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SME Bankruptcy Prediction Using Convolutional Neural Networks

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Failure to repay obligations to creditors, whether credit institutions or business partners, causes serious economic problems not only for the debtor but also for its stakeholders. Preventing this problem requires identifying the potential threat. This paper explores the potential use of Convolutional Neural Networks (CNN) in identifying businesses at risk of bankruptcy. It is based on a graphical representation of differences in company performance and selected macroeconomic indicators. In our research, we used the GoogLeNet neural network architecture. The approach used allowed to display the financial situation of a company so that the generated CNN could identify active companies and companies at risk of bankruptcy with high accuracy. The procedure was applied to data of companies operating in the construction industry in the Czech Republic. The accuracy of the model was evaluated using receiver operating characteristic (ROC) curve and area under the curve (AUC). The use of CNN has yielded high forecast accuracy, demonstrating the ability to efficiently process graphical displays of financial data and capture differences between healthy and risky companies. The indicators identified in the constructed model can be used as input variables in an early warning system for financial distress.

Keywords: *Convolutional Neural Network; Bankruptcy; SMOTE; Financial Ratios; Macroeconomic Indicators; Construction.*

Introduction

Research has been conducted into the prediction of company bankruptcies for more than half a century now. Interest often increases in connection with a deteriorating economic situation for companies, as is the case today. Business failure can cause significant economic costs not only for business owners, but also for creditors, suppliers, customers and other stakeholders. The management of each company is faced with this problem when providing business loans associated with the sale of its products. In particular, businesses with a large number of customers have no chance of identifying a potentially insolvent customer with the use of ordinary risk assessment tools. The aim is to create automated credit risk management systems that can identify problem customers extremely quickly and provide this information to credit managers.

Research into the prediction of financial distress, particularly that of large companies, is a relatively frequent topic. Two basic trends can be observed in this area: Altman's approach utilising accounting ratios and Merton's structural approach based on the employment of market-driven variables (Karas, 2022). Less attention is paid to predicting the business bankrupt of small and medium-sized enterprises (SMEs), which is the predominant form of business in both the CEE region and the EU as a whole. Koleda and Lace (2009) and Ekes and Koloszar (2014) have focused on SMEs bankruptcy prediction in recent years. Both studies indicate that models originally developed using data from large enterprises do not yield satisfactory results when applied to SMEs bankruptcy prediction. This confirms the need to derive these models from SME-specific data and to explore new approaches to predictive model development to achieve the highest possible prediction accuracy. This is due to the limited availability of data and incomplete information. The development of deep learning and artificial intelligence (AI) can facilitate the resolution of problems associated with the prediction of financial distress in SMEs.

Traditional corporate bankruptcy prediction methods based on statistical models often face limitations in capturing complex, non-linear relationships between financial indicators. With increasing technological progress and the development of artificial intelligence, it is possible to improve existing prediction models and look for deeper links between individual indicators. Artificial intelligence methods based on deep learning are currently coming to the forefront. The use of deep learning models in the area of financial management is, however, extremely limited. An exception to this can be seen in publications considering the prediction of stock price fluctuations, where deep neural networks (most often recurrent neural networks) are used for time series analysis (Chong *et al.*, 2017; Jayanth Balaji *et al.,* 2018). One example of deep learning are convolutional neural networks (CNNs), intended primarily for the recognition of objects in images (Gao and Lim, 2019), which is employed primarily in self-driving cars (Farag, 2019). Their application also extends to other areas, such as voice processing (Mohamed *et al.,* 2012), text data (Mai *et al.,* 2019; Borchert *et al.,* 2023), electrical (e.g. ECG) signals (Zha *et al.,* 2019), and the detection of fraud in mobile telecommunications (Chouiekh & El Haj, 2018). There is, however, extremely little research presenting the application of CNNs in economics. This creates opportunities for innovative approaches, where numerical economic data are transformed into visual representations, such as graphs. This enables the use of CNNs to detect hidden patterns in the data that cannot be fully captured by numerical representation alone. The advantage of this method is that

CNNs can effectively analyse not only individual financial indicators but also their interrelationships and developmental trends. Integrating CNNs into economic models makes it possible to better capture non-linearity and complex relationships between variables, leading to the increased accuracy of forecasting and modelling. The publication by Hosaka (2019), who attempted to apply CNNs to the prediction of bankruptcy in Japanese companies traded on the stock exchange, can be given as an example of one of the few such applications.

The principal goal of our research is to create a bankruptcy prediction model using a CNN. It was first necessary to create a dataset of the accounting data of small and medium-sized enterprises operating in the construction industry that contained both data on financially healthy (active) enterprises and data on enterprises with financial problems. We allocated data covering three years to each company, from with we calculated 45 financial ratios in each year. We subsequently reduced the number of indicators by excluding one of the highly correlated indicators from further processing. The problem of an unbalanced dataset had to be resolved in view of the fact that the number of companies with financial problems is significantly smaller than the number of financially healthy companies. The SMOTE (Synthetic Minority Oversampling Technique) method, which allows the expansion of the dataset to include additional observations, was used to resolve this problem. This method was chosen for its ability to generate new cases from existing data without creating duplicates of the original samples. This helps to reduce overfitting while preserving valuable information (Fernandez *et al.,* 2018). Graphical representations of financial ratios and macroeconomic indicators were then generated using MATLAB software and served as input variables for neural network learning models. This software was also used to develop predictive models. Statistical analysis was performed using IBM SPSS Statistics. The CNN is applied to SMEs in the construction industry. These companies have a large number of suppliers and the sector holds a significant position in the economy. Although the number of bankrupt companies in this field is relatively large, the corresponding attention is not paid to this in bankruptcy prediction. The dataset created was divided into a training subset and a validation subset, while various ratios for the division of the set into these subsets were tested. In contrast to the research conducted on the data of Japanese companies (Hosaka, 2019), we tested several variants of the graphical representation of financial data (financial ratios). The results obtained show that CNNs make it possible to identify companies at risk of financial problems with great accuracy.

