer [17], Thai DA [5], Iranian Kurdestani Modified Altman Model [23]
x_6	Ratio of total debts to total assets	Ohlson [30], Beaver[4], Zmijewski [51], Flamer [17], Grice [18], Wallace [47], Farajzadeh Genetic Model [16]
x_7	Ratio of current debts to current assets	Ohlson [30]
x_8	Ratio of net profit to total assets	Beaver [4], Deakin [13], Ohlson [30], Zmijewski [51], Wallace [47]
x_9	Ratio of operating cash flow to total debt	Ohlson [30]
x_{10}	Changes in net profit	Ohlson [30]
x_{11}	Pre-tax profit to current debt	Springate [43]
x_{12}	Cash Flow to Total Assets	Beaver [4], Deakin [13], Wallace [47]

Table 1: Continue

Symbol	**Financial Ratio**	**Researchers**
x_{13}	Current assets to current debts	Zmijewski [51], Deakin [13], Wallace [47]
x_{14}	Equity capital to Total Assets	CA_Score [26]
x_{15}	Sale of previous year to previous year assets	CA_Score [26]
x_{16}	Current Assets to Total Assets	Deakin [13]
x_{17}	Sales to current assets	Deakin [13], Farajzadeh Genetic Model [16]
x_{18}	Cash Flow to Total Debt	Fulmer [17], Mutchler [28]
x_{19}	Current assets to current debt	Mutchler [28]
x_{20}	Total long-term debt to total assets	Mutchler [28], Thai DA [5]
x_{21}	Earnings before Interest and taxes to net sales	Mutchler [28], Farajzadeh Genetic Model [16]
x_{22}	Pre-tax profits to equity capital	Fulmer [17]
x_{23}	Working capital to total debts	Fulmer [17]
x_{24}	Logarithm of Earnings before Interest and taxes	Fulmer [17]
x_{25}	Current debt to total assets	Thai DA [5], Philosophov [32]
x_{26}	Average inventory to sales	Zavgren [50], Thai DA [5]
x_{27}	Average accounts receivable to average inventory	Thai DA [5]
x_{28}	(Cash Inventory + Short Term Investment) to total assets	Thai DA [5]
x_{29}	Current assets to current debts	Beaver [4], Thai DA [5], Wallace [47]
x_{30}	Operating Profit to (total assets – current debt)	Thai DA [5]
x_{31}	Long-term debt to (total assets – current debt)	Thai DA [5]
x_{32}	Sales to (Fixed assets + Net working capital)	Thai DA [5]
x_{33}	Accumulated interest to total debt	Shirata [40]
x_{34}	Debt and equity capital of this year to debt and equity capital of the previous year	Shirata [40]
x_{35}	Ratio of interest expense to average sum of loans, debts, bonds, and Discounted documents	Shirata [40]
x_{36}	Average of sum of accounts and notes payable to sales	Shirata [40]
x_{37}	The difference between net income and operating cash flow to total assets	Grice [18]
x_{38}	Interest to total assets	Philosophov [32]
x_{39}	Immediate assets to total assets	Farajzadeh Genetic Model [16]
x_{40}	Interest expense to gross profit	Farajzadeh Genetic Model [16]

3.2.2 Adjusting Variables Based on Inflation

In order to consider the effect of financial statements inflation, the general price level changes have been used, which is provided by the Central Bank of the Islamic Republic of Iran. To this end, « the total cost of consumer goods and services in urban areas » has been a measure of item adjustment. The first step in the homogenization (adjustment) of financial statements, is the separation of monetary and non-monetary items of the balance sheet and the profit and loss statement. To homogenize the fixed historical assets, since the fixed assets of corporations in Iran are depreciated on the basis of the depreciation schedule under table 151 of the Direct Taxes Act, because the exact date of the getting and related changes them are not available, so the fixed assets of all the sample companies' financial statements have been adjusted according to the following equation:

$$\begin{aligned} &Adjusted\ amount\ of\ fixed\ assets\ at\ balance\ sheet\ date \\ &= Balance\ of\ 2007 \times \frac{Balance\ Sheet\ Date\ Index}{Index\ of\ 2007} \\ &+ Balances\ created\ each\ year \times \frac{Balance\ Sheet\ Date\ Index}{Average\ Creation\ Date\ Index} \end{aligned} \quad (1)$$

