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Cross-National Benchmarking of Bankruptcy Prediction Models Across V4 Economies

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ABSTRACT

In recent years, the prediction of corporate bankruptcy has become an increasingly important topic in financial and economic research, particularly in the manufacturing sector of Central and Eastern Europe. Accurate early-warning models are essential for mitigating financial risks and ensuring business sustainability. This study investigates the comparative performance of classical statistical and machine learning (ML) models for predicting corporate bankruptcy across manufacturing firms in the Visegrad Group (V4) countries, addressing the problem of financial distress forecasting in transitional economies. The purpose of the research is to evaluate whether pooled regional models perform as effectively as country-specific models and to examine the influence of national data characteristics, such as sample size and heterogeneity, on predictive accuracy. A balanced dataset of firm-level financial indicators from Slovakia, the Czech Republic, Hungary, and Poland was employed, and three classification techniques, namely logistic regression (LR), artificial neural networks (ANN), and decision trees (DT), were applied to develop predictive models for individual countries as well as for the combined V4 region. Model performance was assessed using multiple classification metrics including accuracy, F1 score, AUC (area under the receiver operating characteristic curve), precision, and recall, with careful attention to handling class imbalance. The results indicate consistently high discriminatory power across all models, with AUC values ranging from 0.929 to 0.991, classification accuracy between 94.9% and 98.3%, and F1 scores from 0.972 to 0.991. Artificial neural networks slightly outperformed logistic regression and decision trees, particularly in countries with larger samples, while pooled models demonstrated performance comparable to country-specific models, highlighting the generalizability of predictive models across V4 economies. The findings carry practical implications for policymakers, creditors, and business managers, supporting the development of scalable early-warning systems, enhancing risk assessment practices, and informing strategic decision-making in dynamic economic environments. Overall, the study contributes both to the theoretical understanding of model performance in bankruptcy prediction and to applied knowledge for regional economic foresight and business intelligence.

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1. Introduction

Bankruptcy prediction remains a valuable research topic in finance and risk management, with significant implications for lenders, investors, and policymakers [1, 2]. In recent years, the growing accessibility of large-scale financial data and advances in computational methods have significantly expanded the potential of ML in bankruptcy prediction. ML algorithms enable the detection of complex nonlinear relationships and interaction effects among financial indicators that traditional statistical methods may fail to capture. Consequently, ML-based models have been increasingly recognized as powerful tools for early identification of financial distress across diverse industries and economic contexts [3-5]. These developments underscore the growing importance of systematically evaluating ML approaches alongside conventional models to ensure robust and interpretable bankruptcy prediction frameworks.

The successful early identification of susceptible enterprises enables improved resource allocation, reduces financial losses, and fosters economic stability [6, 7]. While numerous models have been suggested for bankruptcy prediction, including conventional statistical methods like logistic regression and advanced machine learning techniques like artificial neural networks and decision trees, their relative performance varies across industries and regional environments [8].

Despite notable advancements, a gap remains in the literature regarding the application and comparative assessment of these models within sector-specific contexts, particularly across Central European markets, notably the Visegrad Group countries [9, 10]. Existing studies often rely on aggregated data or focus on large and mature economies, overlooking the specificities of transition markets and the manufacturing sector, which plays a crucial role in the V4 region. Furthermore, comparative research evaluating multiple modeling paradigms under consistent data and methodological conditions remains limited. According to Asad *et al.,* [11] and Virglerova *et al.,* [12], most existing research relies on aggregated data sets or large economies, with no consideration for the heterogeneity and financial environment of small or transition markets. Moreover, there is no consensus on whether country-specific models outperform composite models trained on pooled regional data and on how the relative performance of the models is affected by disparities in sample size and sectoral characteristics. To address these gaps, this study introduces a systematic comparison of logistic regression, decision tree, and artificial neural network models using harmonized datasets from V4 manufacturing enterprises. The innovative contribution lies in combining a regional (pooled) and national (country-level) modeling perspective, complemented by statistical validation to assess inter-country differences in model performance.

This study closes these gaps by comparing the predictive power of LR, ANN, and DT bankruptcy prediction models for the manufacturing sector in V4 countries. The research aims to answer the following questions:

RQ1: *Which of the applied models, classical statistical or machine learning, achieves higher predictive performance in forecasting bankruptcy among manufacturing firms across V4 countries*?

RQ2: *Does a combined model trained on pooled V4 data provide comparable or superior predictive accuracy relative to country-specific models*?

RQ3: *What are the implications of country-specific data characteristics and sample sizes on model performance*?

By answering these questions, the research adds to academic knowledge and practical use, providing insights into how reliable and flexible bankruptcy prediction models are in emerging European markets and specific industries.

Thus, the main aim of this paper is to develop accurate predictive models for assessing the bankruptcy risk of manufacturing enterprises in the V4 countries. The development of prediction models in the manufacturing sector in the V4 countries is of strategic importance for several reasons. These economies are deeply rooted in manufacturing, particularly in sectors such as automotive, machinery, and electronics, where efficiency, quality, and adaptability are crucial for maintaining global competitiveness. By integrating predictive models based on data analytics, artificial intelligence, or machine learning, manufacturers in the V4 region can significantly enhance production planning, reduce equipment downtime through predictive maintenance, optimize supply chains, and improve product quality. This not only increases operational efficiency but also strengthens the resilience of manufacturing enterprises against market fluctuations, supply disruptions, and rising input costs. Moreover, predictive technologies are a key enabler of Industry 4.0, which is essential for the V4 countries as they strive to transition from traditional manufacturing to smart, digitized production systems. This shift allows them to move up the value chain and reduce dependence on low-cost labor advantages. At the same time, the implementation of prediction models contributes to greater sustainability by enabling more efficient use of energy and raw materials. For the V4 countries, investing in such digital capabilities is not only a matter of economic modernization but also a strategic necessity to ensure long-term industrial competitiveness, innovation capacity, and alignment with European policy priorities.

