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Neural network modelling of non-prosperity of Slovak companies

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ABSTRACT
Early identification of potential financial problems is among important companies' risk management tasks. This paper aims to propose individual and ensemble models based on various types of neural networks. The created models are evaluated based on several quantitative metrics, and the best-proposed models predict the impending financial problems of Slovak companies a year in advance. The precise analysis and cleaning of real data from the financial statements of real Slovak companies result in a data set consisting of the values of nine potential predictors of almost 19 thousand companies. Individual and ensemble models based on MLP and RBF-type neural networks and the Kohonen map are created on the training sample. On the other hand, several metrics quantify the predictive ability of the created models on the test sample. Ensemble models achieved better predictive ability compared to individual models. MLP networks achieved the highest overall accuracy of almost 89 %. However, the non-prosperity of Slovak companies was best identified by RBF networks created by the boosting and bagging technique. The sensitivity of these models is about 87 %. The study found that models based on neural networks can be successfully designed and used to predict financial distress in the Slovak economy.

KEY WORDS
company, Kohonen map, neural network, non-prosperity, predictive ability

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Introduction

Prediction of non-prosperity is one of the most crucial issues for academic researchers and practitioners in risk management. Many researchers and economists have proposed prediction models for reliable and early identification of impending financial problems. These effective tools help decrease the potential threats of the company's bankruptcy on the microeconomic and macroeconomic levels. The models assess corporate financial health in various industries using statistical and other approaches. The neural network technique is among the most used

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tools in this field (Chen & Du, 2009; Fathi et al., 2022; Lin, 2009; Sun & Lei, 2021; Dzikevičius & Stabužytė, 2012).

The paper aims to propose models for predicting the financial problems of Slovak companies using several neural networks such as the Multi-Layer Perceptron (MLP) network, Radial Basis Function (RBF) network, and Kohonen map. These models were compared using selected statistical metrics. Finally, companies were classified in the test sample as prosperous and non-prosperous for all neural networks, and based on this, the quality and prediction ability of created models were identified.

It was found that research on the prediction of financial health offers a wide range of theoretical and empirical findings. However, compared to other research in this area, this study offers universal findings for Slovak companies from all industries, as comprehensive results are presented based on a large sample of Slovak companies. Moreover, the research methodology applies a multi-step solution known as the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology with the application of several types of neural networks and machine learning for determining prosperity in Slovak companies and high-performance indicators. This issue is not sufficiently explored in Slovakia. The results help identify the strengths and weaknesses of the company's management.

The main motivation is based on previous research on a comprehensive assessment of the financial condition of Slovak companies. However, this research usually used such traditional approaches as multidimensional discriminant analysis (MDA) or logistic regression (LR). In addition, models are usually country-specific and reflect a specific macro-environment, including economic and legal aspects of country management primarily, and thus, their use and predictive ability can be considerably limited under the conditions of the Slovak economy.

The research gap consists of identifying the prosperity of Slovak enterprises with a multi-step CRISP-DM methodology, multiple neural networks, and such machine learning as the Kohonen map.

The paper is divided into the following parts: a literature review, methodology, results, discussion, and conclusions. The literature review presents theoretical and practical findings from previous research emphasising the estimation of financial distress using neural networks. The methodology clearly describes the complete process of designing an ANN-based model and quantifying performance and the classification ability of companies into groups of prosperous and non-prosperous companies. The results demonstrate that individual and combined MLP-based models achieve a higher overall prediction ability than other neural networks. The discussion compares the findings with outputs from previous research. In addition, the key limitations are described, and new challenges are comprehensively explained relating to the financial condition of Slovak companies in future research. Finally, the major findings are summarised.

1. Literature review

Ravi Kumar and Ravi (2007) summarised research on financial distress, focusing on applications of statistical and intelligent techniques from 1968 to 2005. These techniques include statistical techniques, neural networks, case-based reasoning, decision trees, operational research, evolutionary algorithms, and rough set-based techniques. Perez (2006) also analysed 30 research studies on the neural network for estimating corporate health. Prusak (2018) similarly reviewed important information on previous research on estimating financial distress in Central and Eastern Europe based on a broad research survey from Google Scholar and Research Gate.

Mihalovič (2016) compared the overall performance of prediction models designed for Slovak companies. These models are created based on 236 companies using discriminant analysis and logistic regression. Logistic regression overcomes discriminant analysis. In addition, the results show that the most important indicators include net income to total assets, current ratio, and current liabilities to total assets. Moreover, Mihalovič (2018) proposed a hybrid model for Slovak companies based on financial statements from 2014 to 2017 using a genetic algorithm. The different models include the genetic algorithm neural network (GA-NN) model, the back-propagation neural network (BP-NN) model, and the MDA-based model. The predictive performance of the models determines that the GA-NN model is better than the others.

