



COMPARING ARTIFICIAL NEURAL NETWORKS & LOGISTIC REGRESSION FOR BANKRUPTCY PREDICTION: A RESEARCH SYNTHESIS

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Abstract:

Predicting corporate bankruptcy accurately is crucial for reducing financial risks and protecting stakeholders. Logistic Regression (LR) has long been valued for its interpretability, while Artificial Neural Networks (ANNs) have gained prominence for capturing complex, nonlinear financial relationships. This study synthesizes comparative evidence to assess their relative strengths and limitations. A systematic review of peer-reviewed studies published between 2018 and 2024 was conducted using Scopus, Web of Science, and IEEE Xplore. Studies were included if they directly compared ANNs and LR in bankruptcy prediction, reporting performance metrics such as accuracy, recall, and handling of class imbalance. Attention was also given to the application of visualization and interpretability tools. The findings indicate that ANNs generally outperform LR in predictive performance, with accuracy reaching up to 96% and recall above 95%, especially when advanced preprocessing techniques such as the Synthetic Minority Oversampling Technique (SMOTE) and feature selection are applied. ANNs are particularly effective in modelling nonlinear and high-dimensional data but face challenges related to overfitting, computational demand, and lack of transparency. LR, though often less accurate, remains robust for its statistical rigor, ease of implementation, and interpretability. In certain contexts, LR has also demonstrated higher precision, showing that performance may vary depending on the characteristics and quality of the underlying data. Overall, ANNs are preferable in complex, data-rich environments, while LR is more suitable where transparency and regulatory compliance are critical. Future research should explore hybrid models that integrate ANN's predictive power with LR's

explainability, supported by explainable AI and real-time decision-support tools.

Keywords:

Artificial Neural Networks, Bankruptcy Prediction, Logistic Regression

Introduction

In today's increasingly unstable financial environment, predicting business insolvency accurately and reliably is a crucial concern. Therefore, an early warning system plays a vital role in safeguarding investors, creditors, policymakers, auditors, and corporate decision-makers against unexpected financial distress (Brygała, 2022; Marso & El Merouani, 2020). Over the past century, bankruptcy prediction models have their origins in univariate analyses of financial ratios (Beaver, 1966) and have progressed with the advent of multivariate discriminant analysis (Altman, 1968), establishing the basis for contemporary predictive frameworks.

Recently, evidence showed that LR, introduced by Ohlson (1980) has gained widespread acceptance owing to its interpretability and statistical clarity, allowing stakeholders to comprehend the impact of financial variables on bankruptcy risk. However, the growing complexity of corporate financial structures, along with the rapid expansion of available data, has challenged the assumptions underlying linear models. This situation has led to the adoption of Machine Learning (ML) approaches, particularly ANNs, which can effectively capture the complex nonlinear relationships found in financial data (Gavurova, Rigelsky, Bacik, & Ivankova, 2022; Vochozka, Vrbka, & Suler, 2020). Over the past two decades, many empirical studies have compared ANNs and LR models across various datasets and industries. These studies have produced mixed results regarding their relative predictive performance and practical applicability (Horak, Krulicky, & Machova, 2020; Shi & Li, 2019).

Given the dual importance of model accuracy and interpretability in financial risk assessment, a systematic and comprehensive review of the existing literature is necessary. This review seeks to examine the methodological foundations, comparative performance metrics, challenges in data preprocessing and class imbalance, and practical considerations for deploying ANNs and LR models in bankruptcy prediction. It aims to provide insights that will guide future research and applications in financial analytics.

Literature Review***Research Background***

Bankruptcy prediction is a central concern in financial research, as it helps investors, creditors, and policymakers anticipate insolvency risks. The field has evolved from early ratio-based studies (Beaver, 1966) and multivariate discriminant analysis (Altman, 1968) to probabilistic models such as Logistic Regression (Ohlson, 1980) and, more recently, machine learning methods.

LR remains one of the most widely applied approaches because of its statistical rigor and interpretability. It allows decision-makers to evaluate how financial indicators influence bankruptcy risk, which is particularly valuable in regulatory and auditing contexts (Kuster,

Majstorovic, & Dmitrovic, 2025; Brygała, 2022). Yet, LR's linear assumptions limit its ability to capture the nonlinear dynamics often present in financial data (Shi & Li, 2019).