The accumulated depreciation homogenization is as follows:

$$\begin{aligned} &Adjusted\ accumulated\ depreciation \\ &= \frac{Historical\ accumulated\ depreciation}{Fixed\ assets\ (historical)} \times Adjusted\ amount\ of\ fixed\ ass \end{aligned} \quad (2)$$

Realization of costs and sales are assumed to be uniform throughout the year, so the average index per year is applied. The depreciation expense each year is calculated proportion to the cost of previous assets and assets acquired during that year and adjusted in the same proportion. The inventory of the first commodity and the end of the period were adjusted according to the first index and the average over the year, respectively. The following equation has been used to adjust investments and other assets:

$$\begin{aligned} &Adjusted\ amount\ at\ balance\ sheet\ date \\ &= Balances\ created\ each\ year \times \frac{Balance\ Sheet\ Date\ Index}{Average\ Creation\ Date\ Index} \end{aligned} \quad (3)$$

Cost of sold goods is adjusted as follows:

$$\begin{aligned} &Cost\ of\ adjusted\ sold\ goods \\ &= (Historical\ cost\ of\ sold\ goods - Historical\ \text{expense}\ of\ depreciation\ ) \\ &\times \frac{Balance\ Sheet\ Date\ Index}{Index\ of\ the\ beginning\ of\ the\ year} \\ &+ Adjusted\ \text{expense}\ of\ depreciation \end{aligned} \quad (4)$$

All monetary items including receivables accounts and documents, cash and bank balance, payable accounts and documents and advances, received financial facilities, income tax payable, long-term debts and compensated absences are not adjusted. To reflect the effects of inflation on monetary items, profits (losses) of keeping monetary items (purchasing power) were calculated.

3.2.3 Choosing the Main Variables

A variable is a concept that is assigned more than two or more values or numbers. In other words, the variable refers to features that can be viewed or measured. And replaced two or more values or numbers [12]. In order to select the main variables (features) in this study, the LARS algorithm is used as a feature selection method out of 40 technical variables that are given as input predictor variables to the system, the variables which increase the accuracy of bankruptcy predictions. In general, feature selection methods are divided into three categories: filtering, covering, and hybrid. LARS algorithm is one of the covering methods that classify the feature according to the learning process and selects an optimal subset from all the features offered to it. Benefits of the feature selection process include increased accuracy and speed in implementing predictive techniques, elimination of Extraneous and irrelevant data and Increasing the intelligibility of models used. The final variables of this research were extracted using LARS algorithm to predict the bankruptcy of companies according to the adjusted financial ratios based on the General Price Index in table of Table 2:

Table 2: The Final Variables to Predict The Bankruptcy

Symbol	**Financial Ratio**
x_1	Ratio of accumulated profits to total assets
x_3	Ratio of Earnings before Interest and taxes to total assets
x_6	Ratio of total debts to total assets
x_8	Ratio of net profit to total assets
x_{32}	Sales to (Fixed assets + Net working capital)
x_{40}	Interest expense to gross profit

3.2.4 Model Estimation and Comparison Based on SVM and Naive Bayesian Algorithms

In order to predict bankruptcy based on financial ratios (adjusted data based on inflation), by two algorithms of support vector machine (SVM) which has performed well in solving classification problems and became popular in recent years in developed countries to predict financial distress and bankruptcy, and the Naive Bayesian algorithm, which is one of the Most usable statistical models to identify probable relationships to predict or evaluate, were used, and after the construction of the model, the Bankruptcy Predictive Power of Estimated models are compared with each other.

