Financial Application of Neural Networks: Two Case Studies in Greece

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Abstract. In the past few years, many researchers have used Artificial Neural Networks (ANNs) to analyze traditional classification and prediction problems in accounting and finance. This paper explores the efficacy of ANNs in detecting firms that issue fraudulent financial statements (FFS) and in predicting corporate bankruptcy. To this end, two experiments have been conducted using representative ANNs algorithms. During the first experiment, ANNs algorithms were trained using a data set of 164 fraud and non-fraud Greek firms in the recent period 2001-2002. During the second experiment, ANNs algorithms were trained using a data set of 150 failed and solvent Greek firms in the recent period 2003-2004. It was found that ANNs could enable experts to predict bankruptcies and fraudulent financial statements with satisfying accuracy.

Keywords: fraud detection, bankruptcy prediction.

1 Introduction

Neural networks are one of the most innovative analytical tools to surface in the financial arena. The availability of vast amounts of historical data in recent years, coupled with the enormous processing power of desktop computers, has enabled the use of automated systems to assist in complex decision making environments. The automated system examines financial ratios as predictors of performance, and assesses posterior probabilities of financial health. Neural Network Applications in the financial world include [6], [16]: currency prediction, futures prediction, bond ratings, debt risk assessment, credit approval and bank theft. The articles [9] and [16] review the literature on artificial neural networks (ANNs) applied to accounting and finance problems. Moreover, Vellido et al. [25] surveyed 123 articles from 1992 through 1998. They included 8 articles in accounting and auditing, and 44 articles in finance (23 on bankruptcy prediction, 11 on credit evaluation, and 10 in other areas).

Researchers have used various techniques and models to detect accounting fraud and predict corporate bankruptcy in circumstances in which, a priori, is likely to exist. However few studies have tested the predictive ability of different ANNs used by means of a common data set. In this study, we carry out an in-depth examination of publicly available data from the financial statements of various firms in order to (a) detect FFS and (b) predict corporate bankruptcy by using ANN learning methods.

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The following section attempts a brief literature review of the techniques for detecting firms that issue fraudulent financial statements and describes the data set of our study. Section 3 attempts a brief literature review of the techniques for predicting corporate bankruptcy and describes the data set of our study. Section 4 presents the experimental results for the representative compared algorithms in our data sets. Finally, section 5 discusses the conclusions and some future research directions.

2 Literature Review for the Issue of FFS

Although it is not a new phenomenon, the number of corporate earnings restatements due to aggressive accounting practices, accounting irregularities, or accounting fraud has increased significantly during the past few years, and it has drawn much attention from investors, analysts, and regulators [23].

The financial statement audit is a monitoring mechanism that helps reduce information asymmetry and protect the interests of the principals, specifically, stockholders and potential stockholders, by providing reasonable assurance that management's financial statements are free from material misstatements. However, in real life, detecting management fraud is a difficult task when using normal audit procedures [2] since there is a shortage of knowledge concerning the characteristics of management fraud. Additionally, given its infrequency, most auditors lack the experience necessary to detect it. Moreover, managers deliberately try to deceive auditors [4].

Nieschwietz et al. [19] provide a comprehensive review of empirical studies related to external auditors' detection of fraudulent financial reporting while Albrecht et al. [2] review the fraud detection aspects of current auditing standards and the empirical research conducted on fraud detection. Ansah et al. [4] investigate the relative influence of the size of audit firms, auditor's position tenure and auditor's year of experience in auditing on the likelihood of detecting fraud in the stock and warehouse cycle. Green and Choi [15] developed a Neural Network fraud classification model. The model used five ratios and three accounts as input. The results showed that Neural Networks have significant capabilities when used as a fraud detection tool. Fanning and Cogger [13] also used a Neural Network to develop a fraud detection model. The input vector consisted of financial ratios and qualitative variables. They compared the performance of their model with linear and quadratic discriminant analysis, as well as logistic regression, and claimed that their model is more effective at 174 detecting fraud than standard statistical methods.