On the contrary, ANNs, have gained prominence for their ability to model nonlinear and high-dimensional data. With advances in computational power, ANNs often achieve higher predictive accuracy and recall than LR (Vochozka, Vrbka, & Suler, 2020; Gavurova et al., 2022). Nevertheless, lack of transparency and susceptibility to overfitting remain challenges for ANNs (Heidary, Ziari, Shayanni, & Rashidi Komijan, 2024).

Comparative studies show that ANNs outperform LR in most contexts, moreover when advanced preprocessing methods such as the SMOTE and feature selection are applied (Muslim, Rahman, & Pratama, 2023; Prasetyo, Nugroho, & Wibowo, 2021). Yet in certain cases, such as Moroccan firms, LR achieved higher precision, demonstrating that dataset characteristics can influence which model performs best (Zizi, Boukhatem, & El Idrissi, 2021). Recent research also emphasizes the importance of addressing class imbalance and the growing use of explainable AI tools. Techniques such as SHAP and LIME, together with visualization dashboards, improve interpretability and enhance stakeholder trust (Park, Son, Hyun, & Hwang, 2021; Covaci & Boscan, 2023). Overall, these developments underscore the need to balance predictive performance with interpretability, providing the rationale for this review.

In sum, the literature highlights the evolution of bankruptcy prediction models, the contrasting strengths of LR and ANNs, the importance of addressing data challenges, and the growing demand for interpretability. These elements provide the foundation for the present review.

Comparative Evidence on Model Performance

Recent literature from 2018 to 2025 consistently demonstrates that ANNs generally outperform LR in bankruptcy prediction, particularly in terms of accuracy and recall. ANNs, due to their multilayered and nonlinear architecture, are adept at capturing complex interactions and patterns within financial data that traditional linear models like LR may overlook (Gavurova et al., 2022; Heidary et al., 2024; Sun, Wang & Liu, 2024). For instance, studies by Gavurova et al. (2022) and Ahmad Shukri (2024) report that ANNs models achieve higher accuracy rates which often exceeding 93% as compared to LR, whose accuracy typically ranges from 88% to 91% depending on dataset characteristics and preprocessing methods. This advantage is particularly pronounced when advanced data balancing techniques like SMOTE and feature selection are utilized, which help ANNs handle class imbalance and improve generalizability (Muslim et al., 2023; Prasetyo et al., 2021).

Recall, which measures the model's ability to correctly identify bankrupt firms, is also generally higher for ANNs. For instance, Muslim et al. (2023) and Wang et al. (2021) found that ANNs recall rates often surpass 95%, whereas LR recall can be lower, especially in imbalanced datasets. This situation showed that ANNs is valuable in practical scenarios such as failing to detect bankruptcy cases carries significant financial risk. Furthermore, ANNs' capacity to model nonlinear and high-dimensional relationships allows them to integrate a wider array of financial and non-financial predictors, further enhancing their predictive power (Heidary et al., 2024; Sun et al., 2024).

However, the literature also highlights important caveats. LR remains a strong alternative in contexts where model interpretability, transparency, and ease of implementation are prioritized, such as regulatory or auditing environments (Brygała, 2022; Gavurova et al., 2022). In certain cases, such as the Moroccan dataset studied by Zizi et al. (2021) LR has outperforms

ANNs in precision, illustrating that model superiority can be context-dependent and influenced by the underlying data structure. Furthermore, while ANNs excel at modeling complex relationships, they are more susceptible to overfitting and require careful tuning and validation, especially in smaller or noisier datasets (Heidary et al., 2024; Muslim et al., 2023).

In summary, the comparative evidence suggests that ANNs offer significant advantages in accuracy, recall, and the ability to model complex relationships in bankruptcy prediction, but LR remains indispensable where interpretability and simplicity are critical. The choice between these models should thus be informed by the specific analytical context, data characteristics, and stakeholder requirements (Gavurova et al., 2022; Sun et al., 2024).

Class Imbalance and Data Preprocessing

One persistent challenge in bankruptcy prediction is the imbalance between bankrupt and non-bankrupt firms. Non-bankrupt companies often dominate datasets, biasing models toward majority-class predictions and producing deceptively high accuracy but poor sensitivity in detecting bankruptcies. This imbalance is problematic because missing a bankruptcy carries greater financial risk than misclassifying a healthy firm (Zhao, Ouenniche, & De Smedt, 2024). To address this issue, researchers apply resampling methods such as SMOTE and its variants (SMOTE-ENN, SMOTE-Tomek), which generate additional minority-class samples and reduce noise, improving classification fairness (Muslim et al., 2023). Complementary strategies such as feature selection and normalization further strengthen model performance by reducing dimensionality and filtering irrelevant indicators (Jiang, Lu, & Xia, 2016).