An Overview of the Literature

Approaches to the creation of bankruptcy models can be divided into models using statistical techniques and models based on soft computing techniques that solve the problem with the use of artificial intelligence. Altman's Z-score was one of the first and most famous bankruptcy prediction models. This model, like many of those that followed, is created by the linear discriminant analysis method and derived from data on large companies operating in the manufacturing industry. Parametric classification methods have also been used in other models (e.g. Zmijewski, 1984; Shumway, 2001, and many others). Their common feature is a focus on large enterprises. Non-parametric classification methods such as classification and regression trees, artificial neural networks, etc. only began to be used later, and attention also began to be paid to SMEs. One of the first studies considering prediction in SMEs was the work by Cressy (1992), though he did not, however, consider it necessary to create a specific model for this group of companies. Altman and Sabato (2007) published a default prediction model derived from data on SMEs with the use of parametric classification methods. This model achieves significantly greater accuracy than other models that have been applied to SMEs. As mentioned previously, another challenge in bankruptcy prediction is the transferability of models. Laitinen and Suvas (2013) tested the accuracy of a model across 30 countries and found that its performance varied significantly across countries. This model was developed using data from all the countries studied. Individual models (derived from the data of each specific country) achieved higher accuracy in identifying bankrupt firms. Factors that cause differences in the accuracy of the models are the concept of liquid assets (liquidity), which may have different content in some European countries, and the volatility of profitability. The explanation for these differences lies in the different legal frameworks and established business practices in each country. These findings clearly confirm the need to develop country-specific models, even if they share the same variables. A similar conclusion was reached by Kovacova et al. (2019) and Prusak and Karas (2024) in their research based on data from V4 countries.

According to Bellovary et al. (2007) and Jones (2023), neural networks, along with multivariate discriminant analysis, are the most promising methods for bankruptcy prediction models. Neural networks, and in particular multilayer neural networks, have been used to design bankruptcy models since the beginning of the 1990s (Du Jardin, 2021). Geng et al. (2015) claim that neural networks are the most effective model for predicting the bankruptcy of companies and, as a non-linear mathematical approach, achieve better results than other classification methods. When comparing prediction accuracy three to five years before bankruptcy, neural networks achieve results 5 to 20 percent better than models created using decision trees or support vector machines (Geng *et al.,* 2015). A model based on a multilayer perceptron has been developed by Brenes et al. (2022). The authors investigated the effect of various settings of the parameters of the neural network, such as the optimisation algorithm, the activation function, the number of neurons and the number of network layers, on prediction accuracy. Twelve different models are published in their paper. The accuracy of the best model achieved a value of 86.06 %. The connection of neural networks with genetic algorithms, which are used in models to set the weights of the neural network, threshold values and the number of hidden nodes, have become extremely popular among authors. Mohamad et al. (2014) reached the conclusion that their hybrid model achieved a better predictive ability than a model based on neural networks alone (the accuracy of prediction increased by an average of 4 pp. with the use of genetic algorithms).

Deep learning is a relatively new field of machine learning. A bankruptcy model based on deep neural networks of the Deep Dense Multilayer Perceptron type was created by Alexandropoulos et al. (2019). The authors used the financial indicators of 50 bankrupt and 150 active Greek firms over a three-year period. These companies came from 24 different branches of industry. Their results indicate that they achieved results 4 to 7 pp. better than the other algorithms investigated (logistic regression, multilayer perceptron, classification and regression trees, *Naive Bayes*) two years and one year, respectively, before bankruptcy with the use of a deep neural network. A model for predicting the bankruptcy of Australian businesses using financial data was developed by Elhoseny et al. (2022). They used the adaptive whale optimisation algorithm with deep learning technique (AWOA-DL) to develop their model. The results show that the proposed model was able to predict the financial distress of companies with 95.8 % accuracy.

Bankruptcy prediction using CNNs can be found for the first time in the research by Hosaka (2019), who created a neural network with input variables in the form of greyscale pixel images. He used data on a total of 2,164 publicly traded Japanese companies in his model. He used the GoogLeNet architecture to train his CNN. He achieved a prediction accuracy of 91.4 % for active companies and 88.9 % for bankrupt companies. Ben Jabeur and Serret (2023) proposed a combined method of company bankruptcy prediction based on the qualitative approach of fuzzy sets and CNN. They used a sample of French companies from 2014−2016 in their research. Their model achieved the highest prediction accuracy of 95 % one year before bankruptcy.

Another topic discussed in the published studies is the selection of financial indicators used to predict bankruptcy. Given the definition of bankruptcy (the inability to meet financial obligations), it is reasonable to use liquidity indicators for bankruptcy prediction. However, these indicators are highly sensitive to the current financial situation and may fluctuate almost daily (especially the cash liquidity ratio), which reduces their predictive power. A more reliable indicator in this respect is current liquidity. Therefore, it is essential to examine the sources of a company's income (cash flow to the firm) and its expenditure. This leads us to operating cash flow or EBITDA, which represents operating profit adjusted for depreciation and serves as an approximation of operating cash flow. In the bankruptcy models, these indicators are mostly in the form of profitability ratios, such as operating profit to sales or assets, EBITDA to sales and operating profit to assets. A company with consistently high profitability over the long term tends to be more stable, has an optimised financial structure, and is able to invest in new technologies and development. Its stability is less affected by changes in external conditions, whether macroeconomic or industry-specific. A company's expenditure is affected both by its compulsory payments (e.g., loan repayments, including financial leasing, interest payments, etc.) and by the cost of input factors (materials, energy, services, wages). As expenditure on inputs is reflected in profitability ratios, there is no need to track them separately in bankruptcy prediction models. Instead, the focus should be on expenditures related to the company's financing sources. These include dividends, but more importantly, mandatory debt repayments and interest payments. The ability to service debt is incorporated into bankruptcy prediction models through indicators such as debt maturity, interest coverage, and leverage ratios. A wide range of financial indicators can be used for any financial aspect affecting the stability of a company. For our research, we used financial indicators of companies that had been identified as statistically significant in earlier research. The most frequent indicators (see Table 1) include the current ratio (current assets to current liabilities, CA/CL), working capital to total assets (WC/TA) (Korol, 2019), total liabilities to total assets (TL/TA) (Prusak, 2018; Brenes *et al.,* 2022; Valaskova *et al.,* 2023), different variants of the return on assets (EBIT/TA, EAT/TA or EBITDA/TA) and return to sales (Korol, 2019; Dvorsky *et al.,* 2023). Most models use indicators on just one year (specifically, the year before bankruptcy), which Balcaen and Ooghe (2006) consider to be a weakness of bankruptcy prediction models. In view of the fact that the deterioration of a company's financial situation occurs gradually, these authors used what are known as change indicators, which express the year-on-year change (growth or decline) of the indicator. The change in total assets (ΔTA) or the change in sales (ΔS) (Tian and Yu, 2017), or the size of the company (logarithm of assets) might be mentioned here. In our research, we used indicators from three years before the bankruptcy. This allowed us to see the trend in their development.