Balina et al. (2021) considered prediction models among the key tools in insolvency prediction for Polish companies based on such relevant methods as discriminant analysis, logistic regression, and decision trees. Their research primarily focused on construction companies. Geng et al. (2015) found that the accuracy of the neural network model is statistically significantly higher than the accuracy of other models in different time windows. On the other hand, the accuracy of majority voting is better than a neural network in a three-year and four-year time window. Dube et al. (2021) promoted neural networks as an alternative way of identifying financial problems for companies listed on the Johannesburg Stock Exchange (JSE) from 2000 to 2019. The neural network correctly identifies over 80 % of financial services companies and almost 97 % of manufacturing companies. Moreover, the model detects the problems up to five years before the bankruptcy. Shin and Lee (2002) emphasised that neural networks are an outstanding alternative to traditional methods of predicting financial distress. Horak et al. (2020) designed and compared six models based on Czech industrial companies using support vector machines and artificial neural networks. These models were compared to identify the most relevant model. Their study shows that a neural model is better than a support vector machine.

Zhang et al. (1999) presented potential possibilities for using neural networks to predict financial distress. The neural network classifies companies as healthy and unhealthy better than logistic regression. Korol (2019) applied various models such as fuzzy sets, recurrent and multi-layer artificial neural networks, and decision trees. One of the critical issues is to assess the effectiveness of prediction models. For example, the fuzzy model achieves more than 96 % correct bankruptcy classification one year before bankruptcy.

On the other hand, all dynamic models, such as fuzzy sets, multi-layer neural networks, and recurrent neural networks, demonstrate relevant approaches in estimating financial distress for outstanding results in the six years before the bankruptcy. The effectiveness for all models is more than 80 %. Dynamic models are better than the decision tree model in all years. The results show that the effectiveness of the dynamic tree model decreases with increasing forecast time. Zhou et al. (2010) explained that macroeconomic indicators affect corporate performance. Their findings demonstrate that the accuracy of the neural network model with macroeconomic variables is better for US businesses than the model without these indicators. Horváthová et al. (2021) concluded that neural networks are a suitable tool for identifying potential threats of financial bankruptcy compared to MDA-based models.

Papana and Spyridou (2020) proposed a prediction model for Greek companies based on four methods: linear discriminant analysis, logistic regression, decision trees, and neural networks. These models are based on 50 financial indicators divided into profitability, liquidity, contribution, efficiency, leverage, and other financial ratios. They found that nine indicators, such as earnings before interest and taxes (EBIT) to total assets, current assets to current liabilities, net earnings to total assets, total equity to fixed assets, fixed assets to total assets, total equity to total liabilities, reserves to total assets, and total equity to total assets, have statistically different averages between prosperous and non-prosperous companies. Total results for all proposed models show that discriminant analysis achieves the best overall performance compared to other models for predicting bankruptcy one year before. Conversely, the decision tree was the worst of all the models. Mateos-Ronco and Mas (2011) developed prediction models focusing on agricultural enterprises in Spain.

On the other hand, Becerra-Vicario et al. (2020) proposed a predictive model for Spanish restaurants using logistic regression and a deep recurrent neural network. This research is based on 28 financial indicators classified on efficiency, liquidity and cash flow, profitability, solvency, and non-financial ratios of 460 companies from 2008 to 2017. Data is drawn from the Iberian Balance Analysis System (SABI). The total sample is divided into a training (70 %) and a test (30 %) sub-sample. The results demonstrate that the neural network is better than logistic regression. Liquidity, profitability, and solvency ratios are important indicators. One of the non-financial indicators, such as quality certificate, is also statistically significant in predicting a company's financial distress. Moreover, the dataset includes other non-financial variables such as the company's age and status of belonging to a business chain.

Bagheri et al. (2012) found that the neural network model has better accuracy than the logistic regression model. Lee and Choi (2013) found that the BP-NN model is better than multiple discriminant analysis. These results are based on 100 financial indicators from 229 companies from various sectors, such as construction, retail, and manufacturing (91 companies in financial distress) from 2000 to 2009. These indicators are classified into five groups: growth, productivity, stability, liquidity, and asset quality. Using a t-test, they identified 46, 40, and 58 significant indicators out of all 100 for selected industries such as construction, trade, and manufacturing. First, productivity and liquidity are essential for the construction sector. Second, productivity and stability are important for business companies. And third, growth, productivity, and stability are the most important indicators of the production sector. In addition, the results demonstrate that asset quality is not an important indicator in all sectors. Finally, their research compared the accuracy of models on the BP-NN and multivariate discriminant analysis. The results show that the BP-NN model performs better in all sectors than discriminant analysis. Nevertheless, the model accuracy is higher than 80 % for the overall sample, regardless of the sectors. Azadnia et al. (2017) similarly estimated the financial distress of companies listed on the Iranian Stock Exchange based on such inputs as growth, profitability, productivity, and asset quality using fuzzy neural networks. This model achieves excellent performance in predicting financial distress. Moreover, Lee and Choi (2013) presented the relative strength of independent variables. At first, the most critical indicator is retained earnings to the total asset as part of stability. Secondly, productivity is important for the construction and manufacturing sectors. Operating income to the total asset has the highest weight (0.50) for construction companies, and the net profit ratio before income tax expense per capita has the highest weight (0.33) for construction companies.

