Financial Risk and Management:
An International Journal
Volume 4, Number 2, 2025

The Effectiveness of Machine Learning Techniques in Corporate Bankruptcy Risk Prediction

Urbanus Wawan[1]

[1] Universitas Katolik Widya Mandala, Surabaya, Indonesia

Abstract

Article history:
Received: September 19, 2025
Revised: October 11, 2025
Accepted: November 4, 2025
Published: December 30, 2025

Keywords:
Corporate Bankruptcy Prediction,
Financial Distress,
Machine Learning,
Risk Management,
Systematic Literature Review.

Identifier:
Zera Open
Page: 110-123
https://zeraopen.com/journal/frmij

This article examines how effective machine learning techniques are in predicting corporate bankruptcy risk in a context where early warning signals are crucial for lenders, investors, and regulators to contain financial instability. The study conducts a systematic literature review of peer reviewed research published between 2020 and 2024 that applies machine learning models to corporate bankruptcy and financial distress prediction. The evidence shows that ensemble, deep learning, and sequential models generally outperform traditional statistical approaches, particularly when class imbalance is addressed and financial data are enriched with market, textual, or governance related features. The article discusses these findings through a narrative and thematic synthesis that compares algorithms, feature sets, sampling strategies, and validation designs across different countries and sectors. The main findings highlight that modelling choices and data design strongly condition performance, that interpretability and governance remain underdeveloped, and that future work should link predictive gains more clearly to tangible improvements in risk management outcomes.

©2025 The Author(s).
This is an open-access article under CC-BY-SA license (https://creativecommons.org/licence/by-sa/4.0/)

1. Introduction

Corporate bankruptcy risk prediction has long been a central concern in financial risk management because sudden firm failures can transmit distress through credit markets, supply chains, and the broader real economy. Early warning signals help lenders, investors, and regulators to reprice risk, provision for losses, and design timely interventions that mitigate contagion. While traditional statistical models based on financial ratios remain widely used, recent crises and advances in data availability have intensified interest in machine learning techniques that can exploit high dimensional and nonlinear patterns in corporate financial and non-financial information (Narvekar & Guha, 2021; Mahmoud & Arifin, 2024). Within this context, machine learning is increasingly viewed as a potential tool for improving the accuracy and robustness of bankruptcy risk prediction.

Over the past few years, machine learning methods have become prominent in corporate bankruptcy and financial distress prediction, often delivering higher accuracy than classical logit or discriminant models. Tree based ensembles, support vector machines, and deep learning architectures have been applied to diverse corporate samples, showing that nonlinear models better capture complex interactions among capital structure, profitability, liquidity, and governance indicators (Pavlicko et al., 2021; Jabeur & Serret, 2023). Recent studies extend this paradigm by addressing class imbalance, concept drift, and temporal dynamics, and by incorporating richer feature sets that combine financial, management, textual, and social responsibility information in order to maintain performance as macroeconomic and firm specific conditions evolve (Song et al., 2024). In parallel, researchers increasingly integrate alternative data, including textual disclosures and online interaction content, demonstrating that qualitative information can materially enhance distress prediction beyond traditional accounting ratios (Zhao et al., 2023).

Systematic reviews of bankruptcy prediction models highlight that this wave of machine learning adoption has produced a highly fragmented evidence base. Studies differ in sample composition, predictor sets, rebalancing strategies, validation windows, and performance metrics, making it difficult to generalize about the relative effectiveness of specific algorithms or modelling choices (Dasilas & Rigani, 2024; Mahmoud & Arifin, 2024). There is also growing recognition that model performance is context dependent: sectoral features, institutional environments, and crisis versus non crisis periods can significantly alter the marginal benefits of moving from traditional statistical models to more complex machine learning techniques (Deng et al., 2024; Toudas et al., 2024). At the same time, practical implementation raises additional concerns around interpretability, stability over time, and the risk of overfitting in small or noisy corporate datasets.

Against this backdrop, a systematic literature review focused specifically on the effectiveness of machine learning techniques in corporate bankruptcy risk prediction is needed to consolidate recent evidence and identify robust patterns. This article undertakes a structured review of peer reviewed empirical research published between 2020 and 2024 that applies machine learning methods to corporate bankruptcy or financial distress prediction. Using transparent search, screening, and data extraction procedures across major scholarly databases, the review maps the distribution of algorithms, data types, sampling designs, and evaluation metrics. It then synthesizes comparative findings on predictive performance, robustness, and interpretability, with particular attention to how machine learning models perform relative to traditional benchmarks across different institutional and crisis settings. By doing so, the article aims to clarify under what conditions machine learning techniques provide meaningful risk management gains, and where their added complexity may yield limited incremental benefit for corporate bankruptcy risk prediction.

2. Literature Review

The recent literature on corporate bankruptcy and financial distress prediction shows a clear shift from traditional statistical models toward a wide range of machine learning techniques. Systematic reviews emphasize that ensemble methods, support vector machines, and deep learning models frequently outperform classical discriminant analysis and logit models in terms of overall accuracy, sensitivity, and robustness, particularly when dealing with nonlinear relationships and high dimensional data (Dasilas & Rigani, 2024; Mahmoud & Arifin, 2024). Comparative studies across multiple algorithms confirm that tree-based ensembles and hybrid models tend to deliver the most stable performance, especially when they are carefully tuned and combined with appropriate sampling strategies to handle class imbalance (Pavlicko et al., 2021; Jabeur & Serret, 2023). At the same time, several contributions caution that gains in predictive performance can depend heavily on the modelling choices, data windows, and validation designs adopted in individual studies.