As mentioned, some authors have also incorporated macroeconomic indicators into their models (Nouri & Soltani, 2016; Veganzones & Severin, 2020; Karas, 2022, and others). This approach assumes that the economic situation of firms is influenced by external conditions and combining corporate and macroeconomic indicators can contribute towards increasing the discriminatory power of models. Liou and Smith (2006) include inflation among the most important indicators. The growth of gross domestic product can be mentioned as another indicator. This indicator was used by Wijaya and Anantadjaya (2014), who hypothesise that increased demand and increasing purchasing power reduce the risk of company bankruptcy. Castro (2013) used interest rates, the growth of which has a positive effect on the occurrence of the risk of bankruptcy, in his model. Memon et al. (2015) found that interest rate variability reduces the accuracy of a bankruptcy model. Construction is a sector that reacts extremely sensitively to the economic development of the country or, under the conditions of globalisation, to worldwide economic development (see, for example, Carling *et al.,* 2007), because its development is significantly influenced by the volume of public contracts and the availability of external financing, in particular bank loans (Karas & Reznakova, 2017). The inclination to build bankruptcy models using macroeconomic indicators stems from the varying accuracy of models derived from firm-level data in different countries (see Belloway *et al.,* 2007).

The list of indicators used is given in the section Data and Methodology.

Data and Methodology

For our research, we used the financial statements for the years 2014–2021 of private companies based in the Czech Republic that are engaged in business in construction (F – Construction, according to the CZ NACE classification). The construction industry is one of the key sectors in the Czech Republic, ranking among the top three in terms of output and number of employees. However, approximately 15% of all bankrupt companies each year come from this sector, making it the second most affected industry in terms of bankruptcies. Only data on companies with complete financial statements were used in the research. The companies belonged to the category SMEs as defined by Directive 2013/34/EU. A bankrupt company was defined as a company in bankruptcy or a company in insolvency proceedings, i.e. a company unable to pay its obligations due to over-indebtedness.

We obtained accounting data from the Amadeus and Orbis databases. This data were supplemented by macroeconomic indicators for the same period. In the case of bankrupt companies, we used data for the three years before failure (t-1, t-2, t-3) on companies that went bankrupt in the years 2014–2021. This data was supplemented by the financial statements of financially sound businesses corresponding to the given time period. The final dataset was made up of a total of 520 businesses, of which 69 were bankrupt (and 451 were active).

Based on a literature review, we identified a total of 179 financial indicators that authors have used in bankruptcy prediction models. In our research, we use the 36 most frequently cited financial indicators (each used in at least five studies) and nine macroeconomic indicators (see for example Alaka et al. (2016), Ben Jabeur (2017), Tian and Yu (2017), Volkov et al. (2017), Huang a Tserng (2018), Korol (2019), Balina et al. (2021), Brenes et al. (2022) or Valaskova et al. (2023)). The indicators used are listed in Table 1.

Table 1

Financial Ratios and Macroeconomic Indicators

Financial ratios					
No.	**Abbreviation**	**Indicator**	**No.**	**Abbreviation**	**Indicator**
1	*CA/CL*	*Current assets/current liabilities*	19	TL/E	Total liabilities/equity
2	*TL/TA*	*Total liabilities/total assets*	20	EBIT/S	EBIT/sales
3	*S/TA*	*Sales/total assets*	21	*I/dS*	*Inventories/daily sales*
4	*EBIT/TA*	*EBIT/total assets*	22	LL/E	Long-term liabilities/equity
5	*WC/TA*	*Working capital/total assets*	23	QA/CL	Quick assets/current liabilities
6	*C/CL*	*Cash/current liabilities*	24	S/R	Sales/accounts receivable
7	QA/CL	Quick assets/current liabilities	25	*WC/S*	*Working capital/sales*
8	*CL/TA*	*Current liabilities/total assets*	26	*CF/TL*	*Cash flow/total liabilities*
9	EAT/S	EAT/sales	27	CL/dS	Current liabilities/daily sales
10	*CF/S*	*Cash flow/sales*	28	EBITDA/TA	EBITDA/total assets
11	*C/TA*	*Cash/total assets*	29	EBT/S	EBT/sales
12	*CA/dS*	*Current assets/daily sales*	30	LL/TA	Long-term liabilities/total assets
13	CL/TL	Current liabilities/total liabilities	31	R/dS	Receivables/daily sales
14	EAT/TA	EAT/total assets	32	S/CA	Sales/current assets
15	*CF/TA*	*Cash flow/total assets*	33	S/FA	Sales/fixed assets
16	*CA/TA*	*Current assets/total assets*	34	ΔTA	Change total assets
17	*E/TA*	*Equity/total assets*	35	ΔS	Change sales
18	*A*	*Log of total assets*	36	TL<>TA	Are Total Liabilities higher than Total Assets? Yes = 1, No = 0

Macroeconomic indicators			
Abbreviation	**Indicator**	**Abbreviation**	**Indicator**
TOut	Output Total (mil. CZK)	INFL	Inflation rate Total (%)
COut	Output Construction (mil. CZK)	PRIBOR	Prague InterBank Offered Rate (in %)
TGDP	GDP Total (mil. CZK)	REPO	REPO rate (annual average %)
TGVA	GVA Total (mil. CZK)	UNEMP	Unemployment rate (%)
CGVA	GVA Construction (mil. CZK)		

Research questions (RQ) were determined on the basis of the review of the literature:

RQ1: Which financial indicators are most suitable for predicting the bankruptcies of construction companies in the Czech Republic?

RQ2: Does the use of a convolutional neural network model for the prediction of company bankruptcy result in high efficiency?

RQ3: Which type of data visualisation is most appropriate for the prediction of company bankruptcy?

During the preparation of the data for processing, we first identified extreme values using Grubbs' test. These values of financial indicators were removed from the dataset using a Winsorised Mean, which replaces a certain percentage of extreme values (on both the minimum and maximum side) with a less extreme neighbouring value. We then considered the selection of financial ratios that are suitable predictors. The Mann-Whitney U test was used for this purpose (McClenaghan, 2022). This test identified financial ratios for which there is a statistically significant difference between the groups of bankrupt and active businesses. The Mann-Whitney U test was used due to its robustness to outliers. This test does not require the input data to follow a normal distribution, which is often not the case for financial data. The strength of the relationship between individual indicators was measured using Spearman's rank correlation coefficient. Forward and backward logistic regression, for which the significance of indicators was assessed on the basis of the Wald test, was used for the final selection of predictors.

