ECONOMICS
& Sociology

Letkovsky, S., Jencova, S., Vasanicova, P., Gavura, S., & Bacik, R. (2023). Predicting bankruptcy using artificial intelligence: The case of the engineering industry. *Economics and Sociology*, *16*(4), 178-190. doi:10.14254/2071-789X.2023/16-4/8

PREDICTING BANKRUPTCY USING ARTIFICIAL INTELLIGENCE: THE CASE OF THE ENGINEERING INDUSTRY

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Received: October, 2022
1st Revision: October, 2023
Accepted: December, 2023

DOI: 10.14254/2071-789X.2023/16-4/8

ABSTRACT. Bankruptcy prediction is a powerful early-warning tool and plays a crucial role in various aspects of financial and business management. It is vital for safeguarding investments, maintaining financial stability, making informed credit decisions, and contributing to the overall health of the economy. This paper aims to develop bankruptcy prediction models for the Slovak engineering industry and to compare their effectiveness. Predictions are generated using the classical logistic regression (LR) method as well as artificial intelligence (AI) techniques (artificial neural networks (ANN) and support vector machines (SVM)). Research sample consists of 825 businesses operating in the engineering industry (Manufacture of machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment). The selection of eight financial indicators is grounded in prior research and existing literature. The results show high accuracy for all used methods. The SVM outcomes indicate a level of accuracy on the test set that is nearly indistinguishable from that of the ANN model. The use of AI techniques demonstrates their effective predictive capabilities and holds a significant position within the realm of tools for forecasting bankruptcy.

JEL Classification: C45, G33 ***Keywords***: bankruptcy prediction, artificial neural network, support vector machine, logistic regression, engineering industry

Introduction

A financially healthy company is able to pay its obligations and make a profit. Conversely, the inability to repay the company's debt on time can lead to bankruptcy. Business bankruptcy is not sudden and is usually the result of a chain of negative events and bad decisions with fatal consequences. It emphasizes the need for constant control of the business's condition by the management. Bankruptcy prediction helps management in making decisions and creditors in analyzing the risk of (potential) debtors. The basis of prediction models is to find a function that divides a group of businesses into bankrupt and non-bankrupt, with the highest possible accuracy (Kocisova et al., 2018; Istudor et al., 2022). The first steps of modeling include the selection of suitable predictors. The existing literature does not indicate the exact procedure of applying the model in specific conditions; therefore, it is important to examine individual models and their use in different conditions (country, industry, size).

Due to the impact of globalization and the consequences of the COVID-19 pandemic, it is no longer important to decide whether to predict bankruptcy at all but rather how to increase the accuracy of such predictions (Kitowski et al., 2022; Dinu & Bunea, 2022; Poliakov et al., 2023). The common element of most models is the prediction time horizon from 1 to 3 years. As the prediction time increases, the accuracy decreases significantly. Updating models applied for current conditions and increasing their effectiveness (accuracy) are constantly necessary due to turbulent changes in the business environment.

The main aim of this paper is to develop bankruptcy prediction models for the Slovak engineering industry and to compare their effectiveness. Predictions are generated using the classical logistic regression (LR) method as well as artificial intelligence (AI) techniques (artificial neural networks (ANN) and support vector machines (SVM)). The analysis aims to determine which of the employed methods is the most efficient. Utilizing bankruptcy prediction models can aid managers in monitoring a company's performance over several years, facilitating the identification of significant trends.

1. Literature review

Bankruptcy prediction is an important part of business control and monitoring. It often used for decision on insurance so it is important to explore the possible links between bankruptcy and related financial indicators (Dankiewicz, 2020). A frequently used method is the evaluation of the business (borrower) by the bank (creditor) for the purpose of providing a loan. Lenders need to evaluate the riskiness of the investment or to find out the creditworthiness of the business. Based on the evaluation of the company's financial situation, it can be classified into a certain credit risk group (Tkacova & Gavurova, 2023). Forecasts (prediction models) can also be used by companies as an early warning system, enabling management to intervene in time (Gavurova *et al.,* 2020). Models can also be referred to as rating models (estimating the probability of failure at a certain time (usually within 1 year)).

