VIII International Scientific Conference
Analysis of International Relations 2017. Methods and Models of Regional Development
Katowice, Poland 21-22 June 2017

CAN ARTIFICIAL NEURAL NETWORKS DETECT FRAUD? A CASE STUDY

Aleksandra Wójcicka

Poznan University of Economics,
Department of Operational Research,
al. Niepodległości 10, 61-875 Poznań, Poland
E-mail: aleksandra.wojcicka@ue.poznan.pl

***Abstract**: Artificial neural networks have been widely applied in many various areas, e.g. optimization, pattern recognition or time series forecasting. They also have been used in classification tasks, for instance to state whether a potential debtor is going to be solvent or, perhaps, in a determined time it is highly probable that they will default and go bankrupt. The efficiency of neural network in that task is similar to other methods like Discriminant Analysis or credit rating methods. However, the question arises if, at that initial moment, it is possible to define the possibility of potential fraud.*

The paper investigates if neural networks can be of any use in prior fraud detection. The problem is presented as specific classification task basing on historical data. Various topologies of neural networks are used. Results of those different methods are juxtaposed, and their performance compared. The study can be classified in applied studies group and the research strategy is descriptive.

***Key words:** credit risk, default, neural networks*

***JEL codes:** G33, G38, C49*

1. Introduction

The default and bankruptcy are a constant part of the economy. The intensification of business operations results in an intensification of negative occurrences such as the loss of liquidity, delays in payments or insolvency. Those, in turn, lead to default or bankruptcy. Those events are usually preceded by a deterioration of economic indicators such as performance indicators (profit / loss) and financial ratios. While such deterioration progresses, the potential bankruptcy is expected at least with some probability. However, bankruptcies can occur due to the deteriorating standing of the company over time. There are cases of bankruptcies due to mismanagement or fraud. While in the first instance the default can be predicted, and certain measures can be taken to prevent it, in the latter, it usually causes a shock among third parties and causes a lot of damage.

The paper investigates whether information included in financial statements provides sufficient input to identify the probability of fraud and whether neural networks can contribute to a detection of such events and if so, which topologies of neural networks would be most useful in detecting anomalies (if they exist) that precede fraud. Or is it maybe information contained in the accrual and cash flow components of current earnings that can seem most helpful? The primary objective of this paper is to define existing challenges in this domain for insufficient data and different types of popular neural networks.

Fraudulent behaviour is not anything new and their detection often requires complex and time-consuming operations. Moreover, it becomes more and more difficult to detect fraud as it evolves along with the technical advancement and an increased number of online operations.

Therefore, new techniques or supportive tools are necessary. Neural networks have also been used for bankruptcy prediction and classification of debtors as well as fraud detections (e.g. FICO® Falcon® Fraud Manager).

The study can be classified in applied studies group and the research strategy is descriptive. The main objective of the study is to deliver an answer whether with the scarce data, neural networks can, in advance, deliver satisfactory rate of fraud detection.

The choice of neural networks used in the research was dictated by their popularity, as well as previous research on their efficiency in debtors' classification (Wójcicka, 2017a, 2017c, 2017d) and determining potential credit risk and default (Wójcicka, 2017b).

2. Neural networks – overview

The idea of neural networks as computing processors has its origin in the way a human brain computes and analyses obtained knowledge. Neural networks in the scientific literature can be defined as "[…] a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: i) Knowledge is acquired by the network from its environment through a learning process; ii) Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge" (Haykin, 2011). A very important issue is the learning algorithm used in network design which influences the whole structure of NN. The different neural networks models used in the paper are Multi-Layer Perceptron (MLP) and Radial Basis Function neural network (RBF).