For Greek data, Spathis [24] constructed a model to detect falsified financial statements. He employed the statistical method of logistic regression. The reported accuracy rate exceeded 84%. Kirkos et al [17] investigate the usefulness of Decision Trees, Neural Networks and Bayesian Belief Networks in the identification of fraudulent financial statements. In terms of performance, the Bayesian Belief Network model achieved the best performance managing to correctly classify 90.3% of the validation sample in a 10-fold cross validation procedure. For both studies [17] and [24], 38 FFS firms were matched with 38 non-FFS firms.

The application of ANN techniques for financial classification is a fertile research area [9], [13], [15]. As a consequence, a main objective for this study is to evaluate the predictive ability of ANN techniques by conducting a number of experiments using representative learning algorithms.

Table 1. Research Variables description

Variables	Variable Description
RLTC/RCR02	Return on Long -term capital / Return on Capital and Reserves 2002
AR/TA 01	Accounts Receivable/Total Assets 2001
TL/TA02	Total liabilities/Total assets 2002
AR/TA02	Accounts Receivable/Total Assets 2002
WC/TA 02	Working capital/total assets 2002
DC/CA02	Deposits and cash/current assets 2002
NFA/TA	Net Fixed Assets/Total Assets
NDAP02	Number of days accounts payable 2002
LTD/TCR02	Long term debt/total capital and reserves 2002
S/TA02	Sales/total assets 2002
RCF/TA02	Results carried forward/total assets 2002
NDAR02	Number of days accounts receivable 2002
CAR/TA	Change Accounts Receivable/Total Assets
WCL02	Working capital leveraged 2002
ITURN02	Inventory turnover 2002
TA/CR02	Total Assets/Capital and Reserves 2002
EBIT/TA02	Earnings before interest and tax/total assets 2002
CFO02	Cash flows from operations 2002
CFO01	Cash flows from operations 2001
CR02	Current assets to current liabilities 2002
GOCF	Growth of Operational Cash Flow
CAR/NS	Change Accounts Receivable/Net Sales
EBT02/EBIT02	Earnings before tax 2002/Earnings before interest and tax 2002
Z-SCORE02	Altman z-score 2002
CR/TL02	Capital and Reserves/total liabilities 2002

2.1 Data Description

Our sample contained data from 164 Greek listed on the Athens Stock Exchange manufacturing firms (no financial companies were included). Auditors checked all the firms in the sample. For 41 of these firms, there was published indication or proof of involvement in issuing FFS. The classification of a financial statement as false was based on the following parameters: inclusion in the auditors' report of serious doubts as to the accuracy of the accounts, observations by the tax authorities regarding serious taxation intransigencies which significantly altered the company's annual balance sheet and income statement, the application of Greek legislation regarding negative net worth, the inclusion of the company in the Athens Stock Exchange categories of "under observation and "negotiation suspended" for reasons associated with the falsification of the company's financial data and, the existence of court proceedings pending with respect to FFS or serious taxation contraventions. The 41 FFS firms were matched with 123 non-FFS firms. All the variables used in the sample were extracted from formal financial statements, such as balance sheets and income statements. This implies that the usefulness of this study is not restricted by the fact that only Greek company data was used. The selection of variables to be used as candidates for participation in the input vector was based upon prior research work, linked to the topic of FFS [13], [15], [24]. Additional variables were added in an attempt to catch as many as possible predictors not previously identified. Table 1 provides a brief description of the financial variables used in the present study.