Prediction begins with comparing indicators of healthy and bankrupt enterprises (Fitzpatrick, 1932), followed by discriminant analysis (Fisher, 1936), and scoring model (Beaver, 1966) using linear discriminant analysis (LDA) that is most frequently used as comparing method. Altman (1968) used LDA to separate bankrupt and non-bankrupt companies while he applied five financial indicators (known as z-score). The sample of the original model consisted of foreign joint-stock companies; therefore, for the conditions of the Slovak Republic, its validity is insufficient. Several studies have addressed this issue, e.g., Váchal *et al*. (2013) modified the model for other conditions (e.g., production enterprises); Kabát *et al*. (2013) modified the model for limited liability companies in Slovak Republic. Furthermore, the popularity of discriminant analysis increased due to work in the finance field by Taffler (1982). The next stage of development involves the application of statistical methods such as logit (LR) (Ohlson, 1980) and probit (Zmijewski, 1984). Methods operate under the assumption of a logistic probability distribution (LR) or cumulative probability distribution (probit). Currently, LR is still among the leading methods of bankruptcy analysis (e.g., Du Jardin, 2018; Ptak-Chmielewska, 2019; Ogachi *et al*., 2020; Bogdan, 2021; Sawafta, 2021; Kitowski *et al*. 2022; Gavurova *et al*., 2022; Zultilisna *et al*., 2022).

Nowadays the wide implementation of ICT-based technologies in business environments (Bilan et al., 2023; Roshchyk et al., 2022; Dias et al., 2023) and the increase in data availability facilitate the development of new approaches to analyze and predict business results, including financial distress (Durica et al., 2021). With the advancement of technology, AI-based methods have emerged, and the work of Odom and Shard (1990) is considered pioneering in the prediction field using ANN. In addition, studies by Callejón *et al*. (2013), Korol (2019), Gavurova *et al*. (2022) discuss the accuracy of ANN-based prediction. Other well-known bankruptcy prediction models are created by using decision trees (DT) (Shin *et al*., 2005; Apalkova et al., 2022), support vector machine (SVM) (Li and Sun, 2009; Yoon and Kwon, 2010; Iturriaga and Sanz, 2015; Barboza *et al*., 2017; Du Jardin, 2018; Kim *et al*., 2018; Hosaka, 2019; Ptak-Chmielewska, 2019; Zoričák *et al*., 2020; Amzile & Habachi, 2022). The current trend is to apply prediction improvement techniques (Sigrist and Leuenberger, 2023) and optimalization (Ansari *et al*., 2020) or combination of methods to hybrid models (Chen *et al*., 2021; Jankova, 2023).

We employ VOSviewer to explore existing studies relationships which contain key terms "bankruptcy prediction artificial neural networks logistic regression". Based on the subset of 78 publications indexed in Web of Science Core Collection from 2009 to 2023, *Figure 1* shows the results of a VOSviewer co-occurence analysis, which generates links between key terms. *Table 1* shows five significant clusters identified within VOSviewer and the keywords.

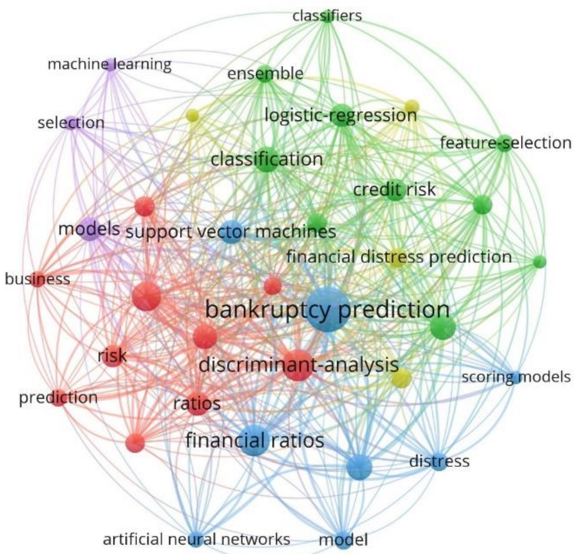

Figure 1. VOSviewer results of co-occurrences in papers indexed in Web of Science Core Collection from 2009 to 2023 with key terms "bankruptcy prediction artificial neural networks logistic regression"
Source: *own compilation in VOSviewer*

Table 1. Results of prediction

Cluster	Colour	Keywords
1	Red	bankruptcy, business, credit scoring, discriminant-analysis, financial distress, neural-networks, performance, prediction, ratios, risk
2	Green	artificial neural-networks, classification, classifiers, corporate bankruptcy, credit risk, ensemble, feature-selection, genetic algorithm, logistic-regression, neural network
3	Blue	artificial neural networks, bankruptcy prediction, distress, financial ratios, logistic regression, model, scoring models, support vector machines
4	Yellow	artificial neural-network, business failure prediction, financial distress prediction, support vector machine
5	Violet	machine learning, models, selection