Predictive models and neural networks need a large number of observations in order to learn, and this is a problem in the case of companies facing financial difficulties. There is often a disparity between the amount of data on active and bankrupt companies, and this can affect the resulting accuracy of the model. We used the synthetic minority oversampling technique (SMOTE) to alleviate the impact of this problem. This algorithm applies an oversampling approach to rebalance the original training set. The key idea of SMOTE is to create synthetic examples by interpolation between several positive instances that lie together. The procedure works as follows. First, the total amount of oversampling *N* is set up (an integer value), after which an iterative process is carried out. From minority class samples a positive class instance is selected at random from the training set k-nearest neighbours *K* (5 by bankcupt) are determined for the selected instance. Finally, *N* of these *K* instances are chosen at random to compute the new instances by interpolation. The difference between the feature vector (sample) under consideration and each neighbour is multiplied by a random number drawn between 0 and 1, and is then added to the previous feature vector (Fernández *et al.,* 2018).

Neural networks are an advanced artificial intelligence tool that is widely used in predictive analysis of economic data. They consist of interconnected layers of artificial neurons. One of the most commonly used training methods is the backpropagation algorithm, which minimises the difference between the expected and actual outputs of the model (Munakata, 2008). CNNs, which were pioneered by Szegedy et al. (2015), are particularly effective in analysing two-dimensional data, such as visual representations of economic indicators (Jirkovsky, 2018a). A key component of CNNs are convolutional layers, which extract information using filters. The structure of these networks enables the identification of fundamental features (such as light and dark areas, edges) in the initial layers, while deeper layers capture more complex patterns. Due to its high computational demands and the need for large training data sets, transfer learning is often applied in economic applications. This method allows for fine-tuning of pre-trained models, which significantly improves efficiency (Jirkovský, 2018b). Among the most well-known architectures are GoogLeNet and AlexNet. In this research, we used the GoogLeNet architecture, which processes visualised economic data with dimensions of 224 × 224 pixels. Its implementation demonstrates that deep learning can significantly contribute to the analysis and prediction of economic trends, such as assessing the financial stability of companies or detecting anomalies in accounting data.

Given that CNNs achieve the best results in image processing, it was necessary to process the values of the indicators (variables) used graphically. The goal was to present a graphical display of data to the prediction model that would reflect the financial situation of a company over time. All indicator values were normalised to the range [0–1], and their graphical representations, generated using MATLAB software, served as input variables for the models (Figure 3). The graphical representations AREA, PLOT, and BARH follow standard visualisation methods, displaying the indicator values through different types of graphs. For the IMAGE I and IMAGE II visualisations, the indicator values are represented in grey scale, where 0 corresponds to black, 1 to white, and intermediate values represent shades of grey.

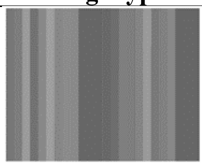
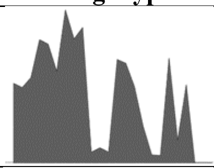
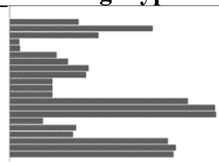
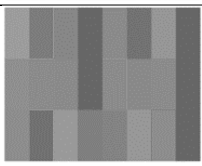
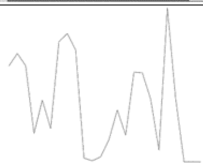
Label	Image type	Label	Image type	Label	Image type
IMAGE I		**AREA**		**BARH**	
IMAGE II		**PLOT**			

Figure 3. Types of Graphical Processing of Indicators

We created several types of models in our research and analysed which type of image best differentiates between active businesses and bankrupt businesses. The number of samples of bankrupt companies was increased by a factor of 1.5 using the SMOTE method, and the expanded dataset (while maintaining the number of active companies) was divided into training data (437 samples) and validation data (187 samples). Training data was used to learn the model and validation data to verify its functionality. The basic CNN parameters for all tested models were set as follows in order to maintain the same conditions for neural network learning: architecture used – GoogLeNet, number of epochs = 40, Mini Batch Size = 5, ratio of training and validation data = 70:30, Initial Learn Rate = 0.0003, Weight Learn Rate Factor = 1; Bias Learn Rate Factor = 1. In the training process, an epoch refers to a complete pass through the entire set of input data used for model learning, during which a series of computations are performed. Each training epoch consists of several iterations. For CNNs, the iteration size is determined by the mini-batch size, which represents a subset of training images used to update weights during each iteration. In Fully Connected Layers and Convolutional Layers, the Weight Learn Rate Factor and Bias Learn Rate Factor can be adjusted to refine the model's classification accuracy. CNNs multiply these factors by the Initial Learning Rate to determine the learning rate for weights and bias in a given layer.

The training of the network was halted after the maximum number of epochs and its accuracy recorded. The goal of this phase was not yet to achieve the greatest possible discriminatory accuracy, but rather to determine which variant of input data is the most suitable for predicting financial failure. The model that achieved the best results in this basic trial was further fine-tuned to classify businesses as accurately as possible. The accuracy of the final model was verified on validation data (coming from the original dataset for model training) and test data (new data on 105 enterprises that were not used for model training).

The discriminatory ability of the model was assessed using the area under the ROC curve (AUC – Area Under the Curve) which establishes the quality of class classification. The ROC curve is a tool for evaluating and optimising binary classification problems (Huang and Tserng, 2018). It depicts the relationship between *specificity* and *sensitivity*, where Specificity = TN/(TN+FP) and Sensitivity (Recall) = TP/(TP+FN), where *TP* (*true positive*) is the number of correctly classified bankrupt businesses, *TN* (*true negative*) is the number of correctly classified active enterprises, *FP* (*false positive*) is the number of active enterprises that the model identified as bankrupt, and *FN* (*false negative*) is the number of bankrupt enterprises that were identified by the model as active.

The values of *1 – Specificity* (or the rate of false positive cases) are shown on the *x-axis* and the values of *Sensitivity* are shown on the *y-axis* of the ROC curve graph (Huang and Tserng, 2018). Assuming that the ROC curve is labelled as a function of *f*, the AUC is defined by the following expression (Zhang et al., 2015):

$$\mathrm{AUC} = \int_0^1 \mathrm{f(FPrate)\ d\ FPrate} = 1 - \int_0^1 \mathrm{f^{-1}(TPrate)\ d\ TPrate} \quad (1)$$

where *FPrate* = FP/(FP+TN) and *TPrate* = TP/(TP+FN).