2. Research methods

In modelling the financial status of Slovak companies, data was used of real Slovak companies from their financial statements from 2018 to 2019. This data was drawn from the Amadeus database by the Bureau von Dijk — Moody's Analytics Company based on their financial statements, such as balance sheets, profit and loss statements, and cash flow statements of all companies from the Slovak Republic. The original dataset consisted of partial data from more than 660 thousand companies. These were companies of various size categories (including micro-enterprises, SMEs, and large and very large enterprises) operating in any economic segment. Subsequently, the data were excluded from the database in the case of many companies that, based on the available data, did not continuously perform economic activities within the Slovak Republic or those for which financial data from both periods were unavailable. In addition, all redundant variables and duplicate cases were removed from this dataset. And for further work with the data, it was supplemented with unique anonymous identifiers.

After a detailed cleaning of the initial data, sixteen financial ratios were determined as potential predictors of non-prosperity. In addition, the company size and the industry were identified according to the terminology SK NACE rev. 2 as potential predictors. Finally, these financial and non-financial indicators from 2018 were used to model the financial status of Slovak companies in 2019.

Multicollinearity was analysed using a correlation matrix and variance inflation factors (VIF). Seven of the sixteen variables were excluded because of the high degree of multicollinearity. Thus, only nine financial ratios were finally identified as potential predictors (Tab. 1). These indicators belong to all four types: profitability, leverage, liquidity, and efficiency (activity) ratios.

The latest comprehensive data unaffected by the COVID-19 pandemic are from 2019. Therefore, the status "company in crisis" is used following the Slovak legislation of 2019 as a target variable for modelling non-prosperity in 2019. In total, 9 497 Slovak companies (12.6 % of all companies) have this status. Therefore, these companies represent samples of non-prosperous companies. On the other hand, 66 152 companies (87.4 % of all) are identified as

Tab. 1. List of potential predictors

Ratio	Ratio type	VIF
Asset Turnover Ratio (SAL/TA)	Efficiency (Activity)	1.614
Current Ratio (CA/CL)	Liquidity	1.741
Return on Equity (ROE)	Profitability	1.014
Return on Assets (ROA)	Profitability	2.484
Debt Ratio (TL/TA)	Leverage	1.840
Cash and Cash Equivalents to Total Assets (CASH/TA)	Liquidity	1.239
Return on Sales (ROS)	Profitability	2.323
Non-current Liabilities to Total Assets (NCL/TA)	Leverage	1.025
Liability Turnover Time (TL/SAL)	Efficiency (Activity)	1.776

Tab. 2. Basic descriptive characteristics of the final dataset

Characteristics	SAL/TA	CA/CL	ROE	ROA	TL/TA	CASH/TA	ROS	NCL/TA	TL/SAL
Mean	1.531	1.774	0.159	0.060	0.892	0.332	0.027	0.014	0.808
Median	1.185	0.940	0.127	0.041	0.820	0.219	0.021	0.000	0.626
Variance	1.968	5.260	0.175	0.033	0.366	0.103	0.019	0.001	0.577
Standard deviation	1.403	2.293	0.419	0.180	0.605	0.321	0.136	0.030	0.760
Minimum	0.000	0.000	-1.145	-0.578	0.000	0.000	-0.516	0.000	0.000
Maximum	7.165	16.060	1.492	0.755	2.982	1.988	0.632	0.152	4.040
Interquartile range	1.687	1.362	0.388	0.151	0.778	0.498	0.071	0.007	0.726
Skewness	1.290	2.667	0.175	0.267	0.933	0.830	0.141	2.766	1.863
Kurtosis	1.615	8.006	1.145	1.907	0.679	-0.511	4.029	7.069	3.620

prosperous. Such large disproportionality could significantly distort the models' learning, and especially their predictive ability. Therefore, 9 497 companies were randomly selected to create balanced samples and verified the sample representativeness.

The final data set contained the data of exactly 18 994 companies. Tab. 2 describes the basic statistics of financial ratios in the dataset. The characteristics of variability, especially the standard deviation and interquartile range, point to a relatively high variability of the values of individual variables. It can be deduced that these are not variables with a normal probability distribution based on the skewness coefficient and kurtosis coefficient values. However, this is not a problem because the artificial neural networks used in modelling do not require to meet the normality assumption. In addition to the financial ratios mentioned above, potential predictors were the company size and economic activity category indicators according to the SK NACE nomenclature. Considering the number of individual size categories, micro and small companies were merged into the category of small-sized companies. The second category was medium-sized companies, and the third category was large-sized companies created by merging large and very large companies. The distribution of size categories in a set of prosperous and non-prosperous companies is illustrated in Tab. 3.