Source: *own compilation according to VOSviewer*

In prediction, financial indicators represent network inputs and bankruptcy is a binary value (1–bankrupt, 0–non-bankrupt). The choice of predictors is also important factor for the model's effectiveness. Similarly, even here, the exact number and type of indicators that are the most suitable for predicting bankruptcy are not specified. Several existing studies use statistical methods to select the strongest predictors from a larger set. Vochozka (2020), and Chen *et al*. (2021) describe their ambiguity. Mihalovič (2018) applies an evolutionary algorithm to their selection. A large body of literature has focused on forecasting bankruptcy in businesses for an extended period. *Table 2* presents overview of studies focused on bankruptcy prediction. We only present papers that predicted bankruptcy using linear or multidimensional discriminant analysis, LR, SVM or ANN.

Table 2. Overview of studies focused on bankruptcy prediction

Author(s)	Year	Research Sample					Accuracy [%]				
		Size			Period from to	Country	Statistical			Data Mining	
		Non-bankrupt	Bankrupt	Total			LDA	MDA	**LR**	**SVM**	**ANN**
Shin *et al.*	2005	1,160	1,160	2,320	1996 1999	South Korea				**75**	**74**
Yoon and Kwon	2010	5,000	5,000	10,000	2000 2002	South Korea		69 / 70.1	**68.9 / 70.1**	**79 / 74.2**	**78.5 / 73.1**
Youn and Gu	2010	102	102	204	2000 2005	Korea			**83.33**		**87.75**
Rafiei *et al.*	2011	122	58	180	2008	Iran		80.6 / 79.9			**98.6 / 96.3**
Callejón *et al.*	2013	500	500	1,000	2007 2009	EU					**92.5 / 92.1**
Iturriaga and Sanz	2015	386	386	772	2002 2012	USA		77.9	**81.7**	**89.4**	**93.3**
Barboza *et al.*	2017	41,155	586	41,741	1985 2013	USA and Canada		64.8 / 52.2	**82.7 / 76.3**	**88.8 / 79.8**	**84.9 / 73**
Du Jardin	2018	6,000	120	6,120	2006 2014	France		76.8 / 80.6	**78.3 / 80.8**	**79.4 / 80.9**	**79.7 / 81.5**
Kim *et al.*	2018	144	144	288	2000 2013	Korea		77.58	**68.97**	**96.55**	**82.76**
Valaskova *et al.*	2018	76,305	29,403	105,708	2015 2016	Slovakia		58.9			
Hosaka	2019	2,062	102	2,164	2002 2016	Japan	85.1			**87.2**	**84.8**
Korol	2019	300	300	600	2004 2017	EU					**93.4**
Ptak-Chmielewska	2019	495	311	806	2008 2010				**85.4**	**83.5**	**90.7**
Ansari *et al.*	2020			984		USA					**81.5 / 85.5**
Ogachi *et al.*	2020	60	60	120		Kenya			**83**		
Zoričák *et al.*	2020	1,205 – 5,840	14 – 30	1,219 – 5,870	2013 2016	Slovakia				**72 / 89**	

Bogdan	2021	308	297	605	2017 2019	Croatia			**82.8**		
Castillo García and Fernández Miguélez	2021	203	203	406	2017 2019	Spain					**96.5 / 93.8**
Horváthová *et al.*	2021	366	78	444	2016	Slovakia		83.33			**98.3 / 95.9**
Mishraz *et al.*	2021	60	15	75	2015 2019	India	77.33				**86.66**
Gavurova *et al.*	2022	1,500	320	8,415	2018 2019	Slovakia			**89.5 / 89.6**		**91 / 100**
Kitowski *et al.*	2022			50	2017 2018	Poland		average 82.8	**average 90**		
Calabrese	2023			25,343	2015	Great Britain			**70.6**		
Dube *et al.*	2023	21	16	37	2000 2019	South Africa					**96.6**
Sigrist	2023	18,833	1,402	25,344	1961 2020	USA					**93.1**

Source: *own compilation*
Note: LDA denotes linear discriminant analysis, MDA denotes multidimensional discriminant analysis, LR is logistic regression, SVM is support vector machine, and ANN denotes artificial neural networks. The methods used in this paper are highlighted in bold.