Another metric that can be used to measure the accuracy of a model with an unbalanced dataset are F-measures (also referred to as an F-score). Its calculation is given by the relation:

$$\mathrm{F-measures} = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (2)$$

Precision (TP/(TP+FP)) is a metric that quantifies the proportion of correctly identified bankrupt businesses out of the total number of businesses identified as bankrupt (positive cases identified). *Recall* (TP/(TP+FN)) is a metric that quantifies the proportion of correctly identified positive cases (bankrupt enterprises) out of all positive (bankruptcy) cases. A result in the <0,1> interval, where 1 means the greatest accuracy, can be achieved for both indicators of accuracy.

Results

Grubbs' test identified 31 (for active companies) and 33 (for bankrupt companies) financial ratios that contained extreme values in the original data. The replacement of these values with a 5 % Winsorised mean eliminated extreme values for all financial ratios (again verified by Grubbs' test at the 5 % level of significance). Indicators for which there was a statistically significant difference between the groups of active and bankrupt enterprises were identified using the Mann-Whitney U test. An indicator was removed in the event that no statistically significant difference (at a level of significance of α=0.05) was identified between the groups of enterprises for the given indicator in any of the three years.

All values of the given indicator were retained if the indicator was identified as statistically significant in at least one year of the three-year period studied. The reason for this is an attempt to create a model that captures the development of financial indicators in the last three years before bankruptcy. A statistically significant difference was not identified in any year for six indicators (CA/TA, CL/TL, S/FA, S/R, WC/S and WC/TA).

The remaining 39 indicators were tested using Spearman's rank correlation coefficient. For indicators with an absolute correlation coefficient greater than 0.8, one of the correlated indicators was removed. When eliminating strongly correlated indicators, the selection was based on the frequency of dependencies with other indicators or, where applicable, on the indicator's ability to discriminate between active and bankrupt companies using the Mann-Whitney U test. The total number of indicators was reduced to 22. Forward and backward stepwise regression was subsequently performed on these indicators, and indicators that are statistically significant for the classification of bankrupt and active companies (p-value < 0.05) were selected. The Wald statistic results (Table 2) indicate that the most significant predictors in both groups of indicators are the logarithm of assets (A), ratio indicators CL/TA and TL/TA, and information on whether the company has greater total liabilities or assets (TL<>TA). No statistically significant correlation was observed between the selected indicators that would warrant the exclusion of any of them from the model.

The results obtained made it possible to answer research question RQ1. For active and bankrupt companies in the construction industry in the Czech Republic, there are indicators that are able to identify whether the company is headed for bankruptcy or not. The most significant predictor of bankruptcy is the logarithm of assets, which is confirmed by, for example, the research by Tian and Yu (2017), as well as the ratio of short-term liabilities to total assets. The third strongest predictor was the ratio of profit after tax to sales, which was also used by Huang and Tseng (2018). The logarithm of assets serves as an indicator of the size of the enterprise, confirming the assumption that larger enterprises are less prone to bankruptcy. The short-term liabilities to total assets ratio measures the proportion of a company's assets financed by short-term liabilities. This indicator shows that short-term financing is predominant in the Czech construction industry. A high value of this indicator may signal a mismatch between the maturity of liabilities and the lifespan of assets, which could indicate a risk of insolvency. Given that construction companies typically do not have a high proportion of fixed assets (as, under Czech accounting standards, assets acquired through financial leasing are not recorded in the balance sheet), the relevance of this indicator is entirely logical. It represents one of the less traditional measures of a company's (in)solvency. The profit after tax to sales ratio measures a company's ability to generate profit per unit of revenue and generate cash. The higher this ratio, the lower the probability of bankruptcy, even in deteriorating economic conditions. The use of this indicator for bankruptcy prediction is well justified.

Table 2

Reduced Number of Indicators Based on Logistic Regression

Indicator	Forward regression		Backward regression	
	Wald (Stat.)	p	Wald (Stat.)	p
A	83.4297	**0.0000**	74.3135	**0.0000**
CL/TA	19.8645	**0.0000**	18.7284	**0.0000**
EAT/S	10.0023	**0.0016**	10.1855	**0.0014**
I/dS	14.1247	**0.0002**	13.9045	**0.0002**
TL/TA	33.8007	**0.0000**	27.9910	**0.0000**
ΔTA	9.4373	**0.0021**	8.4016	**0.0037**
TL<>TA	26.3062	**0.0000**	22.2642	**0.0000**
TGDP	6.1989	**0.0128**		
C/TA			4.2587	**0.0391**
S/I			4.2749	**0.0387**
COut			5.3976	**0.0202**
INFL			4.8953	**0.0269**
PRIBOR			5.7422	**0.0166**

Selected indicators were graphically displayed using MATLAB and utilized to develop models using CNN. In the dataset used, only 13% of the data represented bankrupt companies. Therefore, we had to address the issue of mitigating the risk of model bias in favour of financially healthy companies. The number of observations in the group of bankrupt companies was increased using the SMOTE method. The best results (Table 3) in all studied categories of accuracy were achieved by the model with graphical input processing of the PLOT type.

Table 3

The Overall Accuracy and F-Measures of Models

Type of image	Forward regression				Backward regression			
	Overall accuracy		F-measures		Overall accuracy		F-measures	
	Training	Validation	Training	Validation	Training	Validation	Training	Validation
AREA	0.9977	0.8984	0.9959	0.8119	0.9886	0.8717	0.9798	0.7647
PLOT	0.9977	0.9144	0.9959	0.8462	1.0000	0.8824	1.0000	0.8000
BARH	0.9908	0.8984	0.9835	0.8224	0.9840	0.8717	0.9714	0.7736
IMAGE I	0.9611	0.8984	0.9270	0.8041	0.9222	0.8342	0.8509	0.6990
IMAGE II	0.9817	0.9091	0.9661	0.8350	0.9748	0.8824	0.9547	0.7925

These results clearly indicate that it is possible to use CNNs to identify the imminent bankruptcy of companies with high accuracy (RQ2). The subsequent accuracy of the model is affected by the choice of graphical data processing (RQ3). The lowest discriminatory accuracy of prediction was achieved on the validation data of the model with an IMAGE I display type. In contrast, the best results were achieved using a model with graphical processing of the PLOT type and variables obtained using forward logistic stepwise regression. This model was further fine-tuned using variable parameters that affect the final accuracy of the classification of businesses and that had fixed values during the initial testing of the models (see Data and Methodology). The variable parameters of the model are the size of the dataset, with a varying amount of artificially created data on bankrupt companies tested using the SMOTE method (138, 173, 207, 242, 276 bankrupt companies), a number of epochs in the interval 1–80, an initial learning rate at values of 0.0001, 0.0002 and 0.0003, Mini-Batch size in the interval 2–10, and a ratio of training and validation data at ratio variants of 50/50, 55/45, 60/40, 65/35, 70/30, 75/25, 80/20, 85/15 and 90/10. The most accurate models selected on the basis of the above characteristics come from a dataset of 173 bankrupt and 451 active enterprises. The parameters of the models are as follows:

- **Model 1** – 36 epochs, Initial Learning Rate = 0.0001, Mini-Batch size = 5, 70 % data used for training and 30 % data used for model validation.
- **Model 2** – 54 epochs, Initial Learning Rate = 0.0002, Mini-Batch size = 5, 70 % data used for training and 30 % data used for model validation.
- **Model 3** – 73 epochs, Initial Learning Rate = 0.0003, Mini-Batch size = 9, 70 % data used for training and 30 % data used for model validation.

For testing the best models, validation and test datasets were used:

- **Validation data** – sourced from the years 2011–2018. This subset of the original dataset was not used for model derivation but was used to assess model accuracy.

- **Test data** – sourced from the years 2012–2021. This is new data not previously encountered by the model and was used to evaluate its predictive ability on real, unseen data.

Based on individual characteristics (Precision, Recall), the value of F-measures was calculated for the individual models (Table 4), according to which Model 1 achieves the best results. The suitability of the choice of this model is also confirmed by AUC values (Table 5).

Table 4

Performance Metrics of Selected Models

Model	Validation data			Test data		
	Precision	Recall	F-measures	Precision	Recall	F-measures
Model 1	0.8868	0.9039	0.8952	0.9024	0.8222	0.8605
Model 2	0.8704	0.9039	0.8868	0.9000	0.8000	0.8471
Model 3	0.8571	0.9231	0.8889	0.8780	0.8000	0.8372

Table 5

Results of the Models when Changing Variable Parameters

Model	Validation (in %)		Test (in %)		AUC	
	Active	Bankrupt	Active	Bankrupt	Validation	Testing
Model 1	95.56	90.38	93.33	82.22	0.9614	0.9211
Model 2	94.81	90.38	93.33	80.00	0.9567	0.9152
Model 3	94.07	92.31	91.67	80.00	0.9614	0.9122

The selected Model 1 was further tested at different values of the Weight Learn Rate Factor and Bias Learn Rate Factor (in the interval 1–10) in order to increase the accuracy of the model. The best results were achieved when the Weight Learn Rate Factor was kept at the original value of 1, while the value of the Bias Learn Rate Factor was changed to 8. Based on these variable parameters, the model whose training was performed in 36 epochs, with the number of bankrupt businesses increased by a factor of 1.5, the Initial Learning Rate set to 0.0001, the Mini-Batch size = 5, the ratio of training and validation data set to 70/30, and with the Weight Learn Rate Factor = 1 and the Bias Learn Rate Factor = 8, was chosen as the most suitable model for the prediction of bankruptcy. The model configured in this way achieved an overall accuracy of 93.58 % on the validation data. The model can recognise the data of businesses outside the original set (the test data) on which the quality of prediction was tested with 90.48 % accuracy. The other metrics of the model created are summarised in Table 6.

Table 6

Metrics for Measuring the Performance of the Final Model

Metrics	Validation data	Test data
Overall accuracy	0.9358	0.9048
Type I error (FP/(FP+TN))	0.0593	0.0667
Type II error (FN/(TP+FN))	0.0769	0.1333
Precision	0.8571	0.9070
Recall (sensitivity)	0.9231	0.8667
Specificity	0.9407	0.9333
F-measures	0.8889	0.8864
AUC	0.9642	0.9279

ROC curves (Figure 4) for validation and test data are shown for a more detailed depiction of correctly classified cases. With the validation data, 127 cases of a total number of 135 active businesses were correctly classified, and the model was able to correctly classify 48 companies out of 52 bankrupt businesses. On test data that were not used in model training, 56 cases of a total number of 60 active businesses were correctly classified, and the model correctly classified 39 out of 45 bankrupt businesses.

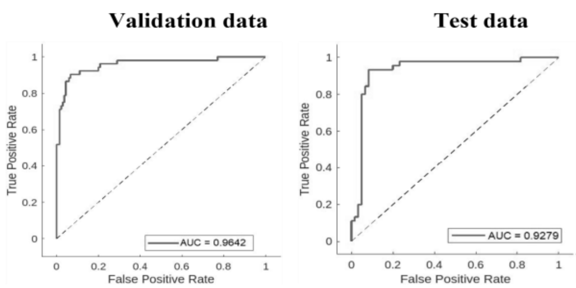


Figure 4. ROC Curves for the Final Model

The CNN makes it possible not only to classify input images, but also to determine the probability with which a given input resembles the features of a specific class graphically (i.e. an active or bankrupt business). Figure 5 shows the graphical processing of the indicators of six companies, based on which the model classified the companies into specific categories and assigned the probability of their belonging to the given group. The images are created from the values of the indicators for three consecutive periods.

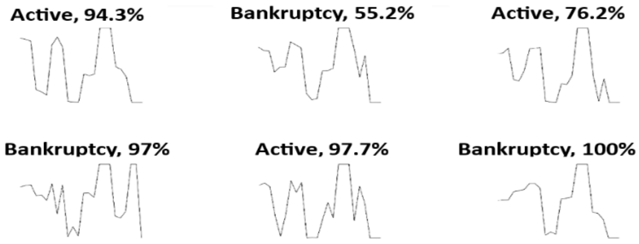


Figure 5. Classification of Businesses by the CNN

Discussion

In our research, we focused on creating a model for predicting the bankruptcy of construction companies using a CNN. The aim was to provide credit risk managers with a comprehensive tool for identifying creditors with whom a threat of insolvency is associated and for making a decision on payment conditions for the given customer on the basis of these results (e.g. to require the use of a payment guarantee instrument). The model created can also be used by investors, whom it can help reveal a company threatened by bankruptcy and thereby prevent the depreciation of potentially invested money, or can be used by a company itself to monitor and evaluate its own financial situation.