To this end, three methodological methods, specifically LR, ANN, and DT, are employed to contrast their relative effectiveness in identifying financial distress in manufacturing enterprises. The selection of these three techniques is grounded in their established credibility and broad acceptance across multiple disciplines. Logistic regression has long been considered a robust statistical baseline for binary classification tasks, while decision trees and artificial neural networks have demonstrated strong performance and adaptability in financial prediction problems. Recent studies have confirmed their reliability and interpretability in bankruptcy prediction and other decision-making contexts [13-15].

These techniques are particularly effective in the context of this task because of their ability to represent complex, potentially non-linear relationships between financial variables and demonstrate reduced reliance on the rigorous assumptions of traditional statistical models. The analytical framework in this study is structured in two steps. Initially, a complex model is estimated using the pooled data from all the V4 nations, providing a benchmark for model performance across the regional manufacturing economy. Subsequently, the study disaggregates the sample by separate countries, allowing close investigation of country-level predictive capacity and insight into the degree to which domestic market environments and economic structures influence model performance. Model performance is assessed based on established evaluation metrics, including AUC, accuracy, precision, recall, and F1 score. By comparing results on the pooled and per-country datasets, this research aims to identify not only the most predictive model but also to quantify the extent to which regional specificity contributes to model strength. The approach taken in this paper aligns with recent developments in the field, providing a comparative cross-national analysis based on robust modeling techniques.

The study is structured into several main sections. The Literature review section covers past research on bankruptcy prediction, with emphasis on financial ratios of distress and favorite modeling methods. The Methodology section describes data collection from the ORBIS database, the criteria for selecting manufacturing enterprises, and the usage of LR, ANN, and DT as primary prediction methods. The Results and Discussion section presents model performance on the full dataset and regional subgroups, comparing results with the prior literature to validate the effectiveness of each model in capturing financial distress among V4 manufacturing enterprises. The Conclusions section summarizes key findings and reflects upon their policy implications for policymakers, banks, and manufacturing enterprises. Future opportunities for research are indicated, for example, the inclusion of additional financial and non-financial variables to improve the prediction of bankruptcy in the manufacturing sector.

2. Literature Review

Bankruptcy prediction has been the focus of extensive research worldwide, with a range of methodological paradigms that cover classical statistical techniques and modern ML approaches. Initial studies focused on traditional models, such as LR and multiple discriminant analysis (MDA), with a primary utilization of financial ratios in predicting corporate failure. Altman's [16] Z-score model was the foundation for many subsequent studies worldwide. More recent research has included ML algorithms like ANN, DT, support vector machines (SVM), and ensemble methods for modeling complex, nonlinear relationships in financial data [17-19].

Recent studies have further validated the performance of various ML models. Hardinata *et al.,* [20] noted the limitations of neural networks in handling heterogeneous data modalities, which may hinder their performance. Gepp and Kumar [21] noted that classification and regression DT had better performance compared to other models and featured competitive misclassification costs. Furthermore, ensemble learning approaches such as Bagged-pSVM and Boosted-pSVM proposed by Chen *et al.,* [22] achieved high predictive performance on benchmark datasets, while Soui *et al.,* [23] demonstrated the performance of automatic encoders combined with softmax classifiers. Extreme gradient boosting (XGBoost) was demonstrated by Ptak-Chmielewska [24] and Zieba *et al.,* [25] to outperform traditional models in bankruptcy prediction with overfitting resistance and improved classification accuracy. Hybrid models involving LR and SVM also yielded promising results [26].

Studies from outside Europe are useful for providing standardized benchmarks to evaluate model performance. Moon and Kim [27] applied LR, ANN, and random forest (RF) models to South Korean enterprises and recorded AUC scores between 0.85 and 0.94, with ANN slightly ahead in terms of accuracy (over 92 %). Similarly, Kim and Sohn [28] likened LR and SVM for bankruptcy prediction in Korean manufacturing enterprises with F1 scores above 0.90. In the US context, Khashman [29] demonstrated ANN to be superior to conventional models based on accuracy and AUC with figures of 0.95 and above. These worldwide studies confirm both the efficacy and competitiveness of ML and classical models in different economic environments, especially sectoral ones such as manufacturing.

The first hypothesis, that classical and machine learning models can perform equally well, or nearly so, in certain sectors depending on data quality and model calibration, is based on these global findings:

H1: *Machine learning models (e.g., ANN, DT) are expected to achieve equal or superior predictive performance compared to classical statistical models (e.g., LR) in forecasting bankruptcy within the manufacturing sector*.

Moving the focus to Central and Eastern Europe (CEE), research has indicated widespread use of LR and other statistical methods, especially in V4 nations. Prusak and Karas [30] provide an extensive bibliometric overview indicating LR as the most applied in forecasting bankruptcy within the area. Previous Slovak studies by Chrastinova [31] and Gurcik [32] employed MDA, and Adamko and Svabova [33] demonstrated the excellent discriminative power of Altman-based LR models with AUC between 0.81 and 0.88. At the same time, studies such as Gregova *et al.,* [34] and Horvathova *et al.,* [35] have proven that ANNs narrowly outperform LR with more than 94% accuracy, with Durica *et al.,* [36] concluding ANN and DT accuracy figures of 96.5% and 93.2%, respectively, in Slovak environments. In the Czech Republic, Dvoracek *et al.,* [37, 38] have also proven that ANN outperforms

LR by a narrow margin, with Nemec and Pavlik [39] concluding LR accuracy at around 84%. Polish research, as presented by Korol [40] and Pisula *et al.,* [41], preferred the use of ANN and DT models, whose precision is often higher than 90%. Hungarian research indicates some limitations of DT methods to smaller datasets, as provided by Szeverin and Laszlo [42] and Nyitrai and Virag [43], who also suffered from overfitting.

Additional regional studies align with these findings, while Shrivastava *et al.,* [44] advocated Bayesian models to predict early failures in Indian firms and Garcia *et al.,* [45] had discovered greater accuracy of linear models in dissimilarity spaces. Agrawal and Maheshwari [46] and Alifiah [47] demonstrated the significance of financial ratios and industry-specific variables, thereby justifying the use of context-aware predictors. Ben Jabeur and Serret [48] illustrated the advantage of partial least squares LR in addressing multicollinearity and missing data problems.