The dataset was further divided into training (80 % of the whole) and testing (the remaining 20 %) samples. The test sample is used only for evaluating proposed models. These models are trained on a training sample using a five-fold cross-validation technique to avoid the overtraining problem of the models.

Artificial neural networks (ANNs) were applied to model the non-prosperity of Slovak companies. These models usually achieve a very high predictive ability. Furthermore, Multi-Layer Perceptron networks (MLP) and networks with a radial basis function (RBF) were created as an activation function. These two types belong to supervised learning algorithms. As a representative of unsupervised learning algorithms, Self-Organising Maps (SOM), also called Kohonen maps, were used.

MLPs are multi-layer ANNs. Zacharis (2016) explained that the typical ANN model consists of a three-layer network of interconnected nodes: the input, hidden, and output layers. Ayer et al. (2010) argued that the structure of biological neural networks inspires neural networks. Networks consist of highly interconnected nodes, and their overall ability helps to estimate output. These networks can solve complex problems because each hidden layer can extract features and recognise patterns from the input vector. The process classifies data for modelling the

Tab. 3. Size structure of companies in the final dataset

Category	Status of the company		Total	Percentage of total
	Prosperous	Non-prosperous		
small-sized	7970	8552	16 522	86.99 %
medium-sized	1368	800	2168	11.41 %
large-sized	159	145	304	1.60 %
Total	9497	9497	18 994	100 %

non-prosperity of companies. The sigmoid, hyperbolic tangent or Rectified Linear Unit (ReLU) function is often used as an activation function in these networks. RBF networks are three-layer neural networks, where the first layer is the input layer, the second (hidden) layer is formed by RBF neurons performing individual radial functions, and the third layer is the output layer and is formed by perceptrons. The activating function of process RBF neurons is some of the radial basic functions. The most used is the Gaussian function.

ANNs are created as individual or ensemble classifiers using boosting and bagging. These classification models classify companies into two groups: prosperous and non-prosperous.

Finally, Self-Organising Maps (SOM) developed by Professor Kohonen (so-called Kohonen maps) were applied. The Kohonen maps explain classification problems by creating clusters of neurons with similar properties. These networks (maps) consist of two layers of neurons, with learning taking place in the output layer in the form of competition. Clusters of similar neurons are formed in the output layer, for example, belonging to one of the classification classes. Each input layer neuron is connected to all output layer neurons. The Euclidean distance identifies the best neuron. One of the advantages of the Kohonen map is the visual presentation of any number of inputs through a two-dimensional grid consisting of output neurons. These clusters are interpreted with a two-dimensional lattice in which the same neurons are located close to each other.

The quality of all models is verified based on a testing sub-sample. Thus, a classification table (so-called confusion matrix) is compiled for the companies in this sample. The matrix determines the proportion of non-prosperous companies with correct classification (True Positives, TP) and non-prosperous companies with incorrect classification to prosperous companies (False Negatives, FN). Moreover, the matrix determines the proportion of prosperous companies classified as True Negatives (TN) and False Positives (FP). Based on the classification table, several qualitative metrics were derived. These metrics test the model's quality:

- Overall Accuracy — the ratio of correctly classified companies (in the whole test sample)

$$ACC = \frac{TP + TN}{TN + FN + FP + TP}$$

- True Positive Rate (sensitivity, TPR) — the ratio of correctly classified non-prosperous companies

$$TPR = \frac{TP}{TP + FN}$$

- True Negative Rate (specificity, TNR) — the ratio of correctly classified prosperous companies

$$TNR = \frac{TN}{TN + FP}$$

- Precise (PR)

$$PR = \frac{TP}{TP + FP}$$

- $F1$-score — frequently used measure of quality

$$F1 = 2 \cdot \left(\frac{PR \cdot TPR}{PR + TPR}\right)$$

- Mathews Correlation Coefficient (MCC) — equivalent to the classical Pearson correlation coefficient

$$MCC = \frac{TP \cdot TN + FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}.$$

Moreover, the Area Under the Curve (AUC) is applied, that is, the area under the Receiver Operating Characteristic (ROC) curve, which relates 1-specificity (1-TNR) with sensitivity (TPR). The maximum (the best) possible AUC value is one. If the AUC value is close to one, the model achieves high classification ability.

The preparation of the dataset, the creation of models and their validation were carried out in the data mining software IBM SPSS Modeler.