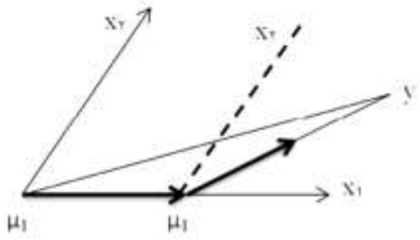
4 Least Angle Regression Algorithm

Suppose we want to find a linear relationship between a number of potential variables and a response variable, that is, to construct a model for the relationship between them. The LARS algorithm is a tool to determine which variables should be included in the model, along with the coefficients of each variable [15]. Here's how LARS works:

1. For simplicity, we assume that we have standardized our explanatory variables mean and variance to zero and our response variable mean is also zero.
2. There are no variables in the model at startup.
3. The variable x_1 is found to have the highest correlation with the residuals (note that the highest correlation with the residuals is equivalent to the lowest residual angle).
4. The direction of this variable is followed to the extent that the other variable (x_2) has the same correlation.
5. At this point the movement begins in a direction where the residual has a correlation equal to $x_1$and x_2(in other words, the residual builds an angle equal to two variables) And the move goes on until a variable like x_3, builds a correlation equal to the residual.
6. Likewise, the work continues until we know that our model has grown sufficiently.

for example in the diagram below, x_1 and x_2 are our variables and the answer is y.

Our model starts at μ_0. The residual ($\mu_1 y$ vector), makes a smaller angle with x_1 in comparison to x_2, so we move in the direction of x_1. At point μ_1, the residual angle is equal to x_1 and x_2.



Therefore, a new movement begins in a new direction where this angle equality (correlation equality) is maintained. If there were other variables, the direction will change again to make an angle equal to the residual, and the work will continue.

5 Support Vector Machine (SVM)

This algorithm finds a specific type of linear models that ensures the highest margin of the hyper plane. Maximizing the margin of the hyper plane will maximize the separation between classes. The nearest training points to the maximum margin of the hyper planes are called the support vectors. These vectors are used only to delineate the boundary between classes [41]. Support vector machines have the following properties:

1– Classifier design with maximum generalization 2- Reaching the overall optimal point of the function 3– Automatic determination of optimal structure and topology for the classifier 4- Modeling nonlinear differentiation functions using nonlinear cores and the concept of internal multiplication in Hilbert spaces. If the data are linearly separated, SVM trains linear machines to produce an optimal level that separates the data without error and with the maximum distance between the plane and the nearest training points (support vector If the training points are defined as $[\chi_i \cdot y_i]$ and the input vector as $\chi_i \in R^n$, and the value of class y_i as i = 1,..., L = {- 1,1}, then in a situation where data can be linearly separated, the rules that separate binary decision making are as follows :

$$Y= sign\ (\Sigma(x.xi)+b) \tag{5}$$

In which y is the output of the equation, y_i is the class value of the teaching sample, and x_i indicates the internal multiplication. x = (x_1 , x_2 ..... x_i) vector indicates an input data and i = 1, … , n and x_i vectors are the support vectors. a_i and b parameters determine the hyper plane. If the data are not linearly separated, then the relation is changed as follows:

$$Y= sig\ n\ (\Sigma(x.xi)+b) \tag{6}$$

$k(x.x_i)$ function is a Kernel function which generates internal multipliers to create machines with different types of nonlinear decision levels in the data space [35].

6 Naive Bayesian Algorithm

The Bayesian theorem is a method of probabilistic calculation in which the probability of an event occurring in the future depends on an event that has already occurred. This theory is capable of self-learning in a widely used intelligent system. Bayesian theory can be used to predict future events based on present events according to statistics and probability theory. The Naive Bayesian classification is based on the Bayes theorem and the assumptions of independence between predictors. A Bayesian model is simple and easy build, and without complex duplicate parameters it will be useful for very large datasets. Despite its simplicity, the Bayesian category is often interesting and widely used. Naive Bayesian theorem provides the posterior probability calculation method $P(x|c. P(c|x). P(c). P(x))$, the Naive Bayesian classification assumes that the effect of the value of a(x) prediction on a(c) data class is independent of the values of the other predictors. This is the assumption of conditional independence of the class.

$$\underbrace{P(c \mid x)}_{\text{Posterior Probability}} = \frac{\overbrace{P(x \mid c)}^{\text{Likelihood}}\,\overbrace{P(c)}^{\text{Class Prior Probability}}}{\underbrace{P(x)}_{\text{Predictor Prior Probability}}}$$

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

$P(c|x)$ is the posterior probability of the predictor (feature) class (target).
$P(c)$ is the previous probability of class.
$P(x|c)$ is the probability that the predictor class probability is given.
$P(x)$ is the former probability of the predictor [46].