Studies confirm that these preprocessing techniques improve the recall of both ANNs and LR, making predictions more reliable. For instance, analyses of Indonesian and Taiwanese datasets reported that SMOTE raised recall above 95 percent, reducing bias toward non-bankrupt firms and improving stability (Muslim et al., 2023; Ahmad Shukri, 2024). Feature selection has also simplified models while maintaining or even enhancing predictive accuracy, thereby supporting interpretability (Prasetyo et al., 2021).

Overall, research shows that preprocessing is essential for reliable bankruptcy prediction. By improving recall, reducing false negatives, and supporting fairer outcomes, effective data handling ensures that both ANNs and LR can be applied more robustly in practice.

Visualization and Interpretability Tools

Recent literature from 2018 to 2025 highlights the growing importance of visualization and interpretability tools in bankruptcy prediction to enhance model transparency and stakeholder trust. As machine learning models, particularly complex ones like artificial neural networks and ensemble methods, increasingly outperform traditional statistical approaches, their “black-box” nature raises concerns regarding explainability (Park, Son, Hyun, & Hwang, 2021; Park & Yang, 2022). To address this, XAI techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) have been widely adopted. These methods provide both global and local interpretability by quantifying the contribution of individual financial ratios such as Debt-to-Equity Ratio, Altman Z-Score components, liquidity ratios, and profitability measures to the bankruptcy prediction outcomes (Park et al., 2021).

Moreover, visualization tools like interactive dashboards have been integrated to present these interpretability insights in user-friendly formats, facilitating real-time decision-making and risk assessment by financial analysts and credit institutions (Covaci & Boscan, 2023). Studies demonstrate that combining convolutional neural networks with explainability frameworks improves both predictive accuracy and the transparency of model decisions, making advanced AI models more acceptable in regulated environments (Tang, Wang, & Liu, 2023). Overall, the literature underscores that embedding visualization and interpretability tools within bankruptcy prediction frameworks is essential for enhancing model credibility, regulatory compliance, and practical adoption in financial risk management (Park et. al, 2021; Park & Yang, 2022).

Review Methodology

This systematic review focuses on peer-reviewed literature published between 2018 and 2024 that investigates the application of LR and ANNs in bankruptcy prediction. Relevant studies were identified through a structured search of major scholarly databases, including Scopus, Web of Science, and IEEE Xplore, utilizing keywords such as “bankruptcy prediction,” “logistic regression,” “artificial neural networks,” and “dashboard visualization.” The inclusion criteria emphasized empirical research that directly compared LR and ANNs models within the context of bankruptcy prediction, with particular attention given to studies evaluating model performance, interpretability, and the use of data visualization tools. To ensure a comprehensive synthesis of recent methodological advancements and visualization trends, studies from the past two decades were considered, though the primary focus remained on research published in the last six years to capture the most current developments. This approach aligns with best practices in systematic review methodology and supports a robust comparative analysis of predictive modelling techniques in financial risk assessment (Brygała, 2022; Gavurova et al., 2022; Shi & Li, 2019).

Findings

The comparative results presented in Table 1 and Table 2 indicate a consistent trend in which ANNs generally outperform LR in bankruptcy prediction across a variety of datasets and economic contexts.

Table 1: Summarizing Comparative Performance Metrics (Accuracy, Recall) For ANNs And LR Across Key Studies

Study	Dataset/Context	ANN Accuracy	LR Accuracy	ANN Recall	LR Recall	Key Findings
Gavurova et al. (2022)	European companies	94%	91%	0.95	0.92	ANN outperforms LR overall
Zizi et al. (2021)	Moroccan companies	92%	93%	0.90	0.91	LR more precise in this set
Horak et al. (2020)	Czech firms	89%	87%	0.88	0.85	ANN better on recall
Muslim et al. (2023)	Indonesian firms	95%	90%	0.96	0.91	SMOTE improved fairness for both models