A second strand of research focuses on enriching the information set used for prediction and dealing explicitly with data and class imbalance problems. Recent work integrates financial, management, textual, and social responsibility variables into unified feature spaces to capture a more comprehensive view of firm behaviour and risk, showing that broader feature sets can significantly improve distress prediction relative to traditional ratio-based models (Zhao et al., 2023; Song et al., 2024). Other studies explore deep learning architectures and hybrid ensemble schemes for highly imbalanced datasets, where bankrupt firms represent only a small fraction of observations, and find that combinations of oversampling, cost sensitive learning, and ensemble methods can materially enhance the detection of rare default events (Smiti & Soui, 2020; Deng et al., 2024; Ling & Wang, 2024). Evidence from emerging market settings, particularly Chinese listed firms, further suggests that ensemble machine learning models are able to adapt to noisy and incomplete data environments, although the magnitude of improvement over simpler models still varies across countries and sectors (Ling & Wang, 2024).

A third cluster of contributions engages more directly with issues of interpretability, context dependence, and model comparison. Sector specific studies, such as those on construction firms or industry focused samples, highlight that the relative performance of machine learning versus traditional models can differ across sectors and institutional settings, underscoring the importance of tailoring models to the characteristics of particular industries (Toudas et al., 2024). Interpretable ensemble approaches and post hoc explanation tools are increasingly used to clarify the drivers of predicted distress and to reconcile complex models with regulatory and managerial demands for transparency (Deng et al., 2024; Mahmoud & Arifin, 2024). However, existing research still tends to prioritize accuracy metrics over questions of stability across time, sensitivity to economic cycles, and practical implementation issues such as data availability and governance. Overall, the literature indicates that machine learning techniques offer substantial potential for enhancing corporate bankruptcy risk prediction, but that their effectiveness is mediated by the choice of features, sampling strategies, and the institutional and sectoral context in which they are deployed.

3. Methods

This study employs a systematic literature review approach to synthesize recent evidence on the effectiveness of machine learning techniques in corporate bankruptcy and financial distress prediction. The review focuses on peer reviewed journal articles published between 2020 and 2024 in order to capture the latest developments in algorithms, data sources, and evaluation practices. Relevant studies were identified through structured searches in major academic databases such as Scopus, Web of Science, ScienceDirect, and Google Scholar, using combinations of keywords including “corporate bankruptcy prediction”, “financial distress prediction”, “credit risk”, “default prediction”, “machine learning”, and “prediction model”. The search was limited to English language articles. Conference papers, theses, book chapters, non-peer reviewed materials, and studies that did not apply machine learning methods to corporate level bankruptcy or distress prediction were excluded. Reference lists of key articles and recent review papers were also screened to identify additional eligible studies.

A multi stage screening and extraction process was used to refine and analyze the final set of studies. First, titles and abstracts were reviewed to eliminate articles that did not clearly concern corporate bankruptcy or financial distress prediction or that focused solely on macro level or consumer credit risk. Second, full text screening was conducted to retain empirical studies that implemented at least one machine learning technique and reported predictive performance metrics, and to exclude purely theoretical work or studies with insufficient methodological detail. The selected articles were then coded using a structured template capturing publication details, country and sector coverage, sample period, data sources, feature types, machine learning algorithms, comparison models, sampling and validation strategies, and key performance indicators. Given the heterogeneity in methods, datasets, and evaluation designs, the findings were synthesized using a narrative and thematic approach rather than quantitative meta-analysis, with a focus on identifying common design patterns, relative performance of different techniques, and contextual factors that shape the effectiveness of machine learning in corporate bankruptcy risk prediction.

4. Results and Discussion

The synthesis of studies published between 2020 and 2024 shows a consistent pattern that modern machine learning techniques materially improve the prediction of corporate bankruptcy risk relative to traditional statistical models such as discriminant analysis and logistic regression. Tree based ensemble methods, including random forests and gradient boosting variants, generally achieve higher accuracy, a larger area under the Receiver Operating Characteristic (ROC) curve, and better F1 scores, where the F1 score is defined as the harmonic mean of precision and recall and thus balances false positives and false negatives (Narvekar & Guha, 2021; Jabeur & Serret, 2023). Recent work on sequential modelling further indicates that architectures that explicitly account for time ordered financial ratios, such as recurrent neural networks and long short-term memory models, can capture dynamic deterioration paths in firm fundamentals and generate more timely and robust early warning signals (Kim et al., 2022). These gains are not limited to a single market, since evidence from European, North American, and Asian samples points to broadly similar improvements in out of sample predictive performance (Zhao et al., 2023; Ling & Wang, 2024).

The review also highlights that handling class imbalance and enriching the information set are central to the effectiveness of machine learning based bankruptcy prediction systems. Several studies show that naive application of powerful classifiers to highly imbalanced datasets can overestimate firm stability and underestimate distress probabilities, which undermines their usefulness as risk management tools (Smiti & Soui, 2020; Narvekar & Guha, 2021). To address this issue, recent work combines ensemble learners with resampling strategies, cost sensitive learning, or hybrid pipelines that integrate sampling, feature selection, and model training, yielding more balanced sensitivity and specificity across distressed and non-distressed firms (Ling & Wang, 2024; Song et al., 2024). At the same time, there is a clear movement beyond purely accounting based ratios toward augmented feature spaces that include governance indicators, market-based variables, macroeconomic controls, textual disclosure metrics, and corporate social responsibility measures, although the incremental value of such alternative data is sometimes modest once high-quality financial data are included (Zhao et al., 2023; Song et al., 2024).

Another key finding concerns the trade-off between predictive power and interpretability in machine learning based bankruptcy models. Complex ensemble and deep learning architectures often dominate benchmark models in terms of accuracy and discrimination, yet several studies emphasize the need for transparent explanations to support regulatory use, internal capital allocation, and engagement with external stakeholders (Deng et al., 2024; Ling & Wang, 2024). Recent contributions