7 Research Findings

The results of the methodology are provided as follows.

7.1 Descriptive Statistics

Descriptive statistics include a set of methods for collecting, summarizing, classifying, and describing numerical facts. Descriptive statistics of the research variables are presented in Table. 3.

Table 3: Descriptive Statistics of The Research Variables

Symbol	Financial Ratio	**Mean**	*s.d*	***Maximum***	Minimum
x_1	Ratio of accumulated profits to total assets	-0.161	0.559	0.498	-3.833
x_3	Ratio of Earnings before Interest and taxes to total assets	0.015	0.124	0.619	-0.801
x_6	Ratio of total debts to total assets	0.729	0.378	2.908	0.039
x_8	Ratio of net profit to total assets	-0.029	0.134	0.331	-0.869
x_{32}	Sales to (Fixed assets + Net working capital)	-0.074	0.628	2.439	-2.887
x_{40}	Interest expense to gross profit	-0.058	0.060	٠	-0.345

In Table 3, some concepts of descriptive statistics are presented including observations, mean, minimum, maximum, and standard deviation. The main central index is the mean, which represents the equilibrium point and gravity of the distribution and is a good indicator for representing data centrality. For example, the variable mean value of the ratio of Earnings before Interest and taxes to total assets is equal 0.015, indicating that most data are focused around this point. Minimum and maximum are statistical indices that indicate the Scope of data changes in a community.
According to the results, the minimum value for the ratio of Earnings before Interest and taxes to total assets is -0.801, which indicates the minimum value among the data, and the maximum value for the ratio of Earnings before Interest and taxes to total assets is 0.619, indicating the maximum value among data. Standard deviation is one of the most important dispersion parameters and a measure for dispersion is the observation from mean and its value for the ratio of Earnings before Interest and taxes to total assets variable is 0.124.

7.2 Prediction Models

1- Estimated model based on support vector machine algorithm (SVM)
Based on the model and estimates from the SVM algorithm (as shown in Table. 4), the overall prediction accuracy is 99.4%, and in addition, in the SVM algorithm, the model has the ability to predict 100% of healthy and 97% of bankrupt firms.

Table 4: Prediction Accuracy Based on Support Vector Machine Algorithm (SVM)

Bankruptcy Prediction	**Healthy**	*Bankrupt*	***Total***
Correct Prediction Percentage	100%	97.5%	99.4%
False Prediction Percentage	0%	2.5%	0.6%

In addition, Fig 1 shows the comparison of the predicted amount for the cost function (the classification error) in the proposed model and the actual values. The cost function output Figs of the actual model are very close to the cost function Figs of the designed model and have high overlap, so the mean squared error (MSE) is minimal, indicating high accuracy of the designed model classification.

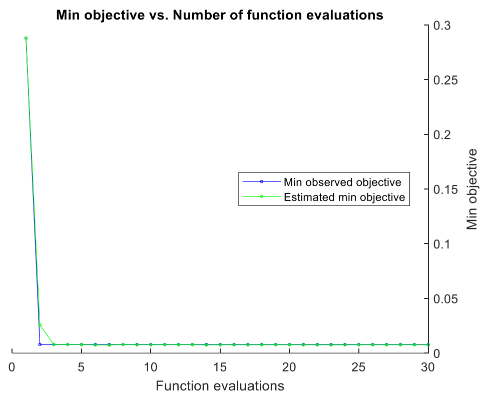


Fig. 1: Comparison of Forecast Value for Cost Function (squared error) in Proposed Model and Actual Values

In Fig. 2, the 3D space of the model designed by the SVM algorithm is plotted.