Prasetyo et al. (2021)	Indonesian SMEs	93%	89%	0.92	0.89	ANN > LR after balancing and feature selection
Vochozka et al. (2020)	Czech/Slovak firms	90%	88%	0.91	0.87	ANN better on complex datasets
Marso & El Merouani (2020)	North African firms	96% (hybrid)	91%	0.97	0.91	Hybrid ANN outperformed standard LR
Ahmad Shukri (2024)	Taiwanese dataset	93% (80:20)	91% (80:20)	0.94	0.92	ANN slightly better; both improved w/ more data
Wang et al. (2021)	Chinese manufacturing	91%	89%	0.92	0.89	ANN better on recall, LR easier to interpret
Lee & Choi (2020)	Korean SMEs	92%	90%	0.93	0.91	ANN higher recall, LR higher specificity

Table 1 provides a comparative summary of recent studies evaluating the performance of ANNs and LR models for bankruptcy prediction across various international datasets. The table presents key metrics, including accuracy and recall, and highlights the relative strengths and weaknesses of each modelling approach in diverse contexts.

A clear trend emerging from Table 1 is that ANNs models generally achieve higher accuracy and recall compared to LR across most studies, particularly when advanced preprocessing techniques such as SMOTE and feature selection are employed. This pattern is evident in studies involving European, Indonesian, and North African datasets, where ANNs consistently outperforms LR in both predictive accuracy and the ability to identify true positives. The superiority of hybrid ANNs approaches, as demonstrated by Marso and El Merouani (2020), further underscores the potential of combining machine learning with optimization techniques to enhance predictive performance. Additionally, the use of data balancing methods like SMOTE is shown to improve fairness and robustness for both ANNs and LR models (Muslim et al., 2023; Prasetyo et al., 2021).

However, the table also reveals context-specific findings and outliers. Notably, Zizi et al. (2021) report that LR slightly outperforms ANNs in terms of precision and recall within their Moroccan dataset, illustrating that the relative effectiveness of each model can depend on specific data characteristics and local context. Similarly, Wang et al. (2021) and Lee & Choi (2020) highlight that while ANNs excels in recall, LR maintains an advantage in interpretability and specificity, which can be crucial in practical, regulated environments. These findings suggest that while ANNs offers advantages in predictive performance, LR remains a valuable tool when interpretability and context-specific requirements are prioritized.

Table 2: Comparative Performance of ANN and LR in Bankruptcy Prediction (2018–2024)

Study	Dataset	ANNs Accuracy	LR Accuracy	Preprocessing / Imbalance Handling	Visualization / Reporting	Notable Findings
Gavurova et al. (2022)	European firms	94%	91%	SMOTE, Normalization	Dashboard, Confusion Matrix	ANN outperformed LR; feature selection important
Zizi et al. (2021)	Moroccan companies	92%	93%	Outlier removal, Feature selection	Confusion Matrix	LR slightly better precision in this context
Horak et al. (2020)	Czech firms	89%	87%	Feature selection	None	ANN recall advantage; both strong on survivors
Muslim et al. (2023)	Indonesian firms	95%	90%	SMOTE, Normalization	None	SMOTE improved fairness for both models
Prasetyo et al. (2021)	Indonesian SMEs	93%	89%	SMOTE, Feature selection	None	ANN > LR after balancing and feature selection
Vochozka et al. (2020)	Czech/Slovak firms	90%	88%	Data cleaning, Normalization	ROC Curve	ANN better on complex datasets
Marso & El Meroua	North African firms	96% (hybrid)	91%	Hybrid ANN, Metaheuristics	None	Hybrid ANN outperformed

ni (2020)						standard LR
Ahmad Shukri (2024)	Taiwanese dataset	93% (80:20)	91% (80:20)	SMOTE, Outlier removal	Dashboard, Confusion Matrix	ANN slightly better; both improve d with more data
Shi & Li (2019)	Review (multi- country)	88–95%	85– 92%	Various	Various	ANN generall y higher accuracy , but less interpret able
Brygała (2022)	European review	89–94%	86– 92%	Various	None	LR favored for interpret ability; ANN for accuracy

Table 2 provides a comparative summary of recent studies evaluating the performance of ANNs and LR models for bankruptcy prediction across various international datasets. As shown in Table 1, ANNs models consistently achieve higher accuracy than LR, particularly when advanced preprocessing and data balancing techniques such as SMOTE and feature selection are applied. These approaches enhance model fairness and stability, contributing to the superior performance of ANNs in many contexts. However, LR remains favored for its interpretability and transparency, especially in regulated financial environments where auditability is critical (Brygała, 2022; Gavurova et al., 2022).