Neural networks in the scope of pattern recognition and classification of entities are broadly analysed. Atiya (2001) presents an empirical approach, basing on the relationship of default and the characteristics of a firm learnt from the data. The conclusions indicate the superiority of neural networks over other techniques and the need for improvements in training methods, architecture selection, or input. Baesens et al. (2003) investigated neural networks' contribution in helping the credit-risk managers in explaining why a particular applicant is classified as either bad or good. They conclude that neural network rule extraction and decision trees are effective and powerful management tools, allowing the construction of advanced and user-friendly decision-support systems for credit-risk evaluation.

Also in work of Pacelli and Azzollini (2011) it is stated that neural networks are particularly suited to analyse and interpret complex and often obscure phenomena and processes.

Still, other research proves that despite the weaknesses, neural networks show good performance when data are noisy or incorrect (see Angelini et al, 2007). In these studies, the most common NN were analysed. Other structures of neural networks, as well as their comparison with other techniques (Decision Trees, Discriminant Analysis, Regression Function etc.) can be found in works of e.g. Khemakhem and Boujelbènea (2015), Ogwueleka et al. (2015), Linder et al. (2004) and many others.

The latest application of neural networks also includes the use of neural networks for big data analysis – deep learning which application can be found in, for instance Najafabadi et al. (2015) where authors claim that Deep Learning has an advantage over traditional machine learning and other engineering algorithms when it comes to massive data input. Neural networks, so far, have been the most successful methods for big data analysis as they can extract abstract features from raw data. For some, neural networks and AI are the major forces which will drive the economy, analyses and business management in the coming years. What appeals to analysts and investors is the fact that the learning process of neural networks is highly automated and can process a huge set of data, finding the patterns, and what is more, it can easily adjust to changing conditions by re-learning process.

However, some researchers indicate that deep learning with massive input is not always advisable as in case of some problems multi-layer network seems to provide better performance than state-of-the-art deep networks (Kasun et al., 2013) and that the number of features or dimensions should rather be reduced than enhanced.

3. Methods and data used in the analysis

The fraud is defined in many ways. However, it is always associated with the deception or misrepresentation. In some definitions it is also described as omission or perversion of truth. It is wildly known that wilful fraud is a criminal offense. It can cover all events from misuse of business credit cards to identity fraud (linked with insurance fraud), etc. One of the most popular definitions, still up-to-date, describes it as "an intentional deception, misappropriation of a company's assets or the manipulation of its financial data to the advantage of the perpetrator" (Levy, 1985). In a competitive environment, fraud can become a business-critical problem if it is very prevalent and if the prevention procedures are not fail-safe (Phua et al., 2010).

The use of neural network in fraud detection is to reduce the manual parts of a screening and constant monitoring process and to classify an object (entity) as a probable perpetrator of fraud. In such approach the task can be considered a classification problem.

Some researchers claim that using neural networks might not be efficient or justified (Wang, 2010). It is due to the fact that the data on fraud is scarce and hard to access. Generally, there is a lack of publicly available real data to perform learning process on. Usually it is not freely accessible and very often confidentiality clauses are connected to all the data connected with the case of fraud. Entities, banks, financial institutions and insurance agencies have such data if their encounter a fraud situation. Companies usually deal with internal fraud, e.g.

misuse of business credit cards. Banks and financial institutions usually encounter fraudulent financial reporting (by management) or abnormal transactions using the financing provided by the bank (as a creditor). The most attention was received by the credit transactional frauds. It should be clearly distinguished that credit transactional frauds should not be identified as bankruptcy or default problems for it seems unjustified to classify those two completely different problems in the same category.

Insurance agencies usually handle four different kinds of fraud which concern: home, crop, automobile and medical insurance. Unfortunately, the data very often is inaccessible. Still, in some research it was indicated that even on a small sample the rate of detecting fraud is higher than the rate of fraud detection by auditors.

In some cases, the data can also come from Commercial Courts. However, those are rare cases, as it should be remembered that, as it was mentioned above, fraud is a criminal offense and hence it is investigated as such.