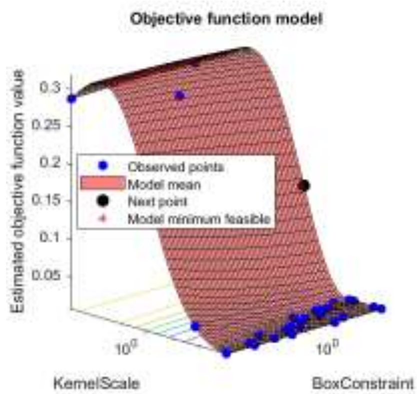


Fig. 2 : Three- Dimensional Graph of the Proposed Model Based on SVM Algorithm

7.3 Estimated model based on the Naive Bayesian algorithm

Based on the model and estimates of the Naive Bayesian algorithm, the overall prediction accuracy is 95.1%. In addition, the algorithm has the ability to predict 98% of healthy and 93% of bankrupt firms.

Table 5: Prediction Accuracy Based on Naive Bayesian Algorithm

Bankruptcy Prediction	**Healthy**	*Bankrupt*	***Total***
Correct Prediction Percentage	98.5%	93.0%	95.1%
False Prediction Percentage	1.5%	7.0%	4.9%

As can be seen, the overall prediction accuracy of the SVM is higher than the Naive Bayesian model and this demonstrates the much greater power of the SVM in generalizability.

8 Conclusion

Bankruptcy prediction is one of the most important researches in the financial field because having a proper understanding of the probability of bankruptcy and taking timely actions can reduce or avoid the high costs of bankruptcy. Banks and credit rating institutions usually use these models to make credit decisions and assign ratings. Predicting bankruptcy and then finding the roots of the problem and solving it can yield very satisfying results. One way to do financial analysis is by examining the types of financial ratios and trends that focus on historical information. Since the financial ratios are extracted and calculated from the items in the balance sheet and the profit and loss statement of the entity, therefore, some key financial ratios are significantly different from the historical items after the historical financial statements are homogenized. Given the importance of inflation and in particular its impact on items in the financial statements, it can damage the financial reporting based on historical cost, which requires further study. Therefore, the purpose of this research was to predict the bankruptcy of companies according to adjusted financial ratios based on price index. We have tried to use all the financial ratios used in the various models available in financial bankruptcy forecasting to design the bankruptcy forecasting model. Therefore, considering the multiplicity of financial ratios used in this study as input predictor variables, the LARS algorithm was used to identify the effective variables. And the best bankruptcy predictor ratios were selected as follows from among the key variables of financial statements and based on theoretical foundations for designing the model:

1- The ratio of total debts to total assets
2- The ratio of accumulated profit to total assets
3- The ratio of net profit to total assets
4- Sale to (fixed assets + net working capital)
5- Interest cost to gross profit
6- The ratio of profit before interest and taxes to total assets

This point is important in examining these ratios, which are based on balance sheet items and as a result, their adjustment based on inflation growth rate is more effective. Also, after selecting the effective financial ratios through the Lars algorithm, Naive Bayesian algorithms and support vector machines were used to derive a high-precision model with the least error in identifying healthy and bankrupt companies. the results of this study showed that The support vector machine model can be a very

powerful alternative to the New Bayesian algorithm. In fact, the research findings showed thatthe overall accuracy of the model designed by the support vector machine algorithm is significantly higher than the overall accuracy of the model designed by the Naive Bayesian algorithm. In particular, the results showed that the generalization power of the support vector machine model is much higher than the model designed by the Naive Bayesian algorithm. In other words, in the years before bankruptcy, the model developed by the support vector machine algorithm can be used more reliably to predict or for credit rating. The findings of this study need to be compared with existing scientific and theoretical views in order to reach a favorable conclusion.
The results of this study confirm the research of Hui and Sun [19], Lee and to [25], Xei et al. [48], Jae [20] and Raee and Falahpour [35] on the ability of support vector machine algorithm in predicting bankruptcy. Given the research findings and the high power of the models extracted in this study, using them can help investors to choose an optimal portfolio and help creditors avoid lending to companies with high risk of bankruptcy. Overall, it can be said that by using the results of this study as the first step and taking preventive measures, we can effectively prevent companies from going bankrupt and also reduce the amount of future damage, of course, if the root and causes of the problem are also addressed after the prediction. Therefore, this and other similar research will be able to confront accounting and economics thinkers with the idea that they can also look at accounting information from a macroeconomic perspective. Also, banks and other financial institutions can use these models to make more accurate and scientific credit decisions, especially banks that intend to implement the internal rating approach of Basel Statements No.2.