3 Literature Review for Bankruptcy Prediction

The problem of Bankruptcy prediction is a classical one in the financial literature (see e.g. [1] for a review). The main impact of Bankruptcy prediction is in bank lending. Banks need to predict the possibility of default of a potential counterparty before they extend a loan. This can lead to sounder lending decisions, and therefore result in significant savings. O'Leary [20] analyzed 15 articles that applied ANNs to predict corporate failure or bankruptcy. For each study, he provided information about the data, the ANN model and software (means of development), the structure of the ANN (input, hidden and output layers) training and testing, and the alternative parametric methods used as a benchmark. He then analyzed the overall ability of the ANN models to perform the prediction task. The primary objectives of [8] were to develop failure prediction models for UK public industrial firms using a recent company sample, via logit analysis and the ANN methodology, and also to explore the incremental information content of operating cash flows in predicting the probability of business failure. NNs achieved the highest overall classification rates for all three years prior to insolvency, with an average classification rate of 78%. Zhang et al. [28] include in their paper a nice review of existing work on NN bankruptcy prediction. The majority of the NN approaches to default prediction use multilayer networks. Many other studies have been conducted for bankruptcy prediction using neural networks [3], [7], [27] and Support Vector Machines (SVM) [22].

Recently the performance of alternative non-parametric approaches has been explored in the Greek context to overcome the aforementioned shortcomings of the statistical and econometric techniques such as rough sets [11] and multicriteria discrimination method [12]. As we have already mentioned, in this paper we analyzed the performance of several ANN models on the problem of Bankruptcy prediction in the Greek context.

3.1 Data Description

Bankruptcy filings in the years 2003 and 2004 were provided directly from the National Bank of Greece directories and the business database of the financial information services company called ICAP, in Greece. Financial statement data for the fiscal years prior to bankruptcy were obtained from ICAP financial directories. The financial statements of these firms were collected for a period of three years. The critical year of failure denoted as year 0, three years before as year –3 and year –1 is the final year prior to bankruptcy filing. As the control sample, each selected bankrupt firm was matched with two non-bankrupt (healthy) firms of exactly the same industry, by carefully comparing the year of the reported data (year –1) assets size and the number of employees. The selected non-bankrupt corporations were within 20% of the selection criteria. Following the prior literature, we examine the probability of a firm's initial filing for bankruptcy and eliminate any observations for a firm after it has filed for bankruptcy during our sample period.

Table 2. Research Variables description

Category	Independent variables	Variable Description
Profitability Variables	OPIMAR	Operating income divided by net sales
	NIMAR	Net income divided by sales
	GIMAR	Gross income divided by sales
	ROE	Net income pre tax divided by Shareholder's equity capital
	ROCE	Net income pre tax divided by capital employed
Liquidity-Leverage Variables	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 Variables	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 variables	GRTA	Growth rate of total assets $(TA_t - TA_{t-1})/(ABS(TA_t)+ ABS(TA_{t-1})$
	GRNI	Growth rate of net income
	GRNS	Growth rate of net sales
Size variable	SIZE	Size of firm is the ln(Total Assets/GDP price index)

Our final bankruptcy sample consists of 50 initial bankruptcies in the year period 2003-2004 and is similar in size but more complete and recent compared to previous studies. The final pooled sample of failed and solvent firms is composed of 150 individual firms with financial data for a three-year period, which attributes 450 firm-year observations. Table 2 provides a brief description of the financial variables used in the present study classified in 5 groups.

4 Experimental Results

WINNOW is the representative of perceptron-based algorithms in our study [18]. It classifies a new instance x into the second-class if $\sum_i x_i w_i > \theta$ and into the first class otherwise. It initializes its weights w_i and θ to 1 and then it accepts a new instance (x, y) applying the threshold rule to compute the predicted class y'. If $y' = 0$ and $y = 1$, then the weights are too low; so, for each feature such that $x_i = 1$, $w_i = w_i \cdot \alpha$, where α is a number greater than 1, called the *promotion parameter*. If $y' = 1$ and $y = 0$, then the weights were too high; so, for each feature $x_i = 1$, it decreases the corresponding weight by setting $w_i = w_i \cdot \beta$, where $0<\beta<1$, called the *demotion parameter*. The vector, which is correct on all examples of the training set, is then used for predicting the labels on the test set.