The *Table 2* shows that the studies focus on companies from different countries. The research samples of the mentioned studies consisted of manufacturing firms (Shin *et al.*, 2005; Rafiei *et al.*, 2011; Kim *et al.*, 2018; Zoričák *et al.*, 2020; Dube *et al.*, 2023), firms operating in tourism industry (Youn and Gu, 2010; Bogdan, 2021; Castillo García and Fernández Miguélez, 2021), banks (Iturriaga and Sanz, 2015; Mishraz *et al.*, 2021), heat supply firms (Horváthová *et al.*, 2021), industrial firms (Callejón *et al.*, 2013), firms from engineering and automotive industries (Gavurova *et al.*, 2022), or not specified small or medium-sized companies (Yoon and Kwon, 2010; Ptak-Chmielewska, 2019; Calabrese, 2023). This paper contributes to the existing literature by constructing a bankruptcy prediction model for the engineering industry.

2. Data and methodology

The main aim of this paper is to develop bankruptcy prediction models for the Slovak engineering industry and to compare their effectiveness. Predictions are generated using the classical LR method as well as AI techniques (ANN and SVM). The analysis aims to determine which of the employed methods is the most efficient.

2.1. Data

The dataset comprised businesses from the Slovak engineering industry, sourced from the Register of the financial statements of the Slovak Republic for the years 2020-2021. According to the NACE Rev. 2, we consider divisions 28–Manufacture of machinery and equipment n.e.c. (this division includes the manufacture of machinery and equipment that act independently on materials either mechanically or thermally or perform operations on materials), 29–Manufacture of motor vehicles, trailers and semi-trailers (this division includes the manufacture of motor vehicles 182odellingting passengers or freight), 30–Manufacture of other transport equipment (this division includes the manufacture of transportation equipment such as ship building and boat manufacturing, the manufacture of railroad rolling stock and locomotives, air and spacecraft and the manufacture of parts thereof). The initial sample count totaled 1629 businesses. After the removal of incomplete data (460) and outlier samples (706), the sets were reduced to 825 samples (89 bankrupt and 736 non-bankrupt). To eliminate outliers, the interquartile range method was employed, with the outlier limit set at three times the interquartile range. Finally, the training set consisted of 557 samples (circa 70%), while the test set contained 248 samples (circa 30%).

The financial indicators selection is grounded in prior research and existing literature (Mihalovič, 2018; Jenčová *et al*., 2020; Gavurova *et al*., 2022). Specifically, we use eight financial indicators from all categories (indebtedness, liquidity, profitability, activity, others):

- Added Value to Sales Ratio (Gross Margin) = AV/S;
- Equity to Total Assets Ratio = E/TA;
- Current Ratio to Total Assets Ratio = CuR/TA;
- Cash to Total Assets Ratio = C/TA
- Return on Equity (Earnings after Taxes to Equity) = ROE;
- Return on Assets (Earnings before Interests and Taxes to Total Assets) = ROA;
- Assets Turnover = AT;
- Net Working Capital to Total Assets Ratio = NWC/TA.

Among the chosen indicators, the gross margin (AV/S) holds significant prominence, as evidenced by Ptak-Chmielewska (2019). The E/TA (Shin *et al*., 2005; Rafiei *et al*., 2011; Bogdan, 2021), CuR/TA, and C/TA (Du Jardin, 2018) indicators are considered significant within the liquidity context. Profitability indicators are among the most used. The ROA has been employed in prediction models since Altman (1968) and subsequently by Callejon *et al*. (2013), Du Jardin (2018), Ptak-Chmielewska (2019), Tumpach *et al*. (2020), Castillo García and Fernández Miguélez (2021), Horváthová *et al*. (2021), and Dube *et al*. (2023). Similarly, the ROE, defined by Fitzpatrick (1932) and emphasized by Lee and Su (2015), Ptak-Chmielewska (2019), Castillo García and Fernández Miguélez (2021), and Dube *et al*. (2023), is deemed one of the most crucial predictors of bankruptcy. The AT indicator, reflecting asset utilization efficiency, was identified as a significant predictor of bankruptcy by Lee and Su (2015), Ogachi *et al*. (2020), Sigrist and Leuenberger (2023). The NWC/TA is last significant indicator used by Altman (1968), Rafiei *et al*. (2011), Valaskova *et al*. (2018), Castillo García and Fernández Miguélez (2021), Sigrist and Leuenberger (2023).