References

[1] Altman, E.I., *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy,* Journal of Finance, 1968, **23**(4), P. 589- 609. Doi:10.1111/j.1540-6261.1968.tb00843.x

[2] Altman, E.I., Haldeman, R.G., Narayanan, p., *ZETA analysis: a new model to identify bankruptcy risk of corporations*, Journal of Banking and Finance, 1977, **1**(1), P. 29- 54. Doi: 10.1016/0378-4266(77)90017-6.

[3] Beaver, W., *Financial Ratios as Predictors of Failures, In Empirical Research in Accounting*, selected studies supplement to the Journal of Accounting research 4, 1966, P.71- 111.

[4] Beaver, W.H., Kennelly, J.W., *Predictive Ability as a Criterion for the Evaluation of Accounting Data*, The Accounting Review, 1968, P. 675.

[5] Buggakupta, S., *The Development of Thai DA Model in Predicting Fallure of Thai listed Companies*, Thai. J. Index, 2003, **22**(1), P. 9- 10.

[6] Campbell, J.Y., Hilscher, J., Szilagyi, J., *IN search of distress risk,* The Journal of Finance, 2008, **63**(6), P.2899- 2939. Doi: 10.1111/j.1540-6261.2008.01416.x

[7] Christidis, A., Gregory, A., *Some new models for Financial distress prediction in the UK*, Xfi-Centre for Finance and Investment Discussion, 2010, P.10. DOI: 10.2139/ssrn.1687166.

[8] Charalambakis, E., Espenlaub, S., Garrett, I., *On the of Prediction Financial Distress for UK Firms: Does the Choice of Accounting and Market Information Matter*, the University of Manchester, 2009.

[9] Cook, H., *The relationship between Earnings Changes and Balance Sheet Composition*, M.Sc, 2005, (in Persian)

[10] Dastgir, M., Zafari, F., *The Role of Accounting Information in Forecasting Stock Returns*, Journal of Stock Exchange, 1388, **85**, P. 48- 55, (in Persian)

[11] Davoodi, A., Dadashi, I., *Stock price prediction using the Chaid rule-based algorithm and particle swarm optimization*, Advances in Mathematical Finance and Applications, 2020, **5**(2), P. 197-213. Doi: 10.22034/amfa.2019.585043.1184

[12] Davoodi, A., Dadashi, I., Azinfar, K., *Stock price analysis using machine learning method(Non-sensory-parametric backup regression algorithm in lin-ear and nonlinear mode)*, Advances in Mathematical Finance and Applications, 2020, Doi: 10.22034/amfa.2019.1869838.1232

[13] Deakin, E.B., *A discriminant analysis of predictors of Business failure*, Journal of Accounting Reaserch, 1972, **10**, P. 167- 179. Doi:10.2307/2490225.

[14] Delen, D., Kuzey, C., Uyar, A., *Measuring firm performance using financial ratios: A decision tree approach*, Expert systems with application, 2013, **40**, P. 3970- 3985. Doi: 10.1016/j.eswa.2013.01.012.

[15] Dibachi, H., Behzadi, M.H., Izadikhah, M., *Stochastic multiplicative DEA model for measuring the efficiency and ranking of DMUs under VRS technology*, Indian Journal of Science and Technology, 2014, **7** (11), P. 1765–1773. Doi: 10.17485/ijst/2014/v7i11.19

[16] Dibachi, H., Behzadi, M.H., Izadikhah, M., *Stochastic Modified MAJ Model for Measuring the Efficiency and Ranking of DMUs*, Indian Journal of Science and Technology, 2015, **8**(8), P. 1-7, Doi: 10.17485/ijst/2015/v8iS8/71505

[17] Efron, B., Hstie, T., Johnstone. I., Tibshirani, R., *Least Angle Regresion*, The Annals of Statistics, 2004, **32**(2), P. 407- 499.