A situation referring confidentiality also applies in case of the current research presented in the paper, therefore the names of the analysed companies, as well as the name of the bank, cannot be revealed. The real data is obtained from a bank operating on Polish market. There are four relatively recent cases of fraud – three of the fraudulent financial reporting and one of the misuse of the resources obtained from the bank on the trade financing contract. The cases cover past four years (first of the investigated frauds was discovered in February 2014) and two of them are still in progress. Due to a small size of a set of historical data the research is conducted in a form of a case study (hereinafter also referred to as an experiment).

The methods used are artificial neural networks of two most popular topologies: Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF). This is also due to the available tool – SANN (STATISTICA Artificial Neural Networks) which an accessible tool with comprehensible tutorial which is very important for many analysts and managers.

4. Findings

As it was mentioned above, the implemented NN were MLP and RBF. Table 1 presents main similarities and differences between the two NN structures.

Tab. 1 Similarities and differences between MLP and RBF neural networks

	MLP	RBF
signal transmission	feedforward	feedforward
process of building the model	one stage	two different, independent stages – at the first stage by means of radial basis functions the probability distribution is established; the network learns the relations between input x and output y at the second stage. On the contrary to MLP the lag is only visible in RBF in the output layer.
threshold	yes	no
type of parameters	weights and thresholds	location and width of basis function and weights binding basis functions with output
functioning time	faster	slower (bigger memory required)
learning time	slower	faster

Source: Own elaboration based on Statistica Help SANN

The companies were compared prior to the analysis in terms of a sector in which they operate, their size (basing on the total assets), number of employees and the legal form. Unfortunately, there were few similarities which are presented in table 2.

Tab. 2 The characteristic of the analysed companies

company	1	2	3	4
sector	industry	trade	trade	services
size (total assets)	over 5 million PLN	over 3 million PLN	over 800 thousand PLN	over 800 thousand PLN
no. of employees	more than 150	more than 100	more than 20	more than 30
legal form	joint stock company	joint stock company	limited liability company	limited liability company

Source: Own elaboration

The sample contains financial statements of companies (a balance sheet, an income statement, a cash flow statement and a statement of changes in equity) and internal documents of the bank – from financial and legal departments. In the study, unsound companies were matched with healthy businesses similar in character, concerning total assets value and sector of economy.

Preliminary data set was divided into groups (learning and testing) in a following manner:

a. learning group (75% of data set), testing group (25% of data set),
b. learning group (50% of data set), testing group (50% of data set).

For the conducted experiment various activation functions were implemented (linear, entropy, logistic, hyperbolic tangent, exponential, sinus, Softmax, Gaussian). The input data included 22 financial ratios and 4 specific indicators of the bank (internal rating of the client, number of delays in payment, number of days of delay in payment, number of corrections of financial statements). The indicators are presented in table 3.

Tab. 3 Input indicators

indicator	indicator	indicator	indicator
Acid-test ratio	Net profit margin ratio	Assets profitability index	Costs increase ratio
Quick ratio	Sale profitability index	Long-term debt ratio	Sales dynamics
Receivables ratio	Costs level ratio	Current assets turnover ratio	Internal rating of the debtor
Stock turnover ratio	Total debt ratio	Short-term investments turnover ratio	Self-financing ratio
	Equity debt ratio		No. of days of delay in payment
Receivables to liabilities ratio	Equity profitability index	Operating activity profitability index	No. of delays in payment
Gross profit margin ratio	Financial surplus rate	Operating ratio	No. of corrections of financial statements

Source: Own elaboration

As the initial input data is large (26 indicators) but the data set regarding the number of objects (entities) is still fairly obscure the author decided to reduce the number of hidden layers to one and number of nods in the hidden layer to maximum 20 (however, it only is the upper cap as the choice was left to SANN and rarely approached that number) as for such limited data the threat of over-fitting is high.

Initially 8 neural networks (for each typology – MLP, RBF) were trained on a full set of input data. Their results (best 3) for 75% learning set and 25% testing set (75/25) are presented in table 4.