Notably, Zizi et al. (2021) found LR to be slightly more precise in their Moroccan dataset, illustrating that model superiority may depend on specific data characteristics and contextual factors. Additionally, hybrid models that combine ANNs with metaheuristic optimization techniques, as reported by Marso and El Merouani (2020), demonstrate even higher predictive accuracy, suggesting promising avenues for future research. Overall, the comparative findings underscore the importance of balancing predictive performance with interpretability and the need to tailor model choice to the application context.

Critical Analysis and Gaps

Despite significant advances in bankruptcy prediction research, several persistent gaps and challenges remain. First, the lack of standardization in datasets, evaluation metrics, and validation protocols across studies continues to impede meaningful cross-comparison and meta-analysis of results (Shi & Li, 2019; Brygała, 2022). This heterogeneity complicates the benchmarking of models and limits the generalizability of findings. Second, a well-documented

trade-off exists between interpretability and predictive accuracy: while ANNs frequently demonstrate superior performance metrics, their “black box” nature undermines transparency and auditability, which are crucial in regulated financial environments. In contrast, LR offers high interpretability but may underperform in complex, non-linear contexts (Gavurova et al., 2022; Zizi et al., 2021). Third, the literature remains disproportionately focused on traditional sectors such as manufacturing and finance, with limited attention paid to underexplored domains like healthcare, technology startups, or emerging markets, thereby restricting the scope of current predictive insights (Marso & El Merouani, 2020). Fourth, although dashboards and visual analytics are increasingly recognized for their value in decision support, few studies report real-time integration of predictive models into operational systems, limiting their practical deployment and stakeholder engagement (Covaci & Boscan, 2023). Lastly, issues of data imbalance and overfitting particularly pronounced in ANNs applications pose risks to model robustness and external validity, underscoring the need for more rigorous controls and transparent reporting of model development processes (Muslim et al., 2023; Prasetyo et al., 2021). Addressing these gaps is essential for advancing both the methodological rigor and real-world impact of bankruptcy prediction research.

Future Directions

Looking ahead, several promising avenues can advance the field of bankruptcy prediction and address existing limitations. First, the development of hybrid models that combine the strengths of ANNs and LR is potentially through ensemble or optimization techniques will offers the potential to improve both predictive accuracy and model robustness (Gavurova et al., 2022; Marso & El Merouani, 2020). Second, the integration of XAI methods, such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), or surrogate modeling, can help bridge the interpretability gap for ANN-based solutions, making them more suitable for high-stakes financial decision-making (Covaci & Boscan, 2023; Shi & Li, 2019). Third, establishing cross-industry benchmarks through the use of shared, standardized datasets and evaluation protocols would facilitate more meaningful comparisons across studies and sectors, ultimately enhancing the generalizability of research findings (Brygała, 2022). Fourth, the deployment of interactive dashboards and real-time visualization tools can empower practitioners by translating complex model outputs into actionable insights, thereby supporting timely and informed decision-making (Covaci & Boscan, 2023). Finally, the establishment of clear standards for model governance including transparency, auditability, and ethical use remains essential for fostering trust and accountability in predictive analytics, especially as models are increasingly integrated into operational financial systems (Muslim et al., 2023; Prasetyo et al., 2021). Collectively, these directions highlight the need for methodological innovation, interdisciplinary collaboration, and a continued focus on practical deployment to ensure the next generation of bankruptcy prediction models are both accurate and trustworthy.

Conclusion

In summary, this review has synthesized the comparative strengths and limitations of logistic regression and artificial neural networks in the context of bankruptcy prediction. While artificial neural networks frequently demonstrate superior predictive accuracy and adaptability to complex, non-linear financial data, their inherent opacity and computational complexity present significant barriers to widespread adoption, particularly in settings where model transparency and regulatory compliance are paramount (Gavurova et al., 2022; Shi & Li, 2019). Logistic regression, by contrast, remains an enduring and robust choice for practitioners who

prioritize interpretability, auditability, and ease of implementation, even if this sometimes comes at the expense of marginally lower predictive performance (Brygala, 2022; Zizi et al., 2021). The ongoing tension between model performance and transparency underscores the importance of context-sensitive model selection in financial analytics. Future research should focus on the development of hybrid modelling approaches, the integration of explainable artificial intelligence techniques, and the practical deployment of predictive models through interactive visualization and decision-support systems (Covaci & Boscan, 2023; Muslim et al., 2023). Addressing these priorities will be essential for advancing both the methodological rigor and real-world utility of bankruptcy prediction models in increasingly dynamic and data-rich financial environments.

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