A Deep Dense Neural Network for Bankruptcy Prediction

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Abstract. Bankruptcy prediction is a problem that is becoming more and more interesting. This problem concerns in particular financial and accounting researchers. Nevertheless, it is a field that gathers the focus of companies, creditors, investors and in general firms which are interested in investments or transactions. Because of a variety of parameters, such as multiple accounting ratios or many potential explanatory variables, the complexity of this problem is very high. For this reason, the probability for a company to go bankrupt or not is very difficult to be calculated. Moreover, the precise determination of the bankruptcy is a very important issue. All the above details constitute a complex problem and by taking into account the data that need to be processed, we conclude that machine learning techniques and reliable predictive models are necessary. In this paper, the effectiveness of a dense deep neural network in bankruptcy prediction relating to solvent Greek firms is tested. The experimental results showed that the provided scheme gives promising outcomes.

Keywords: Bankruptcy prediction · Artificial Neural Networks · Prediction models

1 Introduction

Bankruptcy is a vitally important problem with a variety of aspects that are particularly relevant to an economic system. There are different types of bankruptcies and their consequences in the field of business and society are many and varied [2]. Banks are very interested in this problem. Firstly, a creditor in order to approve a loan must take into account a number of parameters such as the age, the consistency in payments, proximity to any other loans, and therefore predict the probability of bankruptcy. Such decisions are very important for the development of a company and consequently for the economy of a country. If

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such decisions are taken very carefully, the economic system can be strengthened and business growth blossom.

Considering the financial crisis of recent years that has hit many economies in the world, it is easy to understand the importance of timely and credible bankruptcy forecasting. In addition, there is an urgent need for well-structured risk management models as well as correction associated with economic inconsistencies of a bank's customers. The economic and financial stability, as well as the healthy development of enterprises, seems directly related to the prevention of credit risk and bankruptcies in a market, as it is noted in [11].

The basic two approaches in order to predict loan default or bankruptcy are the following: (a) Structural approaches. In these approaches, the interest rates and firm attributes are examined for an outcome of the default probability and (b) Statistical approaches. These methods outcome the desirable probability based on mining the data. This paper aims through a dense deep neural network to accurately predict the possibility of bankruptcy.

The reader may reach informative reviews about the methods used to predict bankruptcy in [5] and [17]. In the first work, various standard statistical methodologies implemented on business failure are studied, while in the second one statistical and intelligent methods are presented. Furthermore, in [4] and [24] the reader can be informed for more recent survey works. Despite the fact that a variety of methods have been developed over the last ten years, there are aspects that need further study. For this reason, there is enough space for new approaches which can handle bankruptcy prediction in a more accurate way. The aim of the researchers is to provide schemes that improve existing models and ensure security and stability in business markets. The settlement of bankruptcy prediction is studying intensely [26] and new techniques have been developed in order to tackle this problem [22].

This study provides a deep dense artificial neural network for bankruptcy prediction. Based on the inherent ability of artificial neural networks in handling difficult problems such as image recognition, speech recognition etc. we test the performance of a Deep Dense Multilayer Perceptron in bankruptcy prediction task.

The rest of the paper is organized as follows. In the next section, a brief presentation of related works is provided. In Sect. 3, we describe the datasets which are used in our work. In Sect. 4 the proposed method is presented, and experimental and comparisons with our method to well-known algorithms are exhibited. Finally, the paper ends with a short discussion and some future research remarks in Sect. 5.

2 Related Work

The problem of timely and valid bankruptcy prediction has attracted interest not only from financial analysts or researchers in the field of economic science but also from researchers in the scientific area of Machine Learning. As it is already mentioned, the methods developed to solve this problem over the last decade are many and varied. Indicatively, we refer the reader to *Artificial Neural Networks* [9], *instance-based learners* [1], *Decision Trees* [8], *Support Vector Machines* [28] among others.