The models are designed as conceptual. Using the created models and their validation, an attempt was made to confirm the research hypothesis about the suitability of using neural networks in modelling the non-prosperity of Slovak companies. For a company outside the analysed sample, the output of the created models is a prediction in the form of classifying this company into a group of prosperous or a group of non-prosperous companies. In addition, the models will also determine the confidence of this prediction.

The paper's authors do not deal with deploying models in practice and, therefore, do not indicate how they could be used to predict financial problems. It is expected to validate and modify the created models on more recent data. Probably, other types of modelling algorithms will be used as well. Only then one final model will be created, which will have to be programmed and used as a software application for real prediction of imminent financial problems.

3. Research results

Data were used from a training sample of 15 235 companies (approx. 80 % of the total number) to create the model. This sample contains 7 629 prosperous and 7 606 non-prosperous companies. The company size (small, medium, and large), industry according to the SK NACE classification and nine financial ratios from 2018 were potential predictors for created models. The aim was to create the best possible models for predicting the non-prosperity in 2019 using such neural networks as MLP and RBF, which belong to supervised learning techniques and SOMs (or Kohonen maps) representing one of the unsupervised learning techniques.

The prediction ability of these models was analysed based on selected metrics calculated from the classification table and the AUC value based on a testing sample including 3 759 companies (approx. 20 % of the total number). Tab. 4 presents and compares these characteristics of the prediction ability for all created models. As demonstrated, the models achieved excellent and comparable results.

Several MLP-type networks were created on the training dataset. The architecture of the MLP network with one layer of hidden neurons, the hyperbolic tangent as the activating function of this layer and descending gradient method as the error minimisation approach proved optimal. The networks were trained as individual classifier MLP_simple and ensemble classifiers using bagging and boosting techniques (MLP_bagg and MLP_boost). The MLP_simple model is a simple topology perceptron neural network with eight neurons in a single hidden layer. It works with all potential predictors, but clearly, the most important is the Debt ratio (TL/TA), which follows from Fig. 1. Other important predictors are Return on Assets (ROA) and Current ratio (CA/CL). The prediction ability of the models is shown in Tab. 4. All these MLP-type models achieved excellent and comparable prediction ability. However, ensemble models achieved a higher predictive ability, which was expected. The MLP_boost and MLP_bagg models achieved the best results because, except for sensitivity (TPR), the values of all other quality characteristics are the highest for these models. The

Tab. 4. Comparison of the characteristics of the predictive ability of the created models

Classifier	*ACC*	*TPR*	*TNR*	*PR*	*F1*	*MCC*	*AUC*
MLP_simple	88.24 %	86.41 %	90.10 %	89.83 %	88.09 %	0.765	0.937
MLP_boost	88.61 %	85.72 %	91.54 %	91.12 %	88.34 %	0.774	0.945
MLP_bagg	88.61 %	86.24 %	91.01 %	90.66 %	88.39 %	0.773	0.944
RBF_simple	83.53 %	84.08 %	82.98 %	83.33 %	83.71 %	0.671	0.910
RBF_boost	85.34 %	87.41 %	83.24 %	84.08 %	85.71 %	0.707	0.928
RBF_bagg	84.49 %	86.94 %	82.01 %	83.03 %	84.94 %	0.690	0.919
Kohonen	80.50 %	80.49 %	80.51 %	80.70 %	80.59 %	0.610	0.895