Tab. 4 Neural networks trained on full set of input data (3 best NN)

neural network	activation function	quality (learning) %	quality (testing) %
MLP 26-20-1	Gauss	67%	100%
MLP 26-20-1	Sinus	67%	50%
RBF 26-20-1	Entropy	50%	50%

Source: Own calculations (SANN)

Previous research (Wójcicka, 2017a, 2017c, 2017d) indicates that reduction of input can lead to improvement of testing quality. Therefore, the sensitivity analysis for each neural network was conducted (SANN Sensitivity Analysis). It is based on sensitivity analysis of the neural network obtained in the process of learning. Sensitivity Analysis in data mining and statistical model building generally refers to the assessment of the importance of predictors in the respective (fitted) models. Given a fitted model with certain model parameters for each predictor, it presents what the effect would be of varying the parameters of the model (for each variable) on the overall model fit. In Statistica Automated Neural Networks, the program computes the Sums of Squares residuals or misclassification rates for the model when the respective predictor is eliminated from the neural net. Ratios (of the reduced model vs. the full model) are also reported, and the predictors can be sorted by their importance or relevance for the particular neural network. In the research after each process of learning the sensitivity analysis of input data (see table 3) was analysed.

There were 9 indicators reduced by both topologies of neural networks. They were as follows: Equity debt ratio, Short-term investments turnover ratio, Gross profit margin ratio, Stock turnover ratio, No. of delays in payment, No. of corrections of financial statements, Sales dynamics, Sale profitability index, Equity profitability index.

The reduced set of generalised input was implemented. New networks were trained (1 hidden layer, maximum 20 nods in the hidden layer). The results from that approach (best 3) are presented in table 5.

Tab. 5 Neural networks trained on limited set of input data (3 best NN)

neural network	activation function	quality (learning) %	quality (testing) %
MLP 17-19-1	Sinus	83%	100%
RBF 17-20-1	Gaussian	83%	100%
RBF 17-17-1	Entropy	67%	100%

Source: Own calculations (SANN)

As it was signalled above the experiment was run also for another division of data (number of entities) belonging to a learning (50%) and testing group (50%). Results for the other division of the set (50/50) were similar (not better than for 75/25) and therefore, they are not presented. The differences in quality of testing were insignificant and the structure of analysed topologies was very similar (concerning the best 3 neural networks) when it comes to activation function and number of nods in a hidden layer. It must be presumed that bigger changes could reveal in case of a bigger entry input (bigger number of companies).

The results obtained in the experiment are satisfactory. It can be concluded that neural networks can be an efficient tool in detecting fraud. It can be cautiously concluded that MLP are a preferable topology of neural networks in case of fraud problem because they achieved better results than RBF topology in case of full input and the same results in case of limited data input.

Some may certainly object to the sample size, however, it must be stressed that this is not a theoretical but a real economic problem, conducted on real data which is scarce and hardly accessible. Therefore, even such a limited experiment is valuable.

5. Conclusions

The fraud is associated with the deception or misrepresentation and in some definitions also with the omission or perversion of truth. It is a criminal offense. It can occur at any time and any tool that can in advance indicate the probable fraudulent behaviour of an entity is very significant. The entities which are mostly exposed to a fraud risk are companies, banks, financial institutions, insurance agencies etc. They encounter frauds of a different character. However, there might be some patterns which need to be identified.

The problem of identification of fraudulent behaviour can be initially reduced to a classification problem and neural networks can be implemented. The set of entities must include good and bad companies (bad = fraudulent). One may consider whether it is worth to run an experiment for such an obscure set of data, the answer still is yes. Without any attempts to improve the detection of fraud, the real progress in that matter will never come. It is also a challenge to build a bigger database which can be constantly enlarged and can constitute a base for implementing more complicated typologies of neural networks or other techniques.