An ensemble classifier scheme that combines well-known learners such as *Decision Trees*, *Back Propagation Neural Networks* and *Support Vector Machines* has proposed in [13] to predict bankruptcy by exploiting only the advantages of individual classifiers. This approach adopts the decision-making strategy of financial institutions where many experts are asked before the final decision is taken. Thus, everyone's opinion counts and a more complete decision is formed about whether will be given a credit, a loan or if there is a risk of a bankrupt company. In particular, the provided approach selectively combine the expected probabilities given by each classifier and the experimental results showed better performance than stacking ensemble using the weighting or voting strategy.

A comparison between several prediction models such as *Artificial Neural Networks*, *Decision Trees*, *Support Vector Machines* and *Logistic Regression* tackling the bankruptcy prediction was made in [21]. The authors taking into account the obtained experimental results and the simplicity of Decision Trees have recommended these models with the minimum support required for a rule in order to tackle the bankruptcy prediction problem.

In [25] a *meta-learning* scheme that is inspired by the stacking methodology has been proposed. This approach combines two-level classifiers to make a bankruptcy prediction. In the first level, data preprocessing takes place in order to filter noisy or unrepresentative training data. Thus, the classifiers in the second level, receive better representative training data and the prediction is more accurate. The experiments conducted by the authors showed that the proposed method exceeds stacked generalization method and also, it obtains a better prediction accuracy than neural networks, decision trees, and logistic regression.

Another study based on ensemble methods as reliable predictive models for solving the bankruptcy prediction problem has been carried out in [27]. Particularly, the authors combined *IG* based feature selection with the standard *Boosting* procedure in order to reinforce the performance of base learners. The proposed *FS-Boosting* approach compared with well-known *Bagging* and *Boosting* approaches achieved promising results and performed the best average accuracy on two of the considering bankruptcy datasets in any condition.

In [14] a recent research study about the performance of semi-supervised methods for addressing bankruptcy prediction task has been conducted. The authors include in their study well-known semi-supervised algorithms such as C4.5, k-Nearest Neighbors and Sequential Minimal Optimization algorithm. The experimental results showed that the semi-supervised algorithms are really competitive with the corresponding supervised algorithms.

Although the problem of accurate bankruptcy prediction is particularly important for various financial institutions, studies that were based on probabilistic models are not so many. Such a study [3] was conducted to address this issue. Specifically, in this work, Gaussian processes classifier was applied in comparison with Support Vector Machines and the Logistic Regression approach. Furthermore, an informative visualization of the conducted experiments was presented, so that the reader can easily understand the content of their study. The experiments conducted showed that Gaussian processes can improve the classification performance and successfully deal with bankruptcy prediction.

Extensive research based on real-world datasets from American firms was conducted in [6]. The authors tested well-known Machine Learning models such as Support Vector Machines, Bagging, Boosting, and Random Forest against Logistic Regression and Artificial Neural Networks. The fundamental point of their study was the usage, of six additional complementary financial indicators, including original Altman's Z-score. This leads to superior performance by Bagging, Boosting, and Random Forest models. Moreover, the last models achieved the highest accuracy relating to all the other methods.

An algorithm, named TACD, based on the ant colony strategy proposed for predicting bankrupt and non-bankrupt in [18]. The provided model is simple and easy to use. Moreover, this method handles continuous data and thus, data discretization can be avoided. The experimental tests over three real-world datasets and in comparison with several strategies showed that the presented method provides effective results.

Recently, the inherent difficulty of automated decision systems for accurate outcomes using natural language seems to be treated through deep learning techniques [16]. Specifically, the authors tested the effectiveness of deep neural networks over a very difficult problem, the financial decision support. In this research, traditional Machine Learning approaches take part in such as Ridge regression, Random Forest, AdaBoost, Gradient Boosting. In addition, Transfer Learning Techniques were tested, such as RNN with pre-training and LSTM with both pre-training and word embeddings. The results obtained showed that deep models give reliable and accurate outcomes and in many cases are better than traditional bag-of-words models.