Voted-perceptron [14] stores more information during training and then use this elaborate information to generate better predictions on the test data. The information it maintains during training is the list of all prediction vectors that were generated after each and every mistake. For each such vector, the algorithm counts the number of iterations the vector "survives" until the next mistake is made; they refer to this count as the "weight" of the prediction vector. To calculate a prediction it computes the binary prediction of each one of the prediction vectors and combines all these predictions by a weighted majority vote. The weights used are the survival times described above. This makes intuitive sense, as "good" prediction vectors tend to survive for a long time and thus have larger weight in the majority vote.

ANN depends upon three fundamental aspects, the input and activation functions of the unit, the network architecture and the weight on each of the input connections. Given that the first two aspects are fixed, the behavior of the ANN is defined by the current values of the weights. The weights of the net to be trained are initially set to random values, and then instances of the training set are repeatedly exposed to the net. The values for the input of an instance are placed on the input units and the output of the net is compared with the desired output for this instance. Then all the weights in the net are adjusted slightly in the direction that would bring the output values of the net closer to the values for the desired output. The most well-known and widely used learning algorithm to estimate the values of the weights is the Back Propagation (BP) algorithm [5].

RBF network [5] uses the k-means clustering algorithm to provide the basis functions and learns a logistic regression on top of that. Symmetric multivariate Gaussians are fit to the data from each cluster. It uses the given number of clusters per class. It standardizes all numeric attributes to zero mean and unit variance.

The SVM technique revolves around the notion of a 'margin' that separates two data classes. Maximizing the margin, and thereby creating the largest possible distance between the separating hyperplanes can reduce the upper bound on the expected generalization error [21]. However, most real-world problems involve non-separable data for which no hyperplane exists that successfully separates the positive from negative instances in the training set. The solution is then to map the data into a higher-dimensional space and define a separating hyperplane there. Sequential Minimal Optimization (or SMO) algorithm was the representative of the SVMs as one of the fastest methods to train SVMs [21].

All accuracy estimates were obtained by averaging the results from stratified 10-fold cross-validation in our datasets. It must be mentioned that we used the free available source code for our experiments in order to find the best parameters for each algorithm by the book [26]. The results for the first case study (fraud detection) are presented in Table 3. In Table 3, we also present the accuracy of Logistic Regression (LR) as benchmark algorithm.

Table 3. Accuracy of models in fraud detection (discretized)

	Winnow	BP	Voted Perceptron	RBF	SMO	LR
Total Acc.	75.32	82.91	81.01	77.85	79.11	75.3
Fraud (F)	56.1	56.1	39.0	34.1	39.0	36.6
Non-Fraud (NF)	82.1	92.3	95.7	93.2	93.2	88.9

The Winnow algorithm (with alpha: 2, beta: 0.5) correctly classifies 75.32% of the total sample, 56.1% of the fraud cases and 82.1% of the non-fraud cases. The RBF algorithm (with minimum standard deviation for the clusters: 2, number of clusters for K-Means to generate: 2) manages to correctly classify 77.85% of the total validation sample, 34.1% of the fraud cases and 93.2% of the non-fraud cases. Moreover, BP algorithm (with 1 hidden layer, learning rate: 0.3, momentum: 0.2) succeeds in correctly classifying 56.1% of the fraud cases, 92.3% of the non-fraud cases and 82.91% of the total validation sets. Furthermore, Voted Perceptron algorithm (with maximum number of alterations to the perceptron: 10.000) succeeds in correctly classifying 39% of the fraud cases, 95.7% of the non-fraud cases and 81.01% of the total validation sets. SMO algorithm (with exponent for the polynomial kernel: 1) correctly classifies 79.11% of the total sample, 39% of the fraud cases and 93.2% of the non-fraud cases.

Recently in the area of Machine Learning the concept of combining classifiers is proposed as a new direction for the improvement of the performance of individual classifiers [10]. For this reason, we combined the previous algorithms using the simple voting methodology [10]. Let us consider the voting step as a separate classification problem, whose input is the vector of the responses of the base classifiers. Simple voting uses a predetermined algorithm for this, namely to count the number of predictions for each class in the input and to predict the most frequently predicted class. The intuition is that the models generated using different learning biases are more likely to make errors in different ways.