These findings suggest that while ML methods can provide predictive improvement, conventional methods serve as a reliable baseline for V4 countries' manufacturing sectors.

H2: *A combined bankruptcy prediction model trained on pooled data from all V4 countries provide predictive accuracy comparable to or better than country-specific models*.

The literature also extensively explores the impact of sample size and economic country characteristics on model performance. Some authors note that heterogeneity in the financial environment and smaller data sets may reduce the robustness of models. Szeverin and Laszlo [42] determined that while ANNs outperformed LR in training samples, validation results were undermined by overfitting in more constrained Hungarian data sets. Similarly, Nyitrai and Virag [43] found that outlier handling and segmentation techniques improved AUC values but also indicated the vulnerability of ML models to sample composition. The relatively inferior performance of DT models in Hungary compared to Slovakia or Poland [29] also confirms the vulnerability of certain ML models with small data. These findings underscore the importance of accounting for local data characteristics in model development and emphasize the potential benefits of country-specific, customized modeling approaches.

Previous papers by Klepac and Hampel [49] and Rech *et al.,* [50] point to declining precision in financial distress prediction as enterprises are further away from bankruptcy, a factor that might vary with the economic environment of the country. Sun *et al.,* [51] emphasize the adaptive, comprehensive financial distress systems to consider emerging market risks. Lin and Dong [52] pointed toward the mitigating effect of a favorable historical performance on bankruptcy risk, indicating heterogeneity effects of information.

H3: *Variations in data characteristics and sample sizes across V4 countries affect model performance, with smaller or more heterogeneous datasets leading to reduced predictive accuracy, particularly for models such as DT*.

Even with all the research on bankruptcy prediction around the world and in the V4 countries, there is still a considerable gap in comparing the classical and ML models, particularly in the manufacturing industry of the transitional economies. Although ML methods tend to be more efficient in most foreign studies, their superiority is less evident in the case of the V4 countries, where LR is still yielding stable and explainable outcomes. Furthermore, the scope and limitations of pooling across varying contexts, as well as the conditions under which it remains valid, represent a relatively underexplored area. It remains unclear whether aggregated models based on multi-country data can match or outperform country-specific models, especially given the differing economic, regulatory, and financial reporting environments within the V4 countries. There is also an important gap regarding the effects of variation in data quality, sample size, and country features on the stability and generalizability of predictive models. Smaller or more heterogeneous data sets may disproportionately affect ML models, potentially leading to overfitting or decreased accuracy, as identified through earlier research work in Hungary. Bridging these gaps is not only crucial for enhancing the effectiveness of early warning systems but also for informing policymakers, banks, and manufacturing enterprises in transition economies on the best methodological approaches for their conditions. In attempting to overcome these limitations, this research endeavors to contribute to further, more solid, versatile, and regionally applicable models of bankruptcy prediction to make possible economic stability and successful credit risk management in the V4 manufacturing sector.

3. Methodology

This study aims to develop robust prediction models for bankruptcy risk of manufacturing enterprises in the V4 countries. Therefore, three statistical and ML classification techniques, such as LR, ANN, and DT, are employed. Each methodology offers distinct methodological strengths. LR is interpretable and transparent, while ANN can model complex nonlinear relationships, and DT provides a rule-based decision framework that can accommodate interactions between variables as well as class imbalance. These models are estimated in two steps. Initially, a complex model is developed using a pooled dataset for all V4 countries to provide an equivalent regional perspective. Subsequently, country-specific models are constructed to identify whether disaggregation does improve predictive performance and capture national-level specificity. To provide a comprehensive overview of the analytical workflow, Figure 1 illustrates the sequential stages of the research process.

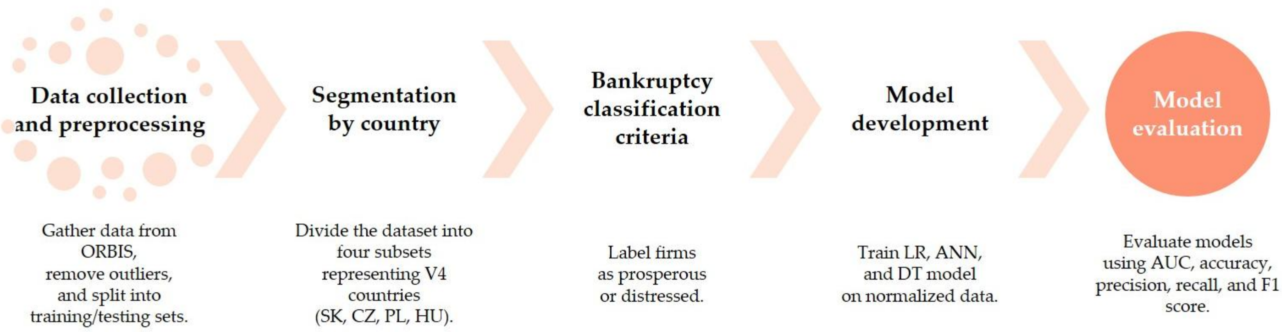

Fig. 1. Research implementation framework of bankruptcy models for the Visegrad Group countries

Through both pooled and disaggregated model construction, the study elucidates the trade-off between regional generalizability and national specificity in bankruptcy prediction. These results possess direct applicability in practice to financial institutions, policymakers, and regulators who aim to enhance early warning systems and ensure targeted interventions in one of the most strategically important sectors of the V4 economies. Furthermore, the study makes a methodological contribution while it compares the predictive power of three approaches, thereby enhancing the validity and interpretability of bankruptcy prediction across transition economies.