In [19] the importance of feature selection process in building strong prediction models is presented. Particularly, the authors studied the appropriate combination between the feature selection technique and the classification method. Thus, both filter and wrapper-based methods were studied regarding the feature selection methods. On the other hand, statistical and machine learning models were studied concerning the classification process. Furthermore, two well-known ensemble techniques, the Bagging and Boosting methods were used in order to make comparisons. This work concluded that the genetic algorithm as the wrapper-based feature selection method performs better than the filter-based one. Moreover, the combination of a genetic algorithm with naive Bayes and Support Vector Machine classifiers without bagging and boosting achieves the best prediction error rates.

In the Greek context, recently, Active Learning approaches for bankruptcy prediction problem was studied in [15]. For a more informative study about bankruptcy prediction problem as well as bankruptcy prediction models the reader is referred to [7].

3 Data Description

The source of the data we use comes from the National Bank of Greece and the business database containing the financial information of the companies, named ICAP. In particular, the bankruptcy deposits that we have included in our study are related to the years 2003 and 2004. In addition, the collection of financial statements for the years before the bankruptcy was taken by the ICAP database. The financial data are related to a period of three years. We denote these years as follows: (a) The bankrupt year is marked as *year 0*, (b) The year before the failure is noted as *year* -1 while (c) Three years before is considered as *year* -3.

In order to build a good bankruptcy sample, we include 50 bankruptcies in the final dataset. For each bankrupt firm, we sampled two healthy firm with about the same characteristics. Thus, our sample consists of 150 individual firms and 450 firm-year observations. Due to missing financial values and ratio overlaps the

Table 1. The used dependent variables.

Class	Variables	Short description
Profitability	OPIMAR	Operating income divided by net sales
	NIMAR	Net income divided by sales
	GIMAR	Gross income divided by sales
	ROCE	Net income pre tax divided by capital employed
	ROE	Net income pre tax divided by shareholder's equity capital
Liquidity-Leverage	EQ/CE	Shareholder's equity to capital employed
	CE/NFA	Capital employed to net fixed assets
	TD/EQ	Total debt to shareholder's equity capital
	CA/CL	Current assets to current liabilities
	QA/CL	Quick assets to current liabilities
	WC/TA	Working capital divided by total assets
Efficiency	COLPER	Average collection period for receivables
	INVTURN	Average turnover period for inventories
	PAYPER	Average payment period to creditors
	S/EQ	Sales divided by Shareholder's equity capital
	S/CE	Sales divided by capital employed
	S/TA	Sales divided by total assets
Growth	GRTA	Growth rate of total assets $(TAt - TAt - 1)/(ABS(TAt) + ABS(TAt - 1)$
	GRNI	Growth rate of net income
	GRNI	Growth rate of net sales
Size	SIZE	Size of firm is the ln(Total assets/GDP price index)

Table 2. Distribution of bankrupted firms across 24 industries and calendar years.

Industry	Year 2003	Year 2004	Total
Advertisement	1	2	3
Agriculture and Farming	1	0	1
Clothing	2	2	4
Constructions	2	0	2
Electronics Equipment	0	1	1
Food	0	2	2
Freight Forwarding	1	0	1
Health Services	0	1	1
Industrial Minerals	0	1	1
Information Technology	0	1	1
Logistics	0	1	1
Machinery	0	2	2
Metal Products	1	0	1
Motor Vehicle Trade & Maintenance	1	0	1
Other Services	0	1	1
Plastic and Rubber	0	1	1
Private Education	1	0	1
Publishing & Printing	1	0	1
Restaurants	0	1	1
Retail Trade	3	7	10
Supermarkets	0	1	1
Telecommunications	0	2	2
Textiles	3	1	4
Wholesale Trade	2	4	6
Total	**19**	**31**	**50**

final input variables were measured on 21. In Table 1, there is a brief description of the financial variables included in the present research. The characteristics of bankrupt firms are exhibited in Table 2.

4 Proposed Method and Experimental Results

Deep Neural Networks have been successfully applied in many difficult tasks such as image processing, speech and image recognition, blueprints identification etc. In the recent years, Deep Learning attracts the interest widely and thus, Deep Networks have been used for tackling the bankruptcy problem.