[18] Farajzadeh Dehkordi, H., *Application of Genetic Algorithm in Bankruptcy Prediction*, M.Sc., Tarbiat Modarres University, 2007, (in Persian)

[19] Fulmer, J.G., *A Bankruptcy Classification Model for Small Firms*, Journal of commercial Bank Lending, 1984, P. 25- 37.

[20] Grice, J, Ingram, R, *Tests of the generalizability of Altman's Bankruptcy prediction model*, Journal of Business Research, 2001, **54**(13), P.53 -61. Doi: 10.1016/S0148-2963(00)00126-0.

[21] Hui, X., Sun, J., *An application of support vector machine to companies financial distress prediction*, Lect. Notes Artif Intell, 2006, **5**, P. 274-282.

[22] Jae, K., *Predictiting financial distress of the South Korean Manufacturing industries*, Expert Systems with Applications, 2012, **39**, P. 9159-9165. Doi: 10.1016/j.eswa.2012.02.058.

[23] Kamijani, A., Saadatfar, J. *Application of Neural Network Models in Predicting Economic Bankruptcy of Stock Exchange Companies*, Economic Research Quarterly, 2006, **6**(6), (in Persian)

[24] Khanqah Barzegari, J., Jamali, Z., *Predicting Stock Returns Using Financial Ratios*, Journal of Accounting and Auditing Research, 2016, **6**(2), 2, P.71- 71. (in Persian)

[25] Kurdestani, G., Tatli, R., *Assessing the Predictive Capacity of Bankruptcy Models*, Quarterly Audit Knowledge, 2014, **14**(55). (in Persian)

[25] Kouki, M., Elkhaldi, A., *Toward a Predicting Model of Firm Bankruptcy, Evidence from the Tunisian Context*. Middle Eastern Finance and Economics, 2011, **14**. P. 26- 43.

[26] Lee, M., To, C., *Comparison of Support Vector Machine and Back Propagation Neural Network in Evaluating the Enterprise Financial Distress*, International Journal of Artificial Intelligence and Applications, 2010, **1**(3). P. 31-43. Doi: 10.5121/ijaia.2010.1303

[26] Legault, J., C.A.- Score, A Warning System for Small Business Failures, Bilanas, 1987, P. 29- 31.

[27] Min, H.J, Lee, C.y., *Bankruptcy prediction usingsupport vector machine with optimal choice of kernel function parameters,* Expert Systems with Applications, 2005, **28**, P. 603 -614. Doi: 10.1016/j.eswa. 2004. 12.008.

[28] Mutchler, J., McKeown, J., Hopwood, W., *towards an explanation of auditor failure to modify the audit opinion of bankrupt companies*, Auditing: A Journal of Practiceand Theory, 1991, **10**, P. 1- 13.

[29] Odom, M., Sharda, R., *A Neural Network Model for Bankruptcy Prediction*, Proceedings of the IEEE International Conference on Neural Networks, 1990, **2**, P. 163-168. Doi: 10.1109/IJCNN.1990.137710.

[30] Ohlson, J.A., *Financial Ratios and the Probabilistic Prediction of Bankruptcy*, Journal of Accounting Research, 1980, **18**(1), P. 109- 131. Doi: 10.2307/2490395.

[31] Pawełek, B., Baryła, M., Pociecha, J., *Study of the classification accuracy measures for predicting corporate bankruptcy taking into account changes in the economic environment*, Argumenta Oeconomica, 2020, **1**(44), P. 5-17. Doi:10.15611/aoe.2020.1.01

[32] Philosophov, L., Philosophov, V., *Corporate Bankruptcyprognosis; An attempt at a combined prediction of the bankruptcy eventand time interval of its occurrence*, International Review of Financial Analysis, 2002, **11**(3). P. 375- 406. Doi:org/10.1016/S1057-5219(02)00081-9.