3.1. Data Description and Preprocessing

The data used for the development of bankruptcy prediction models includes financial information regarding manufacturing enterprises categorized under Section C (Manufacturing) in the ORBIS database, which offers harmonized and standardized firm-level financial reports for countries that make cross-country comparison feasible. The initial sample consisted of 33,684 manufacturing enterprises in the V4 countries. The sample selection was done along their NACE sector classification, encompassing most industrial activities such as food manufacturing, textiles, metalworking, machinery, electronics, and chemicals, which are highly capital-intensive sectors with considerable economic relevance. The independent variables used in modeling are firm-specific financial ratios in 2022, depicting various dimensions of profitability, liquidity, solvency, and efficiency. The financial prosperity status in 2023, represented as the dependent variable, was measured dichotomously to distinguish between prosperous and distressed enterprises. To ensure data accuracy, enterprises with missing or incomplete financial data were systematically eliminated. Outliers were neither adjusted nor removed, ensuring that the entire variability of financial behavior in the real-world business context was retained. This approach preserves the inherent distributional characteristics of the data, thereby enhancing the models' applicability in real-world financial settings, where borderline cases may carry substantial predictive importance. After the removal of incomplete observations, the final sample was formed of 15,708 manufacturing enterprises, among which 14,617 were classified as prosperous and 1,091 as distressed, indicating a moderate level of class imbalance. For developing and testing the predictive models, the dataset was split into training (70 %) and test (30 %) subsets randomly. Given the large sample size and balanced stratification between prosperous and distressed firms, the use of a single train/test split provided sufficient stability of results. Preliminary tests with alternative random splits produced consistent outcomes, indicating that the models were not sensitive to data partitioning. Therefore, a simple hold-out validation was deemed appropriate for this study. Stratified sampling was employed to maintain the original distribution of prosperous and distressed enterprises in both subsets, hence limiting possible bias and enhancing classification accuracy. Once trained and tested on the combined data set, comprising manufacturing enterprises from the entire CEE region, the analysis proceeded to the regional disaggregation phase, focusing specifically on the V4 nations. This step offers the possibility of testing whether models for countries are better than the overall one and permits examination of heterogeneity in prediction patterns related to national economic institutions and systems.

To explore potential differences in national-level bankruptcy dynamics, the pooled CEE dataset is divided into separate countries with a particular emphasis on V4 countries, consisting of Slovakia, the Czech Republic, Poland, and Hungary. Rather than employing a regional clustering strategy, the study constructs and tests separate predictive models for each country. This structure allows for a more detailed evaluation of financial trends at the country level, institutional factors, and model performance with methodological consistency to provide comparability. The sample distribution across the four countries is detailed as follows: 2,242 enterprises from Slovakia, comprising 2,005 classified as prosperous and 237 as distressed; 2,797 enterprises from the Czech Republic, with 2,625 prosperous and 172 distressed; 5,879 enterprises from Poland, including 5,390 prosperous and 489 distressed; and 4,790 enterprises from Hungary, of which 4,597 are prosperous and 193 distressed. This nation-level segmentation ensures that models are developed across their national contexts, with methodological homogeneity to facilitate meaningful cross-country comparison.

While traditional bankruptcy prediction methods such as MDA or Z-score models are reliant upon restrictive linear and distributional assumptions, LR represents an advancement as it enables probabilistic classification within a parametric framework. Compared to that, ANN and DT are more capable of accommodating the specification of intricate, non-linear relationships and uncovering latent interactions among predictors. The originality of this study lies in the use of all three methods in the manufacturing sector of the V4 nations, a territory that is not yet fully mapped in terms of data-driven insolvency prediction. By employing country-specific models, the analysis can conduct a cross-country comparison of forecasting accuracy. This research elucidates the relationship between algorithmic resilience and the unique financial and institutional characteristics of each V4 country.

Independent variables were selected based on empirical facts in prior studies [53-57], focusing on key financial ratios that have been identified to be most indicative of the financial conditions of enterprises. The selected financial indicators and their quantitative interconnections are presented in Table 1.

Table 1
Summarized formulas of financial indicators

Input neuron	Indicator	Algorithm	Input neuron	Indicator	Algorithm
QR	Quick ratio	$\frac{\text{CUAS-STOK}}{\text{CULI}}$	ROA	Return on assets ratio	$\frac{\text{PLAT}}{\text{TOAS}}$
CurrR	Current ratio	$\frac{\text{CUAS}}{\text{CULI}}$	ROE	Return on equity ratio	$\frac{\text{PLAT}}{\text{SHFD}}$
Ins	Insolvency ratio	$\frac{\text{NCLI+CULI}}{\text{DEBT+OCAS}}$	ROS	Return on sales ratio	$\frac{\text{PLAT}}{\text{OPRE+TURN}}$
IT	Inventory turnover ratio	$\frac{\text{OPRE+TURN}}{\text{STOK}}$	TI	Total indebtedness ratio	$\frac{\text{NCLI+CULI}}{\text{TOAS}}$
CollP	Collection period ratio	$\frac{\text{DEBT}}{\text{OPRE+TURN}} \cdot 365$	DE	Debt-to-equity ratio	$\frac{\text{NCLI+CULI}}{\text{SHFD}}$
CredP	Credit period ratio	$\frac{\text{CRED}}{\text{OPRE+TURN}} \cdot 365$	EL	Equity leverage ratio	$\frac{\text{TOAS}}{\text{SHFD}}$

Note: CUAS Current Assets, STOK Stock, DEBT Debtors, TOAS Total Assets, OCAS Other Current Assets, SHFD Shareholders Funds, NCLI Non-Current Liabilities, CULI Current Liabilities, CRED Creditors, TURN Sales, OPRE Operating revenue, PLAT Profit (Loss) After Tax. Source: Gajdosikova *et al.,* [58]

3.2. Definition of Classification Criteria

To enable binary classification in the bankruptcy prediction models, enterprises were categorized into two categories depending on their financial status [59]. The first category comprises successful enterprises, characterized by stable debt levels and the absence of significant financial distress. Distressed enterprises form the second category and are characterized by signs of financial distress, specifically concerning their capital structure. The threshold of classification is defined in terms of the equity-to-debt ratio, a commonly used measure of financial independence and creditworthiness. Following the method proposed by Gregova *et al.,* [34], enterprises with an equity-to-debt ratio below 0.08 are considered financially distressed.