In work [20] the authors studied the application of deep learning methods in bankruptcy forecasting. Specifically, two deep learning architectures were tested and the predictions were based on textual disclosures. The experimental results showed that deep learning models give a promising framework for predicting financial outcomes.

Another deep learning technique was tested in bankruptcy prediction task in [12]. In particular, convolutional neural networks were applied to the prediction of stock price movements. In detail, a set of financial ratios are represented as a grayscale image. Thus, the network was trained and tested based on that image. The experimental results showed that the convolutional neural network has higher performance compared to other traditional methods such as Decision Trees or AdaBoost.

In our work a *Deep Dense Multilayer Perceptron (DDMP)* is applied to address bankruptcy prediction task. Neural networks with two hidden layers can represent functions with any kind of shape. In general, there is not theoretical reason to use neural networks with any more than two hidden layers with simple data sets.

Specifically, we use an artificial neural network with two hidden layers. The decision of the number of neurons in the hidden layers is a very important issue of the neural network architecture. Despite the fact that these layers do not directly interact with the external environment, they have a tremendous influence on the final output. The number of neurons in each of these hidden layers must be carefully considered. The usage of many neurons in the hidden layers can result in various problems. Firstly, too many neurons in the hidden layers may result in overfitting. Overfitting occurs when the neural network has so much information processing capacity that the limited amount of information contained in the training set is not enough to train all the neurons in the hidden layers. A second problem may occur even when the training data is sufficient. An inordinately large number of neurons in the hidden layers can increase the training time of the network. In order to secure the ability of the network to generalize, the number of neurons must be kept as low as possible. If one has a large excess of neurons, the network becomes a memory bank that can recall the training set to perfection, but it does not perform well on samples that were not in the training set.

In the first hidden layer, we used as number of neurons the [2/3] of the number of input attributes and as activation function, the $ReLU$ were used. In the second hidden layer, the [1/3] of the number of input attributes were used as the number of neurons and the $ReLU$ activation function was used again. Moreover, the Drop-out technique (10%) was considered and as loss function the $LOSSBinaryXENT$ function was used.

Dropout is an approach to regularization in neural networks which helps reducing interdependent learning amongst the neurons. In the training phase, for each hidden layer, for each training sample and for each iteration, the dropout procedure ignores a random fraction of nodes (and the corresponding activations). Dropout forces a neural network to learn more robust features that are useful in conjunction with many different random subsets of the other neurons.

Table 3. AUC scores of the algorithms in our bankruptcy dataset.

	Cart	NB	LR	MP	DDMP
2 years before	0.532	0.579	0.586	0.584	**0.627**
1 year before	0.539	0.588	0.643	0.605	**0.664**
Last year	0.671	0.647	0.646	0.648	**0.732**

Dropout roughly doubles the number of iterations required to converge. However, the training time for each epoch is less.

We have compared the *DDMP* method using Keras library [10] with other well-known methods such as the *Logistic Regression*, the simple *Multilayer Perceptron* model with one hidden layer, the *Naive Bayes* approach and the *Cart* method. For, the experiments have been also used the available implementations from Scikit-learn [23]. In Table 3 the obtained results for our comparison are exhibited. We compute Area Under the Receiver Operating Characteristic Curve (AUC) because the examined dataset is imbalanced.

The experimental results showed that the proposed architecture achieves the best results.

5 Discussion and Concluding Remarks

Bankruptcy prediction is a difficult problem. The need of accurate intelligent predictive models is of high importance. In the last decade financial researchers and companies are in position to predict which firms will bankrupt or not. This happens due to several predicting methods which have been developed. However, more accurate models are still required.

According to Table 3, our deep dense network method performs better than other examined algorithms. Nevertheless, it should not be omitted the fact that in our study only financial ratio attributes have been used. Thus, the performance of our approach could be improved if other essential quantitative attributes would be added in the dataset.

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