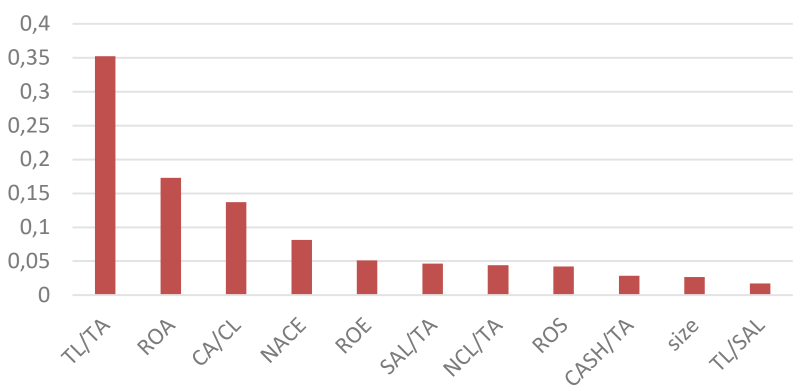

Fig. 1. Predictor importance in model MLP_simple

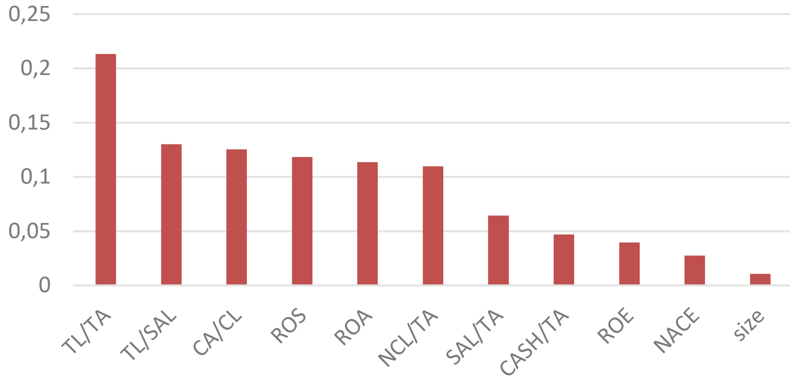

Fig. 2. Predictor importance in model RBF_simple

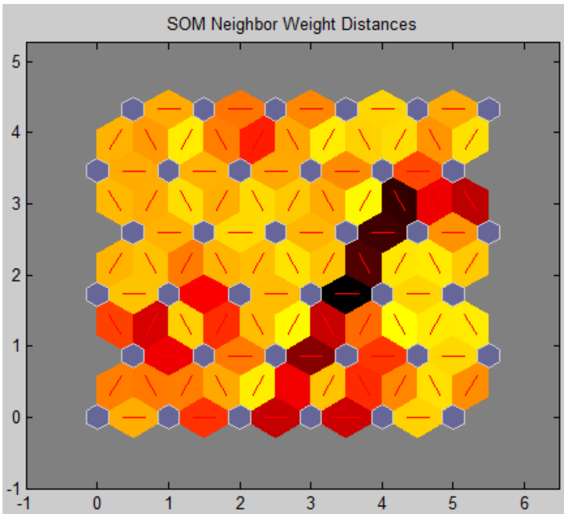

Fig. 3. Kohonen map

MLP_boost model is an ensemble of eleven networks, and the MLP_bagg model combines ten networks. Both models work with all potential predictors, but the most significant are TL/TA, TL/SAL, ROS, ROA, CA/CL, and CASH/TA.

RBF-type networks were also trained with the radial basis function under similar conditions as the activation function. Again, individual and ensemble models were created using the bagging and boosting technique. As shown in Tab. 4, RBF-type models also achieved a very high prediction. However, they do not reach the results of MLP-type models. The ensemble models RBF_bagg and RBF_boost achieved better results than the individual model RBF_simple. Both ensemble models outperform the other models in sensitivity (TPR), so in a set of truly non-prosperous companies, these models have identified companies at risk of financial problems.

The RBF_simple neural network with ten neurons in the hidden layer correctly classified only 83.53 % of companies from the test set. Like the MLP_simple model, this individual model works with all predictors, and the most significant one is the Debt ratio (TL/TA). It is interesting, however, that the values of the other five predictors (TL/SAL, CA/CL, ROS, ROA, and NCL/TA) are approximately equally significant in predicting the prosperity of Slovak companies, which is illustrated in Fig. 2. The mentioned six predictors were also the most significant in the RBF_boost and RBF_bagg ensemble models, where the RBF_boost model is a combination of nine RBF networks, while the RBF_bagg model is an ensemble of ten networks. Interestingly, in both models, all six mentioned predictors are equally significant.

Finally, the Kohonen map was applied to represent unsupervised learning techniques. Only an individual classifier was created that achieves a high prediction ability (ACC=80.5 %, TPR=80.49 %, TNR=80.51 %, PR=80.7 %, F1=80.59 %, MCC=0.61, and AUC=0.895). However, the prediction power is slightly lower than that of MLP-type and RBF-type networks. Interestingly, the Kohonen map classifies companies equally well in both groups of companies. It is because the difference between the sensitivity (TPR=80.49 %), which is the proportion of correctly classified non-prosperous companies, and the sensitivity (TNR=80.51 %), the proportion of correctly classified truly prosperous companies, is only 0.02 %. The output layer of the Kohonen map (Fig. 3) shows the two classification classes (prosperous and non-prosperous) using "pale" areas separated by a line of dark-red-coloured neurons.

4. Discussion of the results

Several prediction models were created based on several types of artificial neural networks. The models were trained (learned) and validated on precisely prepared data of real Slovak businesses from 2018 and 2019 for all of them from any economic segment and size category. The values of several financial ratios from 2018 serve to predict the financial status in 2019. This status can be the company's prosperity, in other words, the company's financial health, or non-prosperity, that is, the company's financial problems. Based on the validation of the quality of the created models on the test set, all models achieved very good results, illustrated in Fig. 4. In terms of overall predictive ability, the best results were achieved by MLP-based models, as they achieved the highest values in all overall quality metrics (ACC, PR, F1, MCC, and AUC). Compared to the individual classifier MLP_simple, the ensemble models MLP_boost and MLP_bagg achieved better (and thus overall best) results, as they correctly classified up to 88.61 % of the companies in the test set.

