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Predicting Business Failure in SMEs: Do Machine Learning Models Outperform the Traditional Statistical Approach?

Abstract. *This study examines the predictive power of traditional statistical and machine learning models for forecasting business failure among small and medium-sized enterprises (SMEs) in Serbia. The research aims to enhance early warning systems for Serbian SMEs and to compare the classical statistical method with machine learning techniques. These methods remain underused in developing regions, where SMEs face increased financial vulnerability and limited analytical resources. Three models were developed to predict business failure one year in advance: logistic regression (LR), decision tree (DT), and k-nearest neighbours (k-NN). The analysis is based on a well-structured dataset of 212 Serbian SMEs with clearly labelled bankruptcy outcomes – with bankruptcy used as a concrete indicator of business failure. Findings show that machine learning models offer improved overall accuracy, while logistic regression remains competitive due to its simplicity and interpretability. These results offer a practical framework for financial risk assessment in Serbia and similar developing economies by identifying key variables, tools, and guidance, helping to close the research gap.*

Keywords: *business failure, bankruptcy, financial analysis, statistics, machine learning, SMEs.*

JEL Classification: C53, C38, G33, L26, C10.

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1. Introduction

The aim of this study is to develop and evaluate business failure (bankruptcy) prediction models for Serbia's SMEs and to identify the most effective forecasting techniques for such markets. Current business conditions require SMEs to adapt rapidly and respond strategically in order to remain competitive. Globally, and especially in Serbia, there remains a significant research gap concerning the development of bankruptcy prediction models. This gap is even more pronounced when focusing exclusively on SMEs and employing advanced techniques such as machine learning, an approach that remains virtually unexplored in Serbia. Similarly, Bešlić Obradović et al. (2018) argue for models suitable for the business environment in the Republic of Serbia. A study by Dejanović (2024) highlights that the adoption of Information and Communication Technologies (ICT) and Artificial Intelligence (AI) in Serbian SME operations is a significant driver of productivity and competitiveness. However, the research also underscores that many SMEs face

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challenges in implementing these technologies due to resource limitations and a lack of strategic planning. In Serbia, the SME sector represents 41% of total turnover; it also represents 29% of exports and 43% of imports (Statistical Office of the Republic of Serbia, 2023). SMEs hold significant importance across all economies. Thus, it is clear that the findings have broader applicability throughout the Western Balkans. Businesses in Albania, Bosnia and Herzegovina, North Macedonia, Montenegro, and Serbia represent approximately 99% of all firms, contribute roughly 65% of value added, and employ approximately 75% of the workforce (OECD, 2022). Moreover, OECD reports confirm that institutional and regulatory frameworks, including fiscal policies, energy regulation, and administrative procedures, are highly homogeneous across the region. Macro factors such as inflation and the recent energy crisis have uniformly impacted the SME landscape region-wide.

At last, it is important to note that all the SMEs are inherently more vulnerable compared to larger firms, making them more sensitive to economic shifts. Consequently, SMEs experience financial crises more acutely than larger enterprises (Virglerova et al., 2021). Additionally, SMEs typically have more limited access to external funding, such as credit, compared to larger entities, making liquidity management more difficult (Shabbir, 2012). Everything being said, the hypotheses were defined:

H₁: *Machine learning and statistical methods can effectively predict business failure (bankruptcy) in the SME sector.*

H₂: *Machine learning algorithms are superior to traditional statistical method in predicting SMEs business failure (bankruptcy).*

Sub-hypotheses for H_2:

$H_{2.1}$: The k-nearest neighbours (k-NN) algorithm will yield higher overall predictive *accuracy* than logistic regression.

$H_{2.2}$: Decision tree algorithm (DT) will yield higher overall predictive *accuracy* than logistic regression (LR).

2. Literature review

In the review, the focus will be on research-relevant models: logistic regression, decision trees, and k-nearest neighbours. Wang et al. (2014) used two datasets, one with 240 companies and another with 132 companies, and developed two DT models. For the first model, 30 financial ratio variables were initially used, achieving an overall accuracy of 71.63%. The second model included 24 financial variables, with an accuracy of 75.99%. Hesari and Akkaya (2018) compared the performance of the DT model with other algorithms in a sample of 176 entities over the period 2009–2014 and found that decision trees achieved the best performance. Lee et al. (2020) developed a decision tree model for SMEs based on a sample of 4,358 entities, with an overall accuracy of 82.7% in the test sample. Non-financial variables were used. In contrast, DiDonato and Nieddu (2015), developed a model with an overall accuracy of 91.6%, tested using cross-validation, based on a sample of 100 SMEs in Italy and the CRT decision tree algorithm. The predictors were exclusively financial variables. In Serbia, the decision tree method has appeared in one study using a classic DT algorithm. The model was not focused on SMEs: Stanišić and co-authors (2013), on a sample of 232 large and medium-sized companies from Serbia, developed a model with 75.4% accuracy for predicting bankruptcy two years in advance on the training dataset, while the AUC for the DT model in the test sample was 0.696. Aker and Karavardar (2023) used several techniques in their study to predict the bankruptcy of Turkish SME companies, including k-NN. Three kNN models were developed on samples of 378, 380, and 385 SMEs, with predictive powers of 87%, 89%, and 92% for one, two, and three years in advance, respectively. Abdullah (2021) developed several insolvency prediction models on a sample of 244 Bangladesh entities listed on the Dhaka Stock Exchange. Data from 2015–2019 were analysed. The developed k-NN model showed an overall accuracy of 82% on the training set and 85% on the test set. García and colleagues (2019) developed bankruptcy prediction models using several algorithms and 14 financial datasets. The number of variables in the models ranged from 12 to 64, while the AUC for the k-NN models ranged from 0.583 to 0.975. The contribution of oversampling techniques was demonstrated by Smiti and Soui (2020). Before oversampling, the k-NN bankruptcy prediction model had an AUC of 0.637–0.480 for predictions from one to five years ahead. After applying oversampling, the AUC significantly improved to 0.856–0.859 for the same prediction period. A review of the existing literature in this area shows that k-NN has not yet been used for bankruptcy prediction in Serbia.