The financial and macroeconomic indicators used most frequently were identified in the research conducted on the basis of the literature review and were subsequently used as potential predictors. Using the described statistical apparatus, we identified financial indicators that have the highest discriminatory ability in predicting the bankruptcy of construction companies in the Czech Republic. These are the logarithm of assets, CL/TA, EAT/S, I/dS, TL/TA, year-on-year change in total assets (ΔTA), the difference between total liabilities and total assets (TL<>TA), and the country's gross domestic product. The logarithm of assets is a frequently used variable in bankruptcy prediction models (see, for example, Callejon *et al.,* 2013; Tian & Yu, 2017 or Veganzones and Severin, 2020). It reflects the fact that smaller firms, which have limited access to financing sources and lower bargaining power with business partners, are more vulnerable to insolvency and the threat of bankruptcy. This finding is consistent with the structure of the Czech construction sector, which is dominated by small enterprises (more than 98% of construction firms have fewer than 19 employees - see MIT, 2025). These firms often act as subcontractors for development projects awarded to large companies through public tenders. These small businesses are burdened by rising input costs which is reflected in a decline in profit margins (EAT/S). We note that price growth in the Czech construction industry in 2014-2021 was 5 percentage points higher than the EU average (MIT, 2025). Additionally, the sector faces long receivables collection periods, particularly from public sector entities. In combination with low profitability, this leads to income shortfalls and liquidity problems.

A characteristic feature of the construction is the long production cycle of the final product (i.e., properties), which results in a high level of inventory of own productions. However, due to limited data availability, it was not possible to extract the value of stocks of own productions directly from company reports. Therefore, the model includes the inventory turnover period (I/dS), as used by Tian and Yu (2017), Du Jardin (2021), and others. A high value of this ratio indicates that firms must finance assets tied up in production over a prolonged period, which increases the need for net working capital, i.e. long-term sources of financing that are less accessible to small businesses. Another significant variable in our model is the change in total assets (ΔTA). This indicator is generally assumed to increase due to investment in fixed assets (Jeong *et al.,* 2012). However, as none of the significant variables in our model are associated with fixed assets, it suggests that the growth in total assets within the construction sector is primarily driven by an increase in inventories.

Three other variables included in the model - CL/TA, TL/TA, and TL<>TA - reflect the specific structure of asset in the construction sector and sources of their financing. Debt financing is the prevailing source of funding in construction, which can lead to a significant rise in leverage (TL/TA) and underscores the importance of its prudent management. Combined with low profitability (EAT/S), excessive leverage can result in negative equity. In our model, the existence of negative equity is expressed through the binary variable TL<>TA, which signals a negative value of equity if it is non-zero. The current liabilities to total assets ratio (CL/TA) provides a more detailed view of debt financing. It supports the assumption that construction companies frequently rely on short-term liabilities to finance their operations. Due to the long production cycle and delays in payments from customers, there may be a shortfall in revenue. As a result, the company may not have the cash to pay its outstanding liabilities. An increase in the value of this indicator can therefore be seen as a clear signal of poor cash flow management and a risk of insolvency.

Our model includes only one macroeconomic variable: total GDP (TGDP). This variable reflects the industry's sensitivity to the business cycle, as both public and private investments in non-financial assets tend to fluctuate with GDP due to future economic uncertainty. Another factor contributing to the stagnation of the construction sector is the protracted permitting process for new construction projects, as well as the high interest rates on long-term or mortgage loans.

In contrast to other studies (e.g., Heo and Yang, 2014; Huang and Tserng, 2018 and others), our results do not confirm the significance of the return on assets (ROA = EBIT/TA). ROA is one of the most frequently used variables in bankruptcy prediction models (Prusak, 2018) and is also included in models specifically developed for the construction industry (see Alaka et al., 2016). It can be assumed that ROA does not exhibit significantly different values between the groups of active and bankrupt businesses, which may explain its lack of significance in our model. Similarly, the final model does not include any indicators measuring the level of net working capital (e.g., WC to Total Assets, WC to Sales), although these were among the 36 financial ratios initially considered and are commonly used in construction-sector bankruptcy models (see Tserng *et al.,* 2014; Heo & Yang, 2014). This may suggest that the inventory turnover period is the key determinant of net working capital levels and that other working capital components are comparatively less important. For the same reason, none of the liquidity indicators or cash flow-based ratios, which are also found in bankruptcy prediction models in the construction industry (see Alaka *et al.,* 2016), were included in the final specification.

The final model we created is one of the few to use the CNN method for bankruptcy prediction. We performed a comparison with a model created using the decision trees method (Durica et al., 2019) derived from data on private Polish companies. This model achieved an accuracy of 76.7 % on the data from our original dataset (520 businesses). It correctly identified 39.6 % of bankrupt companies, while its accuracy was 82.3 % in the case of active enterprises. This lower accuracy may be due to the fact that the model was not derived on data on construction companies and industry affiliation was not taken into account. The advantage of the use of a CNN is the ability to retrain the model and generate graphical displays from new data (while retaining the selected financial indicators), for which reason the model can also be considered generally usable in other industries and other countries. Comparison with other models on our dataset was not possible. This limitation arises from the unavailability of certain input data (the authors used indicators that could not be calculated based on the Orbis database) or the use of a constant in their models that did not work with our data, resulting in outcomes outside the expected range (e.g., Tserng et al., 2014). In addition, AI-based models could not be applied to our dataset because the authors did not disclose their source code. For this reason, we performed a comparison with results published in previous studies.

The results we achieved are among the best if we compare this approach with the results of other prediction models designed using AI methods (Table 7).

In terms of overall accuracy, the model based on the training data achieves an accuracy of more than 99 %. It achieves an accuracy of 93.58 % on the validation data and an accuracy of 90.48 % on the test data. The accuracy of the model by Hosaka (2019), who was the first to use a CNN and the graphical processing of input data to predict the bankruptcy of businesses, was slightly surpassed. His model is based on only one type of graphical display of the results (referred to as IMAGE II) which, according to our results, comes out as the second weakest during validation on the training data. In our research, we found that the accuracy of the resulting model increases with different graphical processing of the data. The best results were achieved by graphical data processing in the form of a PLOT graph. We achieved a significant increase in the accuracy of the model by applying the SMOTE method, which was used to increase the sample of bankrupt companies and partially reduced the highly imbalanced dataset.