However, the mentioned models achieved a relatively lower sensitivity rate (TPR) compared to RBF-based models. Ensemble models of this type achieved sensitivities of 87 %, which means that in a group of non-prosperous companies in 2019, these models correctly identified their non-prosperity in 87 % of cases. The created Kohonen map achieved the lowest results of all models. Therefore, it proved unsuitable for modelling Slovak companies' prosperity.

Based on the results, MLP and RBF networks are suitable tools for modelling the non-prosperity of Slovak companies, especially in ensemble models. It confirmed the validity of the statutory research hypothesis. However, the created models must be further validated on newer data and possibly updated. Only then will it be possible and effective to put them into practice in (not only) Slovak companies from any economic segment and size category. However, some software implementation of the models will be required for this. However, this was no longer the subject of research and this paper.

Constantin and Clipici (2017), Kristianto and Rikumahu (2019) and others developed research on bankruptcy prediction models using neural networks. Similarly, Bielikova et al. (2014), Tumpach et al. (2020), and Korol (2020) examined the financial stability in Central Europe. Using the Kohonen map, Suler (2017) used data from financial statements and other predictors, such as the number of employees in construction companies from 2006 to 2015 in the Southern Bohemian region. On the other hand,

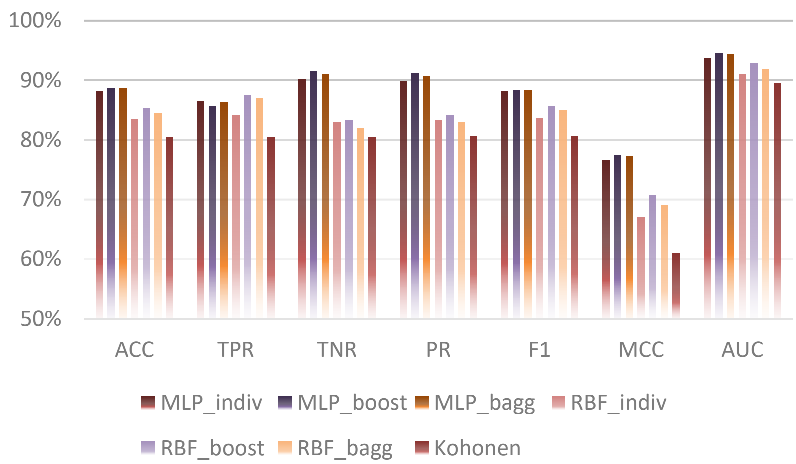

Fig. 4. Graphical comparison of the quality of the created models

a prediction model was proposed for all industries in the Slovak Republic.

Perez (2006) applied a fuzzy neural network for corporate bankruptcy prediction based on data from the companies listed on the Teheran stock exchange. The neural network includes four inputs: growth, profitability, productivity, and asset quality, and the output variable represents Altman Z-score. The model proposed in this paper achieved high model performance in estimating financial failure. It was determined that nine of 16 indicators could potentially estimate financial prosperity in all Slovak industries. These variables are identified based on a comprehensive process aimed at removing redundant indicators because of the high level of multicollinearity. Bagheri et al. (2012) built on previous research on listed companies from the Teheran stock exchange. The research compared ANN and logistic regression. The results demonstrate that neural networks achieved better predictive accuracy than the logit model. On the other hand, the research limitation is the sample size because the total sample consists of only 80 companies.

Similarly, Mokhatab Rafiei et al. (2011) classified healthy and unhealthy companies using ANN, genetic algorithm (GA), and MDA. Compared to other model techniques, the ANN model has the best predictive accuracy, specifically 98.6 % in the training sample and 96.3 % in the testing sample. It was designed based on 180 manufacturing companies on Tehran Stock Exchange for bankruptcy prediction one year before. Neural networks appear to be the popular approach in classifying companies as prosperous and non-prosperous in Iran compared to the Visegrad Group. In this paper, various individual and ensemble models, such as MLP, RBF, and Kohonen maps, were applied to improve predictive accuracy.

Callejón et al. (2013) proposed a neural network based on financial data from thousands of European manufacturing companies from 2007 to 2009. The data were obtained from the Amadeus database by Bureau van Dijk. The sample included 500 active and 500 insolvent companies from Germany, Denmark, Greece, Italy, France, Spain, Portugal, Finland, and Belgium. The indicators were divided into financial stability, profitability, efficiency, and firm size. The total dataset included 17 financial variables. The model correctly classified 92.56 % of companies in the training sample and 92.11 % of companies in a testing sample based on financial data for two years before the bankruptcy. Using the Deep Recurrent Convolutional Neural Network (DRC-NN), Becerra-Vicario et al. (2020) correctly classified more than 93 % of companies one year before bankruptcy, almost 90 % of companies two years before the bankruptcy, and more than 85 % three years before the bankruptcy. Their research filled the research gap in predicting financial failure in the hospitality sector in Spain.