The proposed voting ensemble of Winnow, BP, Voted Perceptron, SMO and RBF correctly classifies 91.2% of the total sample, 85.2% of the fraud cases and 93.3% of the non-fraud cases. In a comparative assessment of the models' performance we can conclude that the ensemble outperforms the simple models and achieve outstanding classification accuracy.

To facilitate the presentation and discussion of the results for the second case study (bankruptcy prediction), each year prior to financial distress is denoted as year –1, year –2, year –3, Year –1 refers to the first year prior to financial distress (e.g., for the firms that faced financial distress in 2004, year –1 refers to 2003); year –2 refers to the second year prior to financial distress (e.g., for the firms that faced financial distress in 2004, year –2 refers to 2002), etc.

In Table 4, there is the classification accuracy for each representative learning algorithm (with the previous referred parameters) for each examined year. We also present the accuracy of Logistic Regression (LR) as benchmark algorithm.

Table 4. Accuracy of the algorithms in bankruptcy prediction

		Winnow	BP	Voted Perceptron	SMO	RBF	LR
Year (-3)	Total Acc.	36.55	64.14	39.31	68.28	67.59	66.21
	Bankrupt	89.8	28.6	81.6	10.2	22.4	22.4
	Non- Bankrupt	9.4	82.3	17.7	97.9	90.6	88.5
Year (-2)	Total Acc.	42.07	69.65	64.83	69.66	71.72	67.59
	Bankrupt	69.4	22.4	2.0	10.2	26.5	22.6
	Non- Bankrupt	28.1	93.8	96.9	100	94.8	90.5
Year (-1)	Total Acc.	62.75	71.03	68.28	72.41	72.41	68.28
	Bankrupt	57.1	61.2	44.9	49.0	24.5	12.2
	Non- Bankrupt	65.6	76.0	80.2	84.4	96.9	96.9

It was found that learning algorithms could enable users to predict bankruptcies with satisfying accuracy long before the final bankruptcy. The experts are in the position to known 3 years before, which of the industries will bankrupt or not with sufficient precision, which reaches the 68% in the initial forecasts (3 years before the examined year) and exceeds the 72% the last year.

The proposed voting ensemble reaches the 71.72% (28.6% of Bankrupt firms and 93.8% of Non-Bankrupt) in the initial forecasts (3 years before the examined year) and exceeds the 73.79% (67.3% of Bankrupt firms and 77.1% of Non-Bankrupt) the last year. In a comparative assessment of the models' performance we can conclude that the ensemble outperforms the simple tested algorithms and achieve outstanding classification accuracy.

5 Conclusion

ANN based financial forecasting has been explored for about a decade. Many research papers are published on various international journals and conferences proceedings [7]. Some research results of financial forecasting found in references.

The aim of this study has been to compare the performance of ANNs techniques in detecting fraudulent financial statements and predicting corporate bankruptcy by using published financial data. According to our experiments, the attributes that mostly influence the induction in bankruptcy prediction are: WC/TA, EQ/CE and GRNI, while, the attributes that mostly influence the induction in detecting fraudulent financial statements are: RLTC/RCR02, AR/TA01, TL/TA02, AR/TA02, WC/TA02, DC/CA02, NFA/TA02, NDAP02. Finally, all the experimental results indicate that published financial statement data contains falsification indicators. In terms of performance, a voting ensemble achieved the best performance. It must be mentioned that our input vector solely consists of financial ratios. Enriching the input vector with qualitative information, such as previous auditors' qualifications or the composition of the administrative board, could increase the accuracy rate. The other open issue is to consider macroeconomic indicators as inputs to the ANN. The prevailing economic conditions (as well as the current interest rates) can have a significant effect on the probability of bankruptcy.

Of course, all the techniques employed in the problem of predicting bankruptcy and FFS can be straight forwardly used in other financial classification problems such as bond rating or credit scoring.

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