Table 7

Comparison with Results Published in Previous Studies

Author(s)	Method	Classification accuracy in %		
		Active	**Bankrupt**	**Total**
Durica et al. (2019)	Classification and Regression Trees	99.50	83.30	98.00
Korol (2019)	Fuzzy Logic	95.60	95.20	95.40
Own model (validation)	Convolutional Neural Networks	**94.07**	**92.31**	**93.58**
Ben Jabeur and Serret (2023)	Convolutional Neural Networks	x	x	92.10
Elhoseny et al. (2022)	AWOA neural networks	92.43	87.62	91.34
Nouri and Soltani (2016)	Logistic regression	96.32	73.97	91.20
Own model (test)	Convolutional Neural Networks	**93.33**	**86.67**	**90.48**
Marso and El Merouani (2020)	Neural Networks	91.81	88.70	90.30
Brenes (2022)	Neural Networks	72.58	95.15	86.67
Rainarli and Aaron (2015)	Fuzzy Logic	x	x	81.54
Shin et al. (2005)	Support Vector Machine	x	x	76.70
Mihalovič (2016)	Logistic Regression	78.95	68.85	73.73
Azayite and Achchab (2016)	Discriminant Analysis	49.50	94.00	71.80
Hosaka (2019)	Convolutional Neural Networks	91.40	85.90	x
Du Jardin (2021)	Self-Organizing Neural networks	85.28	76.84	x

Conclusion

The bankruptcy of a business is a negative event not just for the owner and employees of the bankrupt business, but also for its surroundings, for which reason this topic is consistently the subject of economic research and efforts by individual authors to create a model with the greatest possible power of discrimination. Bankruptcy prediction models are designed for use by external entities to assess the creditworthiness of a company. Their primary goal is to identify businesses at risk of bankruptcy well in advance. This makes them particularly useful to potential creditors, as well as to customers of long-lived products who want assurances about the availability of spare parts and general service support.

A literature review revealed that models achieve better results if they are developed using data from companies operating in the same country and industry in which the model is intended to be applied. The discriminative power of these models can be further improved by using unconventional methods that help to uncover deeper relationships between the selected indicators.

Our research focused on developing a bankruptcy prediction model using CNNs in the construction sector in the Czech Republic. The main objective was to explore the feasibility of using CNNs to build such models. Specifically, we addressed the research questions of which type of data visualisation is most appropriate for the prediction of company bankruptcy (RQ3) and whether a sufficiently high discriminatory power could be achieved (RQ2). In addition, we considered related issues such as the selection of appropriate financial indicators for model development and the challenge of limited observations for bankrupt firms. Data selection was based on a critical literature review. From nearly 200 indicators, we selected the most frequently used business performance metrics, complemented by macroeconomic indicators. Our assumption was that if these indicators had been chosen for bankruptcy prediction in previous studies using other methods, they would also exhibit strong discriminatory power in distinguishing between financially distressed and healthy companies. In addition, the economic rationale of the selected indicators was rigorously assessed based on the analysis of construction companies in the Czech Republic. Highly correlated indicators were excluded through testing, and their selection was justified on an economic basis. Furthermore, our model incorporates the time evolution of a company, taking into account business dynamics. This approach allows for the assessment of financial health by considering changes over time, thereby enhancing the accuracy of bankruptcy prediction.

To solve the problem of insufficient data for bankrupt firms, we used the approach applied by Chawla et al. (2002), who provided a technique for resampling data, i.e. its artificial supplementation from already existing data, using the SMOTE method. Our research shows that using the SMOTE method makes it possible to increase the accuracy of the model as compared to the original results by 27 to 37 %, depending on the type of model constructed. This fact is especially important when creating models for SMEs, which are associated with the unavailability of data or data of lower quality. The quality of the model is increased by the use of data for a longer period of time. When creating the presented model, we used data covering three years, i.e. all the imaging of the businesses is depicted on the basis of this time series. At the same time, however, the number of indicators was reduced according to their discrimination ability in an attempt to simplify the applicability of the model in practice.

The overall accuracy of our model reached 94.5% on the validation dataset and 90.5% on data from a different time period (test dataset). The accuracy achieved is relatively high even when compared to previous research. We assume that the overall accuracy of the model may have been influenced by the length of the time series used. In our research, we used data spanning three years to maintain data consistency. In 2020, government regulations led to an unprecedented restriction on economic activity due to the COVID-19 pandemic. To mitigate the adverse economic conditions, the government provided substantial subsidies, which, paradoxically, led to a decrease in the number of bankrupt companies.

Our research focused on the construction industry in the Czech Republic, which may suggest its restricted application. The principle of the creation and use of a CNN makes it possible, however, to eliminate this restriction and to "retrain" the created network for another branch of industry or another country while using the same indicators and principles of network creation, which can significantly shorten the period required for its creation. The model can be easily transferred to other countries, while the selected predictors apply to the construction industry. Future research should focus on extending the time series of the data and to include qualitative and non-financial indicators as model inputs (e.g., company age, geographical location, etc.). The results produced by the created model confirm unequivocally the potential of the use of CNNs in the field of the economic sciences, specifically in the identification of businesses at risk of bankruptcy. The findings on the most suitable visual representation of financial indicators are also highly valuable in improving the model's discriminatory power. The tested and documented model development methodology allows the model to be easily adapted to different conditions.

The identified predictors have the potential to be applied in the design of early warning systems within construction enterprises. This is particularly relevant for indicators such as total liabilities to total assets (TL/TA), current liabilities to total assets (CL/TA), inventory turnover period (I/dS), and profit margin (EAT/S). Depending on the sophistication of a firm's internal information systems, these indicators can be monitored not only at the aggregate level, but also disaggregated by project, contract, or specific components (e.g., inventories from own production). Including these metrics in internal performance reports could help firms to identify early signs of financial distress, particularly in relation to emerging liquidity constraints. When combined with appropriate visualisation tools, such indicators can function as a real-time management alert system, enhancing a firm's capacity for timely and informed decision-making in risk-prone operational environments.

Further research in this area can be developed in two areas: developing tools for management decision making and improving the accuracy of prediction models. In our research, financial ratios were constructed on an annual basis. For the purposes of corporate management, it would be appropriate to incorporate indicators calculated at a higher frequency (e.g., on a monthly basis) into the model. In combination with AI tools, this approach enables further refinement of early warning systems. Another area for development in the field of bankruptcy prediction is the integration of qualitative indicators into existing models. A deteriorating financial situation is typically evident in corporate financial statements only one to two years prior to bankruptcy. However, certain signals may indicate problems at an earlier stage, and it would therefore be beneficial to incorporate them into predictive models. Identifying such signals requires an examination of employee satisfaction, managerial competence, the quality of information systems, and similar factors. This type of insight can be achieved through a combination of qualitative research methods (e.g., structured interviews, questionnaire surveys) focused on identifying management-related issues and declining employee satisfaction. These findings can then be implemented into bankruptcy prediction models that primarily use financial ratios.

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