The threshold value of the equity-to-debt ratio is legislatively defined by the Slovak Commercial Code (§ 67a), which establishes 0.08 as the limit indicating the onset of financial distress. Because this indicator serves as an early warning signal of insolvency risk, the same threshold was also applied to enterprises from the Czech Republic, Poland, and Hungary. These economies share a comparable level of market development, financial regulation, and accounting standards, making the criterion transferable across the V4 region. A similar regional approach was employed by Valaskova *et al.,* [60] and Michalkova and Ponisciakova [56], who used the same cut-off value in a cross-country bankruptcy prediction analysis of Visegrad Group economies.

The threshold reflects an extremely low level of capitalization, indicating that corporate indebtedness is higher than rational levels and the enterprise is most likely facing a financial crisis. As a response, the dependent variable (Y) is a binary outcome variable, where:

$$\mathrm{Y} = \begin{cases} 0 \text{ for distressed enterprise} \\ 1 \text{ for prosperous enterprise} \end{cases} \tag{1}$$

3.3. Predictive Modeling Methods

Based on the above binary grouping, three model methods were selected for their complementary predictive power in predictive analytics. These models were utilized to cover a spectrum of modeling paradigms with a trade-off between statistical interpretability and computational expense. LR serves as a baseline with a well-established theoretical basis, while DT offers straightforward rule-based decision logic, and ANN can represent nonlinear interactions and high-level patterns, which are best suited for high-dimensional financial data.

Each model was trained with a stratified train/test split, preserving the class ratios between prosperous and distressed enterprises. Input variables were preprocessed using min-max normalization before modeling to ensure convergence and comparability, particularly when training the ANN. Strict preprocessing steps were also used to test for statistical significance, remove multicollinearity, and verify the consistency of financial metrics across regions.

Due to the typical class imbalance of financial distress datasets, no further oversampling or class-weighting adjustments were made. Strong minority-class performance in recall and F1 score justified making this decision. As noted in literature [61], resampling methods are not universally beneficial and may, under certain conditions, result in overfitting or information loss, particularly when baseline model performance is already satisfactory.

Logistic regression (LR) is a central statistical method used for binary classification that has been extremely effective in predicting financial distress. LR outlines the log-odds of the distressed enterprise to be a linear function of financial predictors, transforming them into a probability using the logistic function. The estimation was carried out using the maximum likelihood algorithm, which iteratively adjusts coefficients to minimize the log-likelihood error. LR is valued for its robustness in terms of deviations from normality and homoscedasticity and is therefore particularly appropriate to use with real-world financial data. Its coefficients can be interpreted as odds ratios, providing unequivocal insight into the effect of predictors. For this study, LR was an open and interpretable baseline against which more advanced models were compared.

Artificial neural networks (ANN) were implemented according to a feedforward multilayer perceptron architecture with an input layer consisting of twelve standardized financial indicators, one hidden layer with three neurons, and an output layer with softmax activation. The hyperbolic tangent activation function was used in the hidden layer to maintain nonlinearity, while all input variables were standardized to ensure numerical stability. The model was trained using the scaled conjugate gradient optimization algorithm with a cross-entropy loss function, and early stopping was employed to prevent overfitting. Preliminary testing of alternative configurations was performed, and the selected structure was found to provide a balanced trade-off between model complexity and predictive accuracy. The ANN was accurate in generalization and classification, particularly for weak nonlinearities in financial ratios.

Decision trees (DT), applied via the classification and regression trees (C&RT) algorithm, recursively split data to construct clear decision rules. Node impurity was estimated via the Gini index to inform optimal split choice. Tree growth followed a binary recursive partitioning process until the minimum node size criterion was reached. Post-pruning was employed using cost-complexity pruning to improve generalization and avoid overfitting. DTs were especially useful in identifying prominent predictors and allowing transparent rule-based classification.

To prevent model overfitting and data leakage, each algorithm was trained and validated on separate datasets, with the test data (30%) held out entirely from model training. Regularization mechanisms inherent in SPSS procedures, such as early stopping for the ANN, pruning for the DT, and parameter constraints for the LR, were applied to control model complexity. All financial indicators were derived exclusively from the same fiscal period preceding bankruptcy, ensuring that no future information was introduced during model training. These steps ensured the models' methodological rigor and unbiased generalization performance.

These models combined provide a robust comparative basis for financial distress prediction under different regional and firm-specific conditions. All analyses, including model training, validation, and data preprocessing, were performed in IBM SPSS Statistics, ensuring methodological consistency and reproducibility of results.

3.4. Model Evaluation Metrics

The predictive performance of bankruptcy classification models was assessed rigorously using various complementary metrics, including the AUC of the receiver operating characteristic (ROC) curve. AUC quantifies the discrimination by the model between prosperous and distressed enterprises at varying classification cut-off points, with values closer to 1 reflecting higher discrimination. Along with AUC, metrics like accuracy, precision, recall (sensitivity), and the F1 score were utilized to provide a multi-dimensional evaluation, particularly relevant in the context of financially imbalanced datasets.

Recall measures the proportion of correctly classified distressed enterprises, while specificity measures the correct classification rate of distressed enterprises. Accuracy measures the overall proportion of correctly classified observations of both classes. However, in skewed cases when the distressed enterprises form the minority class, accuracy by itself can be misleading. The F1 score, being the harmonic mean of accuracy (true positive rate out of classified positives) and recall (fraction of actual positives correctly classified), balances between false positive and false negative rates, with a robust metric that compensates for both kinds of errors in classification. To further examine whether the model performance differed significantly across the V4 countries, a one-way ANOVA was conducted using the F1 score as the dependent variable and country as the grouping factor, followed by Tukey's post hoc tests. This procedure enabled statistical verification of cross-country variations in predictive accuracy, adding an additional layer of methodological rigor to the comparative evaluation. Together, these steps offered rigorous and explicit evaluation of model performance to facilitate fair comparison and model selection most appropriate for accurate financial distress prediction.