The conducted research (on the scarce data) proved that neural networks can be useful and can be applied in case of that task. The results show that Multi-Layer Perceptron typology obtains slightly better results than Radial Basis Function, however, the results reached very similar level. It was also presented that

The further research should go in to directions: implementing other topologies or classification methods for fraud detection task and also reducing the number of input data. It should also be considered whether other indicators (than financial ratios) should be included in the input.

References

Angelini E., Tollo G., Rol A. (2008): *A neural network approach for credit risk evaluation*. "The Quarterly Review of Economics and Finance", Vol 48. pp. 733-755.

Atiya A.F. (2001): *Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results*. "IEEE Transactions on Neural Networks", Vol. 12, No. 4, pp. 929-935.

Baesens B., Setiono R., Mues C., Vanthienen J. (2003): *Using Neural Network Rule Extraction and Decision Tables for Credit-Risk Evaluation*. "Management Science", Vol. 49, No. 3, pp. 312-329.

Haykin S. (2011): *Neural Networks and Learning Machines*. Third Edition, PHI Learning Private Limited.

Hinton G.E., Salakhutdinov R.R. (2006): *Reducing the Dimensionality of Data with Neural Networks*. "Science", Vol. 313, No. 5786, pp. 504-507.

Kasun L.L., Zhou H., Huang G., Vong C.M. (2013): *Representational Learning with Extreme Learning Machine for Big Data.* "IEEE Intelligent Systems", Vol. 28, No. 6, pp. 31-34.

Khemakhem S., Boujelbènea Y. (2015): *Credit risk prediction: A comparative study between discriminant analysis and the neural network approach*. "Accounting and Management Information Systems", Vol. 14, No. 1, pp. 60-78.

Levy M.M. (1985): *Financial Fraud: Schemes and Indicia*. "Journal of Accountancy", Vol. 160, No. 2, pp. 78-87.

Linder R., Geier J., Kölliker M.J. (2204): *Artificial neural networks, classification trees and regression: Which method for which customer*? "Database Marketing and Customer Strategy Management", Vol. 11, No. 4, pp. 344-356.

Najafabadi M.M., Villanustre F., Khoshgoftaar T.M., Seliya N., Wald R., Muharemagic E. (2015): *Deep learning applications and challenges in big data analytics*. "Journal of Big Data", Vol. 2, No. 1.

Ogwueleka F.N., Misra S., Colomo-Palacios R., Fernández-Sanz L. (2015): *Neural Network and Classification Approach in Identifying Customer Behaviour in the Banking Sector: A Case Study of an International Bank*. "Human Factors and Ergonomics in Manufacturing and Service Industries", Vol. 25, No. 1, pp. 28-42.

Pacelli V., Azzollini M. (2011): *An Artificial Neural Network Approach for Credit Risk Management*. "Journal of Intelligent Learning Systems and Applications", Vol. 3, No. 2, pp. 103-112.

Phua C., Lee V., Smith K., Gayler R. (2010): *A Comprehensive Survey of Data Mining-based Fraud Detection Research*, "Computing Research Repository".

Wang S. (2010): *A Comprehensive Survey of Data Mining-Based Accounting-Fraud Detection Research*, Intelligent Computation Technology and Automation (ICICTA).

Wójcicka A. (2017a): *Neural networks in credit risk evaluation of construction sector*. "Econometric Research in Finance", Vol. 1, No. 2, pp. 63-77.

Wójcicka A. (2017b): *The dynamic approach to financial ratios analysis: an experimental approach*. Paper presented during *Econometric Research in Finance Workshop*, Warsaw.

Wójcicka A. (2017c): *Credit-risk decision process using neural networks in industrial sectors*. In Choudhry T., Mizerka J. (eds): *Contemporary Trends in Accounting, Finance and Financial Institutions: Proceedings from the International Conference on Accounting, Finance and Financial Institutions (ICAFFI)*. Springer Proceedings in Business and Economics (accepted for publication).

Wójcicka A. (2017d): *Classification of trade sector entities in credibility assessment using neural networks*. "Optimum", Vol. 87, No. 3, pp. 153-161.