[33] Pirishe, R., Dadashi Arani, H., *Presenting Mathematical Model of Bankruptcy Prediction*, Journal of Financial Engineering and Securities Management, 2016, **31**. (in Persian)

[34] Raei, R., Fallahpour, S., *Predicting financial distress of companies using artificial neural networks*, MSc in Financial Management, University of Tehran, 2004. (in Persian)

[35] Raei, R., Fallahpour, S., *Application of Support Vector Machine in Predicting Corporate Financial Distress Using Financial Ratios*, Journal of Accounting and Auditing Reviews, 2008, **15**(53), P. 17- 34. (in Persian)

[36] Rezaei, N., Javaheri, M., *The Predictability Power of Neural Network and Genetic Algo-rithm from Companies' Financial Crisis* Advances in Mathematical Finance and Applications, 2020, **5**(2), P. 183-196. Doi:10.22034/amfa.2019.1863963.1195

[37] Royaee R.A., *Inflation Accounting and Accounting Development Seminar in Iran*, Third Iranian Accounting Seminar, 1993, **9**(56). (in Persian)

[38] Sadeghi, H. Rahimi, P. Barber, Y., *The Impact of Macroeconomic Factors and Governance System on the Financial Crisis of Manufacturing Companies Listed in Tehran Stock Exchange*, Monetary Economics Quarterly, 2014, **21**, P. 107- 127. Doi: 10.22067/pm.v21i8.45860.(in Persian)

[39] Sheikh, M.J., *Investigation of Average Industry Ratios in Listed Companies*, M.Sc, University of Tehran, 1996. (in Persian)

[40] Shirata Cindy Y., *Financial Ratios as Predictors of Bankruptcy in Japan: An Enprical Research.* Tsukuba College of Technology, 1987. Doi:10.1.1.195.2721.

[41] Shin, K.S., Lee, T.S., Kim, H.J., *An application of support vactor machines in bankruptcy prediction model*, Expert Systems with Applications, 2005, **28**, P. 127- 135. Doi: 10.1016/j.eswa.2004.08.009.

[42] Shumway, T., *Forecasting bankruptcy more accurately: A simple hazard model*, The Journal of Business, 2001, **74**(1), P. 101- 124. Doi: 10.1086/209665.

[43] Springate, L., Gord, V., *Predicting the possibility of failure in a Canadian firm*, Unpublished M.B.A Research Project, Simon Fraser university, 1987.

[44] Tamari, M., *Financial ratios as a means of forecasting bankruptcy*, Management International Review, 1996, **6**(4), P. 15-21.

[45] Tinoco Hernandez, M., Wilson, N., *Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables*, International Review of Financial Analysis, 2013, **30**, P. 394- 419. Doi: 10.1016/j.irfa.2013.02.013.

[46] Titterington, D., *Comparison of Discrimination Techniques Applied to a Complex Data-set of Head-Injured Patients (with discussion)*, Journal of the Royal Statistical Society; 1981, P.145- 175. Doi: 10.2307/2981918.

[47] Tone, K., Toloo, M., Izadikhah, M., *A modified slacks-based measure of efficiency in data envelopment analysis*, European Journal of Operational Research, 2020, **287**(2), P.560-571, Doi: 10.1016/j.ejor.2020.04.019.

[48] Wallace W.A., *Risk Assessment by Internal Auditors Using Past Research on Bankruptcy Applying Bankruptcy Models*, Working paper, University of Florida, 2004.

[49] Xie, C., Luo, C., Yu, X., *Fainancial distress prediction based on SVM and MDA methods:the case of Chinese listed companies*, Qual Quant, 2011, **45**, P. 671-686. Doi: 10.1007/s11135-010-9376-y.

[50] Zand Raisi, A., *Financial Statements in Inflation*. the world of economy, 2012, 2561. (in Persian)

[51] Zavgren, C.V., *Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis*. Journal of Business Finance and Accounting, 1985, **12**. P.19- 45. Doi: 10.1111/j.1468-5957.1985.tb00077.x

[52] Zmijewski, M.E., *Methodological Issues Related to the Estimation of Financial Distress prediction Models*, Journal of Accounting Research, 1984, **22**, P.59-82. Doi: 10.2307/2490859.