4. Results

The performance of the three models in classifying the merged V4 dataset is reported in Table 2. All models are highly accurate in correctly classifying prosperous enterprises in the training sample, with correct classification rates exceeding 98 % for all techniques. Among distressed enterprises, the highest correct classification rate was achieved by DT at 76.6 %, followed by ANN with 69.8 %, and LR with 59.2 %. Overall, models demonstrate strong performance on the training sample, with overall accuracy ranging from 93.5 % for DT to 96.9 % for ANN. On the test sample, classification accuracy for prosperous enterprises is greater than 99 % for each model. However, the models decrease correctness in classifying distressed enterprises, each with approximately 53.7 % correctness. The models also perform well on the test set, with accuracy ranging from 93.3 % for DT to 97.1 % for LR. These statistics indicate that although all models are very accurate in identifying prosperous enterprises, it is a slightly tougher task for them to identify distressed enterprises, particularly in unfamiliar cases. Nevertheless, the models possess high overall predictive accuracy on the V4 dataset.

Table 2
Predictive classification accuracy of bankruptcy models for the Visegrad Group countries

Classification										
		LR			ANN			DT		
		Predicted		Percent Correct	Predicted		Percent Correct	Predicted		Percent Correct
Sample	Observed	0	1		0	1		0	1	
Training	0	465	320	59.2%	519	225	69.8%	583	178	76.6%
	1	72	10,171	99.3%	108	9,967	98.9%	133	10,108	98.7%
	Overall Percent	4.9%	95.1%	96.4%	5.8%	94.2%	96.9%	6.5%	93.5%	97.2%
Testing	0	197	109	53.7%	234	113	53.7%	253	77	53.7%
	1	27	4,347	99.2%	41	4,501	99.2%	62	4,314	99.2%
	Overall Percent	4.8%	95.2%	97.1%	5.6%	94.4%	96.9%	6.7%	93.3%	97.0%

Source: own elaboration

The performance metrics of the three models on the aggregated V4 dataset are presented in Table 3. To provide a visual representation of model discrimination, the ROC curves for the models are displayed in Figure 2.

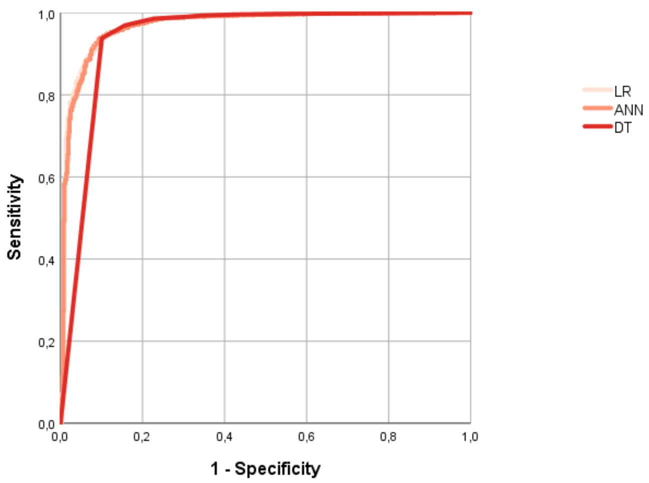

Fig. 2. ROC curves visualization of bankruptcy models for the Visegrad Group countries
Source: own elaboration

All reported metrics were calculated on the test datasets (30% of the data), which were not used during model training, in order to ensure an unbiased evaluation of the models' generalization performance. All three models demonstrate strong predictive capability, as the AUC measures exceed 0.94, a sign of significant discriminatory capability. LR possesses the highest AUC value of 0.974, closely followed by the ANN at 0.969 and the DT with a slightly lower AUC at 0.942. Across all models, precision ranges from approximately 80.32 % for DT to 87.95 % for LR, while recall varies between 64.38 % and 76.67 %, indicating that the models are moderately effective in identifying distressed enterprises despite the inherent class imbalance. F1 scores, which combine both precision and recall, range between 74.34 % and 78.45 %, suggesting balanced yet cautious predictive performance for the minority class. Although the predictive accuracy is lower than for the prosperous class, these results remain satisfactory given the rarity and complexity of financial distress events. Several measures were applied to prevent overfitting and data leakage. The models were validated exclusively on independent test datasets, and early stopping, pruning, and built-in regularization mechanisms were employed within SPSS algorithms to control model complexity. All financial indicators refer strictly to the same fiscal period preceding bankruptcy, eliminating potential data leakage. The obtained results thus provide a reliable and transparent representation of the models' real-world generalization capacity rather than inflated in-sample performance.

Table 3
Performance metrics of bankruptcy models for the Visegrad Group countries

	AUC	Accuracy	Precision	Recall	F1 Score
LR	0.974	0.9709	0.8795	0.6438	0.7434
ANN	0.969	0.9685	0.8509	0.6744	0.7524
DT	0.942	0.9705	0.8032	0.7667	0.7845

Source: own elaboration

To yield results beyond the V4 country-specific characteristics and potential differences in bankruptcy prediction, models were trained and validated on independent data for every member of the V4. This is of scientific value as it enables the examination of whether data heterogeneity influences model performance or generalizability and local circumstances of markets affect model performance, and compares it with those obtained from the aggregate V4 sample.

As evidenced in Table 4, all single-country models exhibit overall solid yet varying performance on all the criteria for evaluation, demonstrating moderate to strong predictive power in all V4 economies. The ROC curves for individual Visegrad Group countries are illustrated in Figure 3, providing a visual comparison of the models' discriminatory performance. In this context, LR demonstrates superior overall performance, achieving the highest AUC of 0.991 in the Czech Republic, indicative of an excellent fit to the domestic dataset.