Finally, Alamsyah et al. (2021) proposed three artificial neural models for several periods depending on the years before the bankruptcy. The results revealed that based on data on companies listed on the Indonesia Stock Exchange (IDX), the ANN-BP model achieved better predictive accuracy (95.6 %) for bankruptcy four years before compared to other models, predicting bankruptcy two or three years before.

Tab. 4. Summary overview

Authors	Data	Sample	Method	Country	ACC	TPR	TNR	MCC	AUC
Zhou et al. (2010)	1980–2006	1 924	MLPSig	USA	76.53	75.07	77.98	n/a	n/a
Zhou et al. (2010)	1980–2006	464	MLPSig	USA	78.61	81.37	75.74	n/a	n/a
Callejón et al. (2013)	2007–2009	1 000	MLP	A few EU countries	92.56	94.88	90.28	.85	n/a
Eriki and Udegbunam (2013)	1987–2006	44	NN	Nigeria	80.00	n/a	n/a	n/a	n/a
Ahmadpour Kasgari et al. (2013)	1999–2006	136	MLP	Iran	95.09	93.33	96.49	n/a	n/a
Mihalovič (2018)	2014–2017	1 280	BP-NN	Slovakia	81.15	n/a	n/a	n/a	n/a
Mihalovič (2018)	2014–2017	1 280	GA-NN	Slovakia	91.89	n/a	n/a	n/a	n/a
Becerra-Vicario et al. (2020)	2008–2017	460	DRCNN	Spain	95.00	n/a	n/a	n/a	.975
Our model	2017–2018	18 994	MLP_boost	Slovakia	88.61	85.72	91.54	.774	.945
Our model	2017–2018	18 994	RBF_boost	Slovakia	85.34	87.41	83.24	.707	.928

Horváthová et al. (2021) applied a feed-forward neural network and multivariate discriminant analysis. The results demonstrated that using the Brier score and Sommer's D in the Slovak heating industry, a neural network is better for assessing financial distress. Pakšiová and Oriskóová (2020) proposed a multi-layer artificial neural network based on 663 Slovak companies from five industries from 2014 to 2017. Gregova et al. (2020) found that neural networks have better model performance based on comparing three methods: logistic regression, random forest, and neural network. The Czech research on financial distress prediction is slightly more developed (Vochozka, 2017; 2018) than Slovak research. The author assessed financial distress in the Czech construction using MLP. Tab. 4 compares neural networks from multiple authors from different countries based on selected performance metrics. It was determined that the two best prediction models proposed in this paper achieved similar performance metrics compared to other models. However, the offered models are based on a sample several times larger than the models from previous research, so the results are more relevant.

Conclusions

This paper provides a set of models for early warning of potential financial problems in real-time for all Slovak industries. MLP and RBF achieved comparable results to the Kohonen map. Boosting and bagging techniques were applied to these neural networks. The results show that these combined models increase the predictive power of individual models. Finally, it was demonstrated that MLP networks achieve higher overall accuracy than RBF. However, the boosting RBF model achieves the highest predictive ability in identifying the non-prosperity of Slovak companies. This model can be applied to small and medium-sized enterprises from various industries. Financial management was optimised with machine learning techniques; these findings help financiers and managers create credit policies after programming them. The prediction model applies financial indicators with artificial intelligence to achieve high efficiency and accuracy in assessing financial conditions. The paper proposes a machine learning approach as a more appropriate methodology than traditional techniques for predicting a company's future financial problems. This approach improves managerial skills to understand complicated aspects and make better decisions. Lenders can use these models for estimating potential financial risks. On the other hand, investors use the application as a tool for investment decision-making. Finally, the model serves as a tool to maintain long-term sustainability.

Limitations. Various limitations of the conducted research exist. First, the neural network-based prediction model does not reflect the limited market opportunities of companies during the global COVID-19 pandemic and their impact on the entire financial and economic side of corporate governance. Second, the model could not be validated on other samples of companies from Central European countries. One of the disadvantages of neural networks is their difficulty in reproducing the model on other samples. A software application has to be created, with the help of which their application to new cases or whole samples of new cases is possible.

Future research. First, future research may focus on designing a comprehensive universal prediction model for companies in all Central European countries. Second, potential research may be focused on combining multiple neural network approaches as part of ensemble models. These models can improve performance metrics and better classification ability for prosperous and non-prosperous companies. Third, the proposed model can be compared with individual models based on other statistical approaches to reliably determine the corporate financial condition.

The paper highlights that neural network models are suitable for identifying financial distress. Therefore, neural networks help financial managers and stakeholders defend against unfavourable financial situations in decision-making. The presented models develop the existing theoretical approach, awareness, and knowledge of neural networks in risk management, focusing on companies from the Slovak Republic because previous research on predicting financial distress is not very developed in Central Europe. The results help to identify strengths and weaknesses in the company's financial management.

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