A pioneer in bankruptcy prediction modelling based on logistic regression is Ohlson (1980). His research indicated that the ratio of net income to total assets and the ratio of total liabilities to assets were the best predictors of bankruptcy. Sricharoenchit and Hensawang (2021) focused solely on the Thailand automotive industry, developing a model with 75% accuracy using financial ratios and corporate governance variables. Papík and Papíková (2024), using a sample of 9,771 Slovak companies, compared logistic regression with machine learning algorithms. Logistic regression achieved an overall accuracy of 68.29% and had the weakest performance compared to six other techniques. In Serbia, a few authors have applied logistic regression for bankruptcy prediction, but not with a focus on SMEs. Stanišić et al. (2013) developed a model with 75% accuracy on a sample of 130 medium and large companies using raw variables and financial ratios of turnover and debt. Bešlić-Obradović and co-authors (2018) developed a model on 126 medium and large companies using only financial variables. The model achieved 82.5% accuracy in the training dataset. For SMEs in Serbia, a logistic regression model was developed by Kušter (2023) on a sample of 100 entities, focusing solely on the efficiency of asset and working capital management.

3. Techniques overview

Three methods will be employed for modelling: decesion trees, k-nearest neighbours, and logistic regression. The first two are categorised as machine learning methods, while the third one is considered traditional statistical. On the one hand, logistic regression is among the most widely used algorithms because it is simple, easy to interpret, and effective for prediction (Gangwani & Zhu, 2024). It is therefore selected as a representative of traditional statistical techniques. On the other hand, decision trees and KNN are also straightforward to interpret, easy to understand, and capable of handling various types of input variables (Aktan, 2011; Le et al., 2025), making them suitable representatives of machine-learning methods. Together, these approaches offer a balance of interpretability, ease of implementation, and predictive performance: qualities that are particularly valuable in developing economies with limited analytical resources.

3.1 Decision trees basics (DT)

Decision trees (DT) represent a non-parametric method frequently employed in classification problems. Each node within a decision tree poses a binary question—"yes" or "no". In constructing decision trees, simplicity is preferred, as less complex trees are more interpretable and less susceptible to overfitting. Theobald (2021) notes that moderate complexity is achieved by selecting only those variables that optimally divide the dataset into homogeneous subsets, thereby reducing the entropy at each branching point. Entropy in this context refers to the variability or disorder within the data across different classes, and it is calculated using the following formula:

$$(-p_1 \log p_1 - p_2 \log p_2) / \log 2$$

Two widely used algorithms in tree generation are CRT/CART and CHAID:
a) CRT or CART (Classification and Regression Trees) applies a binary splitting criterion, where each parent node gives rise to two child nodes. Pruning begins at the terminal nodes and eliminates those that do not improve the model's predictive accuracy.
b) CHAID (Chi-squared Automatic Interaction Detector) utilises the χ^2 (Chi-squared) test to determine optimal splits. Unlike binary splitting methods, this one allows for multi-way splits. Branching continues until no further statistically significant divisions can be made, based on p-values.

3.2 K-nearest neighbours basics (k-NN)

This method falls under the category of supervised learning. The classification of new observations is based on their proximity to existing data points in the feature space. A central aspect of the method is the selection of the parameter *k*, which defines the number of neighbours to consider. When a new data point needs to be classified, the algorithm computes its distance to all points in the training dataset. To mitigate over/underfitting risks, it is common practice to experiment with different k values to identify the one that yields the best classification performance in validation data. In addition to selecting an appropriate *k*, the choice of distance metric used to measure similarity between observations plays a key role in the behaviour of the algorithm. The two most commonly used metrics are Euclidean distance and Cosine similarity:

a) Euclidean distance for two points x_i i x_k in a D-dimensional space is given by the following formula:

$$\sqrt{\sum_{j=1}^{D}\left(x_i^{(j)} - x_k^{(j)}\right)^2}$$

The coordinates of the point x_i are denoted as $x_i^{(1)}$, $x_i^{(2)}$, $x_i^{(D)}$, while the corresponding coordinates of the point x_k *are represented as* $x_k^{(1)}, x_k^{(2)}, x_k^{(D)}$, where *D* refers to the total number of dimensions in the feature space.

b) Cosine similarity for two points x_i i x_k in a D-dimensional space is given by the following formula:

$$s(x_i, x_k) \stackrel{\text{def}}{=} \cos\left(\angle(x_i, x_k)\right) = \frac{\sum_{J=1}^{D} x_i^{(j)} x_k^{(j)}}{\sqrt{\sum_{J=1}^{D}\left(x_i^{(j)}\right)^2}\sqrt{\sum_{J=1}^{D}\left(x_k^{(j)}\right)^2}}$$

The term:

$\sum_{J=1}^{D} x_i^{(j)} x_k^{(j)}$ represents the dot product between the vectors x_i i x_k;

$\sqrt{\sum_{J=1}^{D}\left(x_i^{(j)}\right)^2}$ corresponds to the magnitude of vector x_i;

$\sqrt{\sum_{J=1}^{D}\left(x_k^{(j)}\right)^2}$ denotes the magnitude of vector x_k.

The result of the cosine similarity equation falls within a range from –1, indicating complete dissimilarity (or opposite orientation), to 1, indicating perfect similarity. This value reflects the angle between the two vectors in a multi-dimensional space. In order to apply this method appropriately, it is common practice to scale or standardise the independent variables prior to analysis (Theobald, 2021). This step ensures that all data dimensions contribute equally to the computed distance. As Theobald (2021) notes, the key advantages of this approach lie in its precision and ease of implementation. However, one major drawback is that it may not perform well when applied to large datasets.

3.3 Logistic regression basics (LR)

At its core, logistic regression (logit model) is conceptually related to multiple linear regression. However, the key distinction lies in the nature of the dependent variable: logistic regression allows for categorical outcomes, while predictor variables may be continuous, categorical, or both. In the case of a binary outcome (e.g., solvent vs. bankrupt), the model is referred to as binary logistic regression. The logistic function transforms the linear combination of predictors into a value bounded between 0 and 1:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i})}}$$

The logistic curve is particularly useful for binary classification tasks. As the result approaches 1, the probability of the event increases; if near 0, the event is unlikely. The commonly applied threshold is 0.5 (cut-off point). With more predictors, the model becomes:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n + X_{ni})}}$$

To assess goodness-of-fit more systematically, researchers use pseudo R^2 indices, such as:

a) Hosmer & Lemeshow R^2:

$$\frac{-2LL(of\ the\ model)}{-2LL\ (initial)}$$

b) Cox & Snell R^2:

$$1 - e^{\left[-\frac{2}{n}(LL\ new) - (LL\ baseline)\right]}$$

c) *Nagelkerke R^2* - adjusts Cox & Snell to reach a theoretical maximum of 1:

$$\frac{R^2_{C\&S}}{1 - e^{\left[\frac{2(LL\ baseline)}{n}\right]}}$$

Beyond the overall fit, the Wald statistic evaluates the significance of individual predictors, calculated as the ratio of a coefficient to its standard error. A significant Wald value indicates a meaningful contribution of a given variable to the model:

$$Wald = \frac{b}{\mathrm{SE}_b}$$

Two main strategies are employed in variable selection: Enter method (includes all predictors simultaneously) and Stepwise method (adds predictors one by one forward or backward, based on score statistics, retaining only those that significantly improve the model).

4. Sample and variables

One of the key challenges in business failure (bankruptcy) prediction models is the inherent imbalance in real-world data—far fewer companies go bankrupt compared to those that remain solvent. To address this, many studies have adopted a balanced sample approach, using an equal number of solvent and failed firms. This 1:1 matching strategy is commonly used to improve model accuracy, as seen in a number of empirical studies. This study focuses on a sample of 212 small and medium-sized enterprises (SMEs) operating in the Republic of Serbia. Following standard practice in the literature, the sample was balanced to include 106 solvent firms and 106 firms that had entered bankruptcy proceedings. Such a modelling requires a well-structured sample, which is not only balanced by company status (operating or failed) but also by other criteria: number of employees, revenue, long-term liabilities, and industry. The median number of employees in active (solvent/operating) companies (∑106) for the observed period is 40, while the median number of employees in companies that initiated bankruptcy proceedings (∑106) during the same period is 50. The average value of long-term liabilities for all solvent entities over the period is 15,713,362 thousand RSD (~134,300 EUR), while the average value of long-term liabilities for all entities that initiated bankruptcy proceedings is 15,859,150 thousand RSD (~135,500 EUR). The average revenue for all solvent entities over the six-year period is 45,007,400 thousand RSD (~384,600 EUR), while the average revenue for all entities that initiated bankruptcy proceedings in the same period is 47,397,137 thousand RSD (~405,400 EUR). Financial statements from 2017 to 2022 were used, aiming to predict business failure one year in advance. Model used 212 observations. The sample was split into training and test sets following the 80:20 for k-NN and logistic regression, while for decision trees advanced testing (10-fold) was done in accordance with the literature recommendations and software possibilities.

In line with a more comprehensive approach, the current study defined both dependent and independent variables with a broad scope. The *dependent* variable is binary: 0 for failed companies (entered bankruptcy proceedings) & 1 for solvent companies (healthy and operating). The *independent* variables include **66** in total divided into 5 categories (C):

- 52 financial ratio variables (FI),
- 2 internal non-financial variables (NF),
- 1 macroeconomic hybrid variable (MA),
- 5 trend or variation variables (TR),
- 6 statistical variables (ST).

These variables were derived from Profit and Loss Statements, Balance Sheets, Cash Flow Statements, as well as other publicly available data. A full breakdown of the variables is provided in Table 1.

Table 1. Independent variables overview

Variable	C	Calculation Method	Variable	C	Calculation Method
ROA	FI	Net result / Total Assets	Log_SINV	ST	Log(Sales / Inventories)
CR	FI	Current Assets / Current Liabilities	IEBD	FI	Interest Expenses – Total Debt
WCTA	FI	Working Capital / Total Assets	CRR	TR	(Fixed Assets Change YoY + Working Capital Change YoY) / Operating Cashflows
RER	FI	Retained Earnings / Total Assets	IETR	FI	Interest Expenses / Total Revenue
EBITTA	FI	EBIT / Total Assets	QACL	FI	Quick Assets / Current Liabilities
STA	FI	Sales / Total Assets	INVWC	FI	Inventories / Working Capital
QR	FI	(Current Assets – Inventories) / Current Liabilities	INVCL	FI	Inventories / Current Liabilities
TDTA	FI	Total Debt / Total Assets	CLCA	FI	Current Liabilities / Current Assets
CATA	FI	Current Assets / Total Assets	LTLEFA	FI	(Long-term Liabilities + Equity) / Fixed Assets
OCFTA	FI	Operating Cashflows / Total Assets	FATA	FI	Fixed Assets / Total Assets
OCFTD	FI	Operating Cashflows / Total Debt	OENS	FI	Operating Expenses / Net Sales
QATA	FI	Liquid Assets / Total Assets	SEE	FI	Sales / Number of Employees
CAS	FI	Current Assets / Sales	OIEE	FI	Operating Income / Number of Employees
EBITInt	FI	EBIT / Interest Expenses	FAEE	FI	Fixed Assets / Number of Employees
InvS	FI	Inventories / Sales	TITE	FI	Total Income / Total Expenses
OITA	FI	Operating Income / Total Assets	TETA	FI	Total Expenses / Total Assets
OCFS	FI	Operating Cashflows / Sales	CS	FI	Cash / Sales
NIS	FI	Net Income / Sales	OIG	TR	Operating Income (current year) – Operating income (previous year)
LTDTA	FI	Long-term Debt / Total Assets	NIG	TR	Net Income (current year) – Net Income (previous year)
CCL	FI	Cash / Current Liabilities	TAG	TR	Total Assets (current year) – Total Assets (previous year)
OCFCL	FI	Operating Cashflows / Current Liabilities	TEG	TR	Equity (current year) – Equity (previous year)
WCS	FI	Working Capital / Sales	TAGNP	MA	Total Assets / Gross National Product
CAPA	FI	Capital / Total Assets	Ln_S	ST	Ln(Sales)
NSTA	FI	Net Sales / Total Assets	Ln_CACL	ST	Ln(Current Assets/Current Liabilities)
NCI	FI	No-credit Interval	CLTA	FI	Current Liabilities / Total Assets
Log_TA	ST	Log(Total Assets)	LTLCA	FI	Long-term Liabilities / Current Assets
CFNID	FI	Net Result from Cashflows / Total Debt	CFTL	FI	Cash / Total Liabilities
OCF	FI	Operating Cashflows	SLC	FI	Employees-related expenses / Total Expenses

Variable	C	Calculation Method
OEOI	FI	Operating Expenses / Operating Income
QAS	FI	Quick Assets / Sales
SINV	FI	Sales / Inventories
HC	NF	Headcount (number of employees)
OY	NF	Opereating years prior bankruptcy

Variable	C	Calculation Method
Log_TAGNP	ST	Log(Total Assets/Gross National Product)
Ln_TAGDP	ST	Ln(Total Assets/Gross Domestic Product)
OBSCTA	FI	Off-balance sheet liabilities/Total Assets
SATA	FI	Employees-related expenses / Total Assets
IETA	FI	Interest Expenses / Total Assets

Source: Authors' processing.

5. Analysis and results

5.1 Data preparation and model development

The variables calculation and tabular preparation was done in *Microsoft Excel,* while the modelling was done in IBM's SPSS. Considering large number of independent variables, the Mann-Whitney test was used to reduce dimensionality first. When the value of the Mann-Whitney test is $p < 0.05$ (Asymp. Sig 2-tailed), then the claim that there are statistically significant differences in the values of the variables between the groups is accepted. (Field, 2009). Otherwise, when $p > 0.05$, there are no statistically significant differences between the groups regarding the observed indicator. Table 2 shows results of the remining variables (var.), and 18 variables were eliminated from further modelling considering the test results, meaning that 48 of them remained.

Table 2. MannWhitney results - variables that remained in the further modelling

Var.	Mann-Whitney U	Asymp. Sig. (2-tailed)
ROA	4289	0.00
CR	3556	0.00
WCTA	3205	0.00
RER	3882	0.00
EBITTA	1231	0.00
STA	4294	0.00
QR	3790	0.00
TDTA	2096	0.00
OCFTA	3913	0.00
OCFTD	3691	0.00
CAS	3461	0.00
EBITInt	2322	0.00
INVS	4406	0.01
OITA	4223	0.00
NIS	1265	0.00
LTDTA	4489	0.01

Var.	Mann-Whitney U	Asymp. Sig. (2-tailed)
CCL	2669	0.00
OCFCL	3686	0.00
WCS	3449	0.00
CAPA	2436.5	0.00
NSTA	1889	0.00
NCI	4199	0.00
CFNID	1504	0.00
OCF	4442	0.01
OEOI	2069	0.00
QAS	3383	0.00
HC	4339.5	0.00
IEBD	4657	0.03
CRR	4462	0.01
IETR	3040	0.00
INVWC	4710	0.04
INVCL	3905	0.00

Var.	Mann-Whitney U	Asymp. Sig. (2-tailed)
CLCA	3072	0.00
OENS	3588	0.00
TITE	1319	0.00
CS	4291	0.00
OIG	2499	0.00
NIG	3818	0.00
TAG	2306	0.00
TEG	2040	0.00
Ln_S	3885	0.00
Ln_CACL	3378	0.00
CLTA	2736	0.00
LTLCA	4541	0.02
CFTL	2866	0.00
OBSCTA	4729	0.02
SATA	4669	0.03
IETA	3854	0.00

Source: Authors' processing.

Next, *Spearman's correlation* test was used to further reduce dimensionality. All the variables with high correlation (above 0,9) were eliminated from the further modelling (Figure 1). Strongly red cells indicate a strong positive correlation, while strongly green cells indicate a strong negative correlation. Following the correlation analysis, a *Variance Inflation Factor* (VIF) test was conducted. Based on theoretical frameworks, VIF values exceeding 5 are typically seen as indicators of problematic multicollinearity (Studenmund, 2006). Consequently, all variables with VIF scores above this threshold were excluded from further analysis. The final VIF results for the variables included in the model are presented in Table 3. After filtering based on the VIF criteria (VIF < 5.0), 28 variables remained for use in the modelling.

Table 3. VIF analysis

Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
ROA	2.79	NSTA	2.32	IETR	2.56	Ln S	2.28
RER	1.74	NCI	1.08	INVWC	1.02	Ln CACL	3.04
QR	2.32	CFNID	1.83	TITE	2.54	LTLCA	2.24
TDTA	4.15	OCF	2.00	CS	1.41	CFTL	1.38
EBITInt	1.06	OEOI	1.81	NIG	1.81	OBSCTA	1.56
OITA	2.40	HC	1.55	TAG	1.89	SATA	2.00
OCFCL	1.02	CRR	1.28	TEG	2.80	IETA	2.31

Source: Authors' processing.

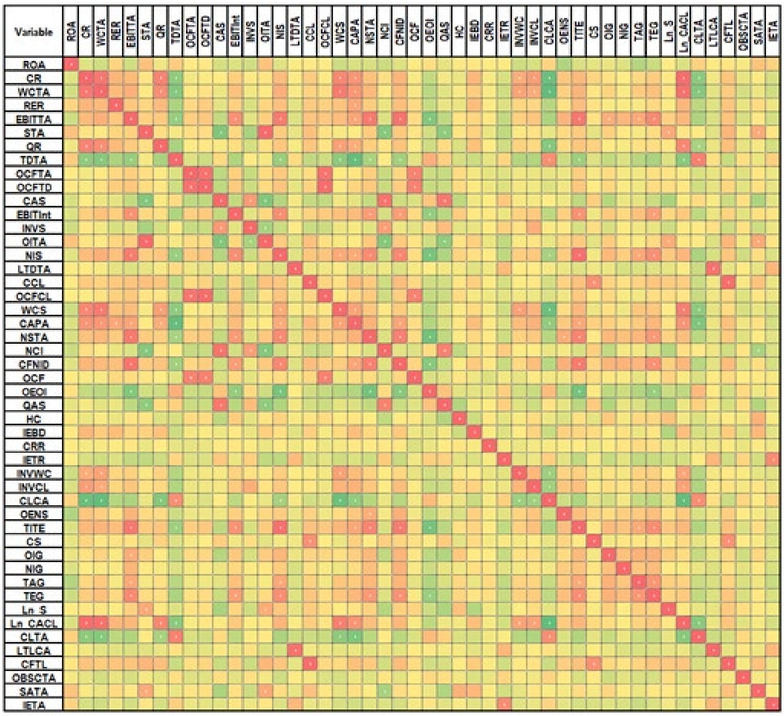

Figure 1. Heatmap based on correlation
Source: Authors' processing.

Once the data was cleaned and reduced in terms of dimensionality, the model development phase started. To ensure a fair comparison, the feature-reduction analyses were conducted prior to modelling to remove redundant variables, allowing all models – Decision Tree, KNN, and Logistic Regression – to be trained on the same set of independent variables. This approach also reduced model complexity, improved interpretability, and mitigated the risk of overfitting.

In the **decision tree analysis**, the entire sample of 212 SMEs was utilised for model development, while evaluation was conducted using 10-fold validation in accordance with established methodological guidelines (Aktan, 2011). As noted by Theobald (2021), decision trees are susceptible to overfitting during the training phase, which may impair their performance when classifying unseen data. Even slight variations in the partitioning of training and test sets can significantly alter the final tree structure and its predictions. Accordingly, rigorous 10-fold validation was employed. The final decision tree for predicting SME business failure (bankruptcy) one year in advance, generated using the CRT algorithm, is presented in Figure 2. Based on the results, the ratio of total revenues to total expenses (TITE) emerges as a significant predictor. This highlights the critical importance of timely and thorough analysis of total revenues, total expenses, their composition, and their relationship. Specifically, maintaining economic efficiency is essential to ensure the sustainability of SME operations. Firms that consistently achieve positive outcomes by generating revenues exceeding expenses tend to meet their obligations and even reinvest in their businesses, thereby reducing the risk of bankruptcy. Conversely, SMEs operating persistently at a loss may face difficulties fulfilling their liabilities, increasing the likelihood of business failure.

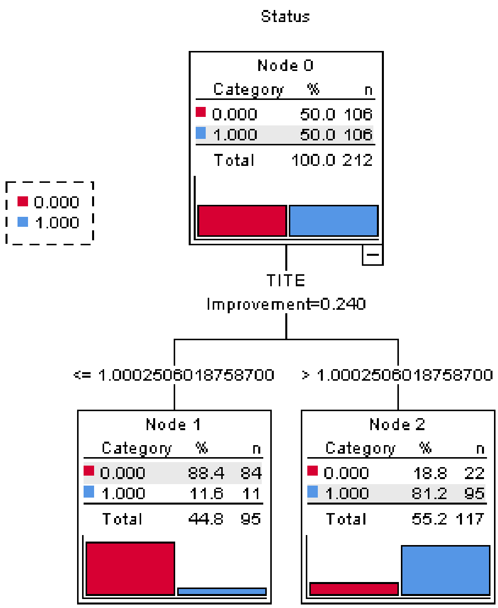

Figure 2. Final decision tree
Source: Authors' processing.

As mentioned, prior to the decision tree development, feature-reduction analyses were performed to eliminate redundant and non-informative variables. After this preprocessing, SPSS generated only a single viable split, as no additional variable satisfied the criteria for further branching. Furthermore, the limited parameter-adjustment options available in SPSS were tested but did not produce any improvement in tree depth or classification performance, resulting in the shallow tree.

Regarding the **k-nearest neighbours** (k-NN) model, the parameter "k" was automatically set to 9 by the software, a choice consistent with recommendations from multiple studies (Garcia et al., 2019; etc.). Additionally, selecting an odd value for "k" reduces the likelihood of ties leading to ambiguous classifications (Theobald, 2021). All variables were normalised according to the following formula: *X_normalized = [x – min(x)] / [max (x) – min (x)].*

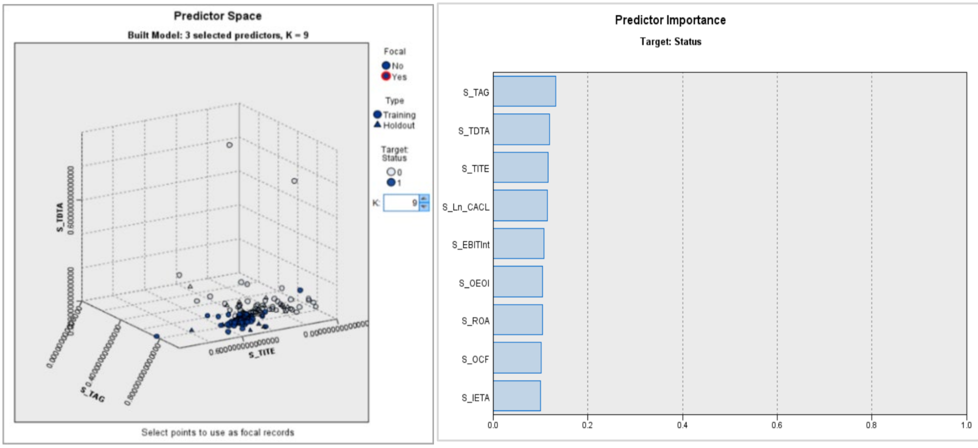

Figure 3. k-NN predictor space and variables importance

Source: Authors' processing.

The Euclidean distance was used as the distance metric, following a precedent in bankruptcy prediction literature (Marchesini, 2020) and reflecting its widespread practical application. Figure 3 illustrates the predictor space along with the relative importance of variables in bankruptcy prediction, where the sum of all variable importances equals 100%. The highest importance score (0.13/1.00) for predicting business failure in advance is attributed to the normalised variable representing total asset growth (S_TAG). The k-NN algorithm further confirms that asset management is critical for SMEs. Changes in total assets must be carefully balanced with cost and revenue trends to ensure sustainable business operations. It is essential to interpret the asset growth indicator within a broader context of business analysis. A sudden increase in asset value, unaccompanied by corresponding revenue growth, signals to stakeholders that the SME may be increasing its debt or mismanaging and inefficiently allocating resources. Conversely, a decline in assets may indicate attempts to cover losses through asset liquidation. A deeper examination of the balance sheet components driving asset fluctuations (such as fixed assets, cash, or inventory) is necessary. For instance, growth in fixed assets may suggest that the SME is investing to expand capacity, aiming for future growth. An increase in assets due to higher cash holdings implies improved liquidity, enabling the firm to meet short-term obligations more effectively. On the other hand, asset growth driven by increased inventory can have dual interpretations: it may reflect anticipation of rising demand or, if demand does not increase, indicate potential operational issues.

The **logistic regression** model is presented below. The selection of key variables was performed using the Stepwise method. The variables with the most significant score were added to the model. The algorithm continued to include variables until no remaining candidate variable had a statistically significant score, with a significance threshold set at 0.05. Additionally, during the modelling process, consideration was given to whether any previously included variables had lost importance and should be removed (Field, 2009). The final model was established in the fourth step.

Table 4. Log regression model – variables included in the equation

Variables in the Equation						
	Observed	**B**	**S.E.**	**Wald**	**df**	**Sig.**
Step 4	**TITE**	13.081793	3.05	18.35	1	0.00
	CS	0.107554	0.04	9.34	1	0.00
	TAG	0.000004	0.00	5.96	1	0.02
	IETA	-58.9551	24.75	5.68	1	0.02
	Constant	-12.14816	3.00	16.40	1	0.00

Source: Authors' processing.

The output appears more recognisable when presented in the form of a function:

$$\boldsymbol{P'}(\boldsymbol{x}) = \frac{1}{1 + e^{-(-12.148161 - 58.955100\,\boldsymbol{IETA} + 0.000004\,\boldsymbol{TAG} + 0.107554\,\boldsymbol{CS} + 13.081793\,\boldsymbol{TITE})}}$$

Logistic regression models require supplementary diagnostics commonly referred to as *goodness-of-fit tests*. One of the key indicators of model adequacy is the *Wald* test, as shown above in Table 4. Based on the results presented in the table, it can be concluded that all included variables have significance levels below 0.05, indicating their relevance in shaping the generated models (Field, 2009). Another important measure of model quality is the *Omnibus test*. In this case, all tested variables yielded significance values below the specified cutoff (0.05), supporting the conclusion that the model parameters are well-fitted (see Table 5). Cox & Snell and Nagelkerke R Square are two pseudo R^2 measures that offer additional insight into the quality and overall fit of the model (Table 5). According to Bešlić-Obradović et al. (2018), pseudo R^2 values range from 0 (no explanatory power) to 1 (perfect fit), and values above 0.4 are typically interpreted as indicating a well-fitting model. In this study, the Cox & Snell R^2 is 0.46 and the Nagelkerke R^2 is 0.61, indicating that the model explains between 46% and 61% of the variance in the dependent variable – suggesting a satisfactory model fit (Table 5). The next step in evaluating model adequacy is the *Hosmer & Lemeshow* (H&L) goodness-of-fit test. As shown in Table 5, the chi-square value for the developed business failure prediction model is 8.304, with a significance level of 0.404. Since this value is well above the critical 0.05 threshold (Ho, 2013), it is concluded that the model demonstrates an acceptable level of fit.

Table 5. Omnibus, Cox & Snell, Nagelkerke and Hosmer & Lemeshow goodnes-of-fit tests

Omnibus Tests of Model Coefficients			
Label	**Chi-square**	**df**	**Sig.**
Step	8.46	1	0.00
Block	102.09	4	0.00
Model	102.09	4	0.00

Model Summary		
-2 Log likelihood	**Cox & Snell R Square**	**Nagelkerke R Square**
128.03	0.46	0.61

Hosmer and Lemeshow Test		
Chi-square	**df**	**Sig.**
8.3	8	0.40

Source: Authors' processing.

5.2 Model results - assessment

The predictive performance of the developed models is comparatively presented in the confusion matrix indicators shown in the Table 6. The following metrics are derived from the confusion matrix:

a) *Accuracy:* This metric is particularly useful for balanced datasets, as is the case in the present study. It reflects the proportion of correctly classified observations within the total sample and is calculated as follows: $(True_{positive} + True_{negative}) / (True_{positive} + True_{negative} + False_{positive} + False_{negative})$

b) *Precision:* It captures the proportion of correctly predicted positive outcomes within all predicted positives. In this context, it reflects the model's ability to accurately identify businesses that eventually declared bankruptcy. The formula is: $(True_{positive}) / (True_{positive} + False_{positive})$

c) *Specificity*: This measure indicates how well the model identifies solvent SMEs. It represents the proportion of correctly classified solvent firms among all that were actually solvent, and is calculated as: $(True_{negative}) / (True_{negative} + False_{positive})$

d) *Sensitivity (or Recall)*: Sensitivity refers to the model's ability to detect failed SMEs correctly. It is defined as the ratio of correctly classified failed firms to the total number of actually failed firms: $(True_{positive}) / (True_{positive} + False_{negative})$

e) *F1-Score*: The F1-score represents a harmonic mean between Precision and Sensitivity. A higher F1-score suggests that the model achieves a better balance between false positives and false negatives. It is computed as: $2 * (Precision * Sensitivity) / (Precision + Sensitivity)$.

Table 6. Comparative analysis of classification results of developed business failure prediction models

Method	TRAINING DATA				
	Accuracy	*Precision*	*Specificity*	*Sensitivity*	*F1 Score*
Logistic regression	**83.7%**	74.7%	78.6%	91.2%	82.1%
Decision tree	**84.4%**	79.2%	81.2%	88.4%	83.6%
K-nearest neighbours	**86.1%**	80.7%	82.6%	90.5%	85.4%
Method	**TESTING DATA**				
	Accuracy	*Precision*	*Specificity*	*Sensitivity*	*F1 Score*
Logistic regression	**82.6%**	73.9%	77.8%	89.5%	81.0%
Decision tree[1]	**83.5%**	*n/a*	*n/a*	*n/a*	*n/a*
K-nearest neighbours	**84.8%**	78.3%	80.8%	90.0%	83.7%

Source: Authors' processing.

6. Discussion

All the three developed models achieved a high level of predictive accuracy, with all *accuracy values* exceeding 80% on both the training and testing datasets. The k-nearest neighbours (k-NN) model demonstrated the highest accuracy (86.1% in the training set and 84.8% in the test set), followed by decision trees (84.4% / 83.5%), and logistic regression (83.7% / 82.6%). These results *confirm the main hypothesis* H_1, as both statistical and machine learning methods successfully predict SME business failure (bankruptcy) with strong accuracy. Additionally, the results support sub-hypotheses $H_{2.1}$ and $H_{2.2}$, as both machine learning algorithms (k-NN and DT) outperform the traditional logistic regression model in terms of predictive accuracy, meaning that H_2 *is confirmed as well.*

The predictive models identified five financial indicators as particularly significant in forecasting SME business failure and those are presented in the Table 7. Each of these variables reflects a fundamental dimension of financial performance—operational efficiency, liquidity, growth dynamics, cost of financing, and leverage. From a managerial perspective, maintaining an income-to-expense ratio above unity is essential to ensure financial sustainability, while a healthy cash-to-sales ratio reflects a firm's ability to meet short-term obligations. Likewise, asset growth should be carefully aligned with revenue and market potential to avoid unsustainable expansion. High levels of debt and interest burdens can severely constrain financial flexibility, making it critical to balance financing structure and capital costs. Therefore, SMEs should adopt a proactive approach to financial management by regularly monitoring these indicators, integrating them into strategic decision-making, and adjusting operational and investment policies accordingly.

[1] Other parameters not available due to SPSS limitation

Table 7. Comparative overview of the selected variables in the developed business failure prediction models

Method	TITE	CS	TAG	IETA	TDTA
Logistic regression	✓	✓	✓	✓	
Decision trees	✓				
K-nearest neighbours			✓		✓

Source: Authors' processing.

Business failure prediction models capable of identifying risk up to one year in advance provide valuable early warning signals for SMEs and their stakeholders. In Serbia's challenging economic environment, where liquidity constraints and structural weaknesses, such as limited financing options, centralised decision-making, and client dependency, are common - these models enable proactive financial planning. Unlike traditional financial analysis, predictive models combine multiple indicators to detect hidden risk patterns, offering a more complete picture of financial health. This allows SME owners not only to address internal vulnerabilities early, but also to evaluate the stability of key business partners. Moreover, the study demonstrates that machine learning techniques, particularly K-nearest neighbours and decision trees, outperform traditional statistical models like logistic regression in predictive accuracy. This confirms the practical value of AI-driven approaches for SME risk assessment and supports their use by both financial institutions and regulators aiming to reduce insolvency rates and strengthen the SME sector. Future studies could replicate the present work, as it employs a set of variables that are well-established in the bankruptcy prediction literature, while further advancing the analysis through more sophisticated machine learning techniques (such as Random Forests) which are not available in IBM SPSS. Additionally, constructing a standard decision tree using all initial variables, without applying VIF-based dimensionality reduction, may offer an alternative modelling perspective. Expanding the research to a larger sample of SMEs across multiple developing countries (e.g., within the Balkans) would also be valuable, not only for strengthening the comparison between statistical and machine learning approaches in business failure prediction, but also for developing a more broadly applicable and robust predictive framework.

7. Conclusions

The adoption of AI-driven business tools and ML applications in Serbia is low, with current research highlighting a considerable lag compared to developed economies. Given that SMEs constitute the backbone of the Serbian and Western Balkans economy in general, the scientific problem was defined and by this research the author aimed to introduce advanced techniques in Serbian SMEs, with possibility for further research replication and application on other Western Balkans countries.

The findings of this study confirm both hypotheses. Predictive models based on statistical and machine learning methods successfully identified failed SMEs with high accuracy, exceeding the 80% threshold in both training and testing datasets. Among the tested algorithms, k-nearest neighbours demonstrated the highest predictive performance, followed closely by decision trees, thereby supporting the superiority of machine learning techniques over traditional logistic regression. Furthermore, several key financial indicators such as total income to total expenses, cash-to-sales ratio, total asset growth, interest expenses relative to total assets, and total debt to total assets were identified as critical predictors of business failure. These insights offer a foundation for targeted financial monitoring and early intervention.

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