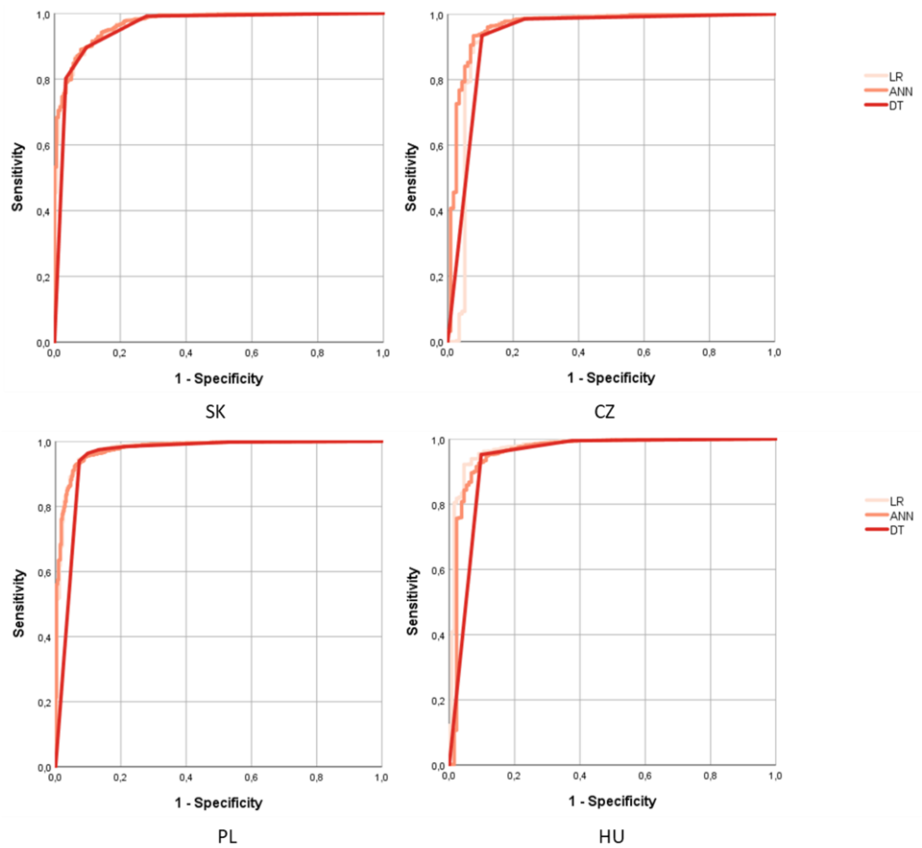

Fig. 3. ROC curves visualization of bankruptcy models for individual Visegrad Group countries

LR and ANN perform equally in Poland and Slovakia, with the AUC being close to or greater than 0.97. The DT model possesses a slightly lower AUC but is nevertheless an effective classifier. For Hungary, the performance of the DT model is low (AUC of 0.929), because of the small sample size and potentially due to market-specific factors affecting the discrimination power of the model. To empirically verify whether the observed differences across countries are statistically significant, a one-way ANOVA using the F1 score as the dependent variable was performed. The analysis confirmed significant variation in model performance among the V4 economies. The Tukey post hoc test further revealed that the mean F1 score for Hungary was significantly lower than for the Czech Republic and marginally lower than for Poland, whereas the remaining pairwise differences were not significant. These results substantiate the claim that Hungary's weaker predictive performance is systematic and data-driven rather than random variation.

Table 4
Performance metrics of bankruptcy models for individual Visegrad Group countries

		AUC	Accuracy	Precision	Recall	F1 Score
SK	LR	0.971	0.9525	0.8571	0.5806	0.6923
	ANN	0.970	0.9548	0.9310	0.6667	0.7770
	DT	0.956	0.9487	0.8235	0.6364	0.7179
CZ	LR	0.991	0.9828	0.8889	0.8421	0.8649
	ANN	0.967	0.9780	0.7778	0.8140	0.7955
	DT	0.950	0.9743	0.8182	0.7895	0.8036
PL	LR	0.977	0.9644	0.8942	0.6414	0.7470
	ANN	0.976	0.9588	0.7810	0.7133	0.7456
	DT	0.956	0.9706	0.8231	0.8288	0.8259
HU	LR	0.973	0.9753	0.8571	0.5000	0.6316
	ANN	0.957	0.9737	0.7609	0.5645	0.6481
	DT	0.929	0.9781	0.7647	0.6610	0.7091

Source: own elaboration

Precision, recall, and F1 scores are consistent in every country and model, confirming the predictions as well-balanced between accurately identifying distressed enterprises and minimizing false positives. Most notably, the ANN model performs equally well in all countries, typically behind LR, as expected due to dataset sizes. Overall, these findings make the use of a single model trained on pooled V4 data reasonable, with potential for fine-tuning or adaptation at the individual country level to account for country-specific market characteristics and to enhance local predictive accuracy. While single-country models maintain good discriminative capacity, their predictive strength varies, with the Czech Republic performing the best among the V4 economies.

5. Discussion

Several studies of bankruptcy prediction in CEE and, more notably, the V4 area directly report performance metrics such as AUC, accuracy, and F1 score, which can be used to perform robust benchmarking against our findings. Adamko and Svabova [33] present AUC values between 0.81 and 0.88 for Altman-based LR models of Slovak enterprises, demonstrating the discriminative capability of conventional methods in the area. Augmenting this, Gregova *et al.,* [34] further report an ANN accuracy of approximately 94.37%, which closely aligns with our estimate, while Horvathova *et al.,* [35] provide evidence of ANN precision of more than 95%, evidencing neural networks' ability to precisely identify financial distress. Simultaneously, Durica *et al.,* [29] also show ANN and DT accuracies of 96.5 % and 93.2 %, respectively, replicating the gap in performance visible in our dataset, as DT has slightly less predictability compared to ANN and LR. These consistent outcomes across multiple studies confirm H1, demonstrating that machine learning models (ANN, DT) achieve predictive performance comparable to logistic regression in bankruptcy forecasting.

Nyitrai and Virag [43] offer insight by showing linear discriminant analysis with CHAID segmentation outperforms ANN on average AUC for Hungarian datasets, illustrating the nuanced impact of preprocessing and segmentation on prediction. Pisula *et al.,* [41] and Korol [40], discussing Polish bankruptcy models, highlight the advantage of ML methods like ANN over conventional models, although with decreased attention to specific measures like F1 score. Broader CEE research by Bozsik [62] and Nemec and Pavlik [39] highlighted the importance of integrating financial and non-financial variables and adaptive modeling techniques, highlighting the requirement for flexible prediction models capable of accommodating economic fluctuations. In addition, Al-Sarraf [63] demonstrated in their research in the MENA region that combining macroeconomic and firm-level variables undoubtedly improved AUC and F1 scores, suggesting that broader variable inclusion may be useful for V4 economies. Tsai [26] also highlighted the superior predictive performance and F1 score of ML models, especially ANNs, in cross-industry bankruptcy prediction.

It was further observed that a combined bankruptcy prediction model trained on pooled V4 data achieved predictive accuracy and AUC values comparable to or exceeding those of the single-country models, thereby confirming H2. This outcome suggests that, despite certain national differences, the shared institutional and economic background of the V4 economies enables generalizable predictive patterns. However, statistically significant differences identified by the ANOVA test indicate that local data characteristics and sample heterogeneity continue to influence model behavior. This finding partially supports H3, as smaller and more heterogeneous datasets, particularly in the Hungarian sample, were associated with lower predictive accuracy.

In general, the better performance measures reported in this study signal competitive or higher predictive capability relative to existing literature (e.g. [64-66]). This confirms the viability of conventional and complicated ML models for effective credit risk estimation in transition economies, as well as reinforcing the importance of embracing regional market peculiarities and sample size considerations in model development and evaluation.

Empirical large-scale research conducted outside the V4 region and the EU environment provides important pointers to the predictive power of models of bankruptcy in different economic environments. Sizan *et al.,* [67] employed several ML methods in the US market and achieved between 0.85 and 0.95 AUC values with collective accuracy above 90 %. Their findings validate the superiority of ensemble learning techniques in detecting weak financial distress signals. Similarly, Sun *et al.,* [68] studied Chinese manufacturing enterprises and demonstrated that ensemble models integrating gradient boosting and neural networks achieved an AUC of 0.93 and accuracy of 92 %, indicative of the effectiveness of integrating multiple algorithmic approaches in providing strong prediction in emerging economies. In other Asian markets, Chen *et al.,* [22] models using financial ratios and macroeconomic factors with F1 scores between 0.88 and 0.94 and concluded that advanced machine learning models such as ANN and XGBoost outperformed traditional LR on both predictive accuracy and precision-recall balance. Moon and Kim [27] investigated Korean enterprises, finding DT and RF models attaining over 90 % accuracy and F1 scores very close to 0.90, and this indicates the robustness and interpretability of the tree-based models in identifying enterprises as financially distressed. Evidence from Latin America and Africa also confirms the applicability of advanced ML methods. Garcia *et al.,* [45] showed that RF classifiers obtained AUC values greater than 0.90 among Mexican enterprises, while Ekbunike *et al.,* [69] showed that genetic algorithm and ensemble classifiers obtained classification accuracy rates greater than 85 % among Nigerian SMEs.

Collectively, these international and regional findings jointly validate H1 and H2, showing that ML models, particularly ANNs, tend to outperform or complement traditional statistical methods across multiple economic contexts. The partial confirmation of H3 further demonstrates that model effectiveness remains context-dependent and sensitive to sample representativeness and data quality. However, the study also highlights that model building must be situated within the context of sectoral and provincial idiosyncrasies, like differences in accounting standards, business cycle differences, and regulatory styles, which have a significant influence on forecasting outcomes and the practicality of bankruptcy prediction. Consequently, while ML models offer substantial improvements in predictive accuracy, their implementation requires careful adaptation to local financial, legal, and economic conditions to ensure reliable and actionable early-warning insights.

6. Conclusions

This study investigated the predictive performance of LR, ANN, and DT to predict bankruptcy in the manufacturing sector in V4 countries. The principal findings validate that all three models possess a high discriminatory power, with very comparable AUC values in Slovakia, the Czech Republic, Poland, and Hungary. In particular, LR remains a robust reference model in predictive tasks, with performance similar to more sophisticated ML methods such as ANN and DT. The results indicate that the financial indicators selected for the model properly capture the risk of bankruptcy in this sector. In addition, the comparatively small performance variation across individual countries and the overall V4 dataset implies that it is possible to develop a unified predictive model, though country-specific models may yield interesting complementary insights. The comparatively weaker performance of DT in Hungary suggests potential challenges related to limited sample size and distinctive market-specific characteristics.

From an economic perspective, these findings are significant. The developed models can be applied by banks, investment funds, and government agencies involved in enterprise risk estimation in the manufacturing sector. The early identification of at-risk enterprises through these models has the potential to reduce non-performing loan losses and enhance the effectiveness of financial support mechanisms. The robustness of the models for V4 nations also supports the creation of universal rating systems with regional market adaptability. However, the less precise ranking of DT in Hungary suggests that in smaller or more heterogeneous markets, extra data collection or specialized modeling methods may be necessary.

Despite promising outcomes, some limitations must be mentioned. The datasets vary in size across countries, and this can affect model stability and generalizability, especially in the case of Hungary. In addition, only financial indicators are used within the analysis without incorporating potential qualitative or macroeconomic variables that could further improve predictive accuracy. Subsequent research might also examine using more detailed data sources and explore other ML approaches, such as ensemble methods or explainable artificial intelligence, to further improve bankruptcy prediction in the manufacturing sector. Additionally, data refinement techniques such as clustering could be implemented in future studies to identify latent firm structures or financial behavior patterns prior to model training, potentially improving classification accuracy and interpretability. Future studies could also apply advanced validation strategies, such as k-fold or repeated cross-validation, to enhance the robustness and generalizability of model performance across different data partitions. Furthermore, research on other industries or nations would be beneficial to experiment with the external validity of the results.

In conclusion, this study ensures that traditional and advanced ML models are feasible platforms for industry-specific bankruptcy prediction. The results contribute to the growing body of evidence supporting the practical applicability of these models in credit risk management and underscore the potential advantages of integrating both universal and country-specific modeling approaches.

Author Contributions

Conceptualization, D.G., K.V. and P.D.; methodology, P.D.; software, D.G.; validation, D.G., K.V. and P.D.; formal analysis, D.G.; investigation, D.G.; resources, D.G.; data curation, P.D.; writing—original draft preparation, D.G.; writing—review and editing, K.V. and P.D.; visualization, D.G.; supervision, K.V. and P.D.; project administration, K.V.; funding acquisition, K.V. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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