2.2. Logistic regression

LR stands as a classic method frequently employed in bankruptcy prediction. This method operates under the assumption of a logistic probability distribution. It is used in analyzing relationship when dependent variable is discrete. Crucial criteria for this method include the non-collinearity of independent variables and an adequate sample size (Ptak-Chmielwska, 2019). The resulting variable ranges from 0 to 1 and indicates the probability of bankruptcy. A commonly used value of cut-off point is 0.5. This point can be different, and its determination must ensure the most optimal distribution (see Brygala, 2022). The formula of LR can be expressed in terms of an odds ratio:

$$\frac{\pi}{1-\pi} = e^{(\alpha + b_1 x_1 + \ldots + b_n x_n)} \tag{1}$$

and then to logit

$$logit(y) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + b_1 x_1 + \ldots + b_n x_n \tag{2}$$

where π is the probability of the event, α is the intercept, b_i are the regression coefficients and x_i predictors. Coefficients are estimated using max-likelihood.

2.3. Support vector machine

SVM is analogous to quadratic optimization and involves searching for hyperplanes in space to maximize the distance from data points. It can deduce the optimal solution based on a limited amount of training sample data. It appears to be an advantage in prediction models in Slovak conditions (there are relatively few bankrupt companies in the research samples of individual industries in the time horizon from 1 to 2 years).

SVM employs a linear model to establish nonlinear class boundaries by mapping inputs to a multidimensional space (Iturriaga and Sanz, 2014). SVM supports both classification and regression tasks, accommodating continuous as well as categorical variables (Ptak-Chmielewska 2019). Cortes and Vapnik (1995) provide a comprehensive elucidation of SVM.

2.3. Artificial neural networks

The principle of an ANN is similar to the brain neural structure in a simplified form (Rafiei *et al*., 2011). Similarity arises when saving information that appears in the form of patterns. The basic unit is a neuron (node), which receives an input signal, transforms it, and provides a certain signal at the output. Same nodes organizing into common groups form layers. The type of layer is created according to the way the nodes are connected (input, hidden, output). Connecting nodes (layers) creates a network. Input nodes (input layer) receive input stimuli (signals) from the outside. Nodes providing output from the network to the environment (system output) form output nodes (layers). All other nodes belonging to the network form hidden nodes (layers). Every network contains at least an input and an output layer (it can also contain no or several hidden layers). As the complexity of the task that the network performs increases, the complexity of the network increases (number of nodes, number of hidden layers).

Too complex network configuration can lead to demanding training and unsatisfactory results. On the contrary, a too simple configuration may not guarantee the ability to adapt to all training samples and thus will not be able to generalize the information obtained. The most frequently used networks in finance are “multi-layer perceptron” (MLP). When information only moves from input to output without feedback, it’s termed “feed forward” (FF), while networks with feedback constitute recurrent networks. In prediction, the backpropagation of error (“backpropagation” (BP)) learning method is most used. A simplified model of a neuron can be written by the following formula:

$$y = f\left(\sum_{0}^{n} x_i w_i\right) \tag{3}$$

where y is output, w_i are synaptic scales, x_i are inputs, and f is activation function.

The number of hidden layers and the number of hidden nodes is one of the decisive factors for the model‘s effectiveness. This parameter is not fixed or defined yet; researchers determine it either randomly or by empirical testing based on previous research. Synaptic scales are initially random and, due to the learning process, are adjusted so that the result converges to the smallest possible error. FF MLP networks with BP achieve relatively high prediction accuracy compared to other models (see *Table 1*).

In this paper, the most suitable neural network type seems to be MLP with FF connections (without recursion) and learning based on BP (the output error (the sum of squared deviations) is applied to individual nodes by backpropagation (adjustment of synaptic weights). Datasets was partitioned into two segments using a random number generator, roughly maintaining a distribution ratio of 70:30 for training and testing. The larger portion comprised samples for model creation (70% of the dataset), while the smaller portion served as the test set (samples excluded from 185odelling). These validation test samples are unknown and verify that the network Is able to extract information from the training and generalize it to the extent that it is able to determine the outcome on new data. The goal is to achieve the highest possible accuracy (effectiveness) within the validation set (especially with bankruptcy samples).

3. Results and discussion

Table 3 presents the prediction results of all proposed models. Considering LR, the average prediction accuracy reached 93.86%. However, the capacity to discriminate bankrupt samples was merely 44.44% for the test set and 43.55% for the training set while achieving a perfect accuracy of 100% for non-bankrupt samples. The goal of the prediction model is to correctly recognize as many bankrupt samples as possible in the test set. Therefore, LR model is insufficient because it was not able to recognize even half of the bankrupt samples. It could partly be attributed to the potentially lower quality of the input data with the limited number of bankruptcy samples. The imbalance between the bankrupt and non-bankrupt sets is an issue investigated by Zoričák *et al*. (2020). Thus, the model tends to shift the weight more to the majority group of samples.

On the contrary, considering ANN, the average prediction accuracy reached only 85.12%, but the capacity to discriminate bankrupt samples was the highest for the test set (74.07%) (i.e., 20 businesses from 27). Remarkably, the results of SVM show the accuracy on the test set almost identical those of the ANN model (70.37%; i.e., 19 businesses from 27) and a perfect accuracy of 100% for the training set. Similar results can be observed in *Table 2*. SVM model has the highest accuracy in the studies by Yoon and Kwon (2010), Barboza *et al*. (2017), Kim *et al*. (2018), Hosaka (2019).

Table 3. Results of prediction

Sample		Predicted								
		LR			**SVM**			**ANN**		
	Observed	0	1	*Correct*	0	1	*Correct*	0	1	*Correct*
Training	0	514	1	*99.81%*	515	0	*100.00%*	446	69	*86.60%*
	1	35	27	*43.55%*	0	62	*100.00%*	12	50	*80.65%*
	Overall	*95.15%*	*4.85%*	*93.76%*	*89.25%*	*10.75%*	*100.00%*	*79.38%*	*20.62%*	*85.96%*
Testing	0	221	0	*100.00%*	193	28	*87.33%*	189	32	*85.52%*
	1	**15**	**12**	***44.44%***	**8**	**19**	***70.37%***	**7**	**20**	***74.07%***
	Overall	*95.16%*	*4.84%*	*93.95%*	*81.05%*	*18.95%*	*85.48%*	*79.03%*	*20.97%*	*84.27%*
	Average			**93.86%**			**92.74%**			**85.12%**

Source: *own compilation*

From the obtained results, we cannot deduce which of the explored methods is the best. It aligns with the observations made by Shin *et al*. (2005) that it is challenging to definitively establish the superiority of any single method. As we mentioned, our data faces the challenge of an imbalance between the bankrupt and non-bankrupt sets. We could use undersampling method, employed by Kim *et al*. (2016) and Wang and Liu (2021), to reduce majority group or to use the oversampling approach, demonstrated by Garcia (2022), to generate artificial samples of the minority group. I''s worth noting that this stud''s primary focus did not involve exploring the impact of data size or imbalance. In the conditions of the Slovak industry, the data source required for analysis is limited by the data quality and the size of the industries.

Conclusion

The occurrence of companies facing bankruptcy and failure is an undesirable phenomenon that consistently poses an important problem. The adverse economic and social repercussions of business failures underscore the need for their serious consideration and treatment.

Considering only the average accuracy of the model, the best model would be LR. However, from a comprehensive point of view, LR model is considered insufficient. In comprehensive evaluation, the SVM model achieves the highest effectiveness (we see high accuracy of bankruptcy samples and average accuracy of almost 93%). The ANN prediction model achieved the highest accuracy of bankrupt samples and, at the same time, comparable accuracy of non-bankrupt samples in the test set with the SVM model. From the above results, we conclude that the ANN-based model achieves good prediction capabilities and has its place in the field of prospective prediction tools. It is also comparable to the SVM model, and it is not possible to clearly determine which one is the best. This conclusion implies the need to examine individual methods in more detail, use multiple models and compare their results.

Acknowledgement

This paper was supported by research grant KEGA No. 001PU-4/2022: "Application of Modern Trends in Quantitative Methods in the Teaching of Financial and Managerial Subjects", VEGA No. 1/0741/20: "The application of variant methods in detecting symptoms of possible bankruptcy of Slovak businesses in order to ensure their sustainable development" and VEGA No. 1/0590/22: "Exploration of natural, social and economic potential of areas with environmental burdens in the Slovak Republic for the development of specific forms of domestic tourism and quantification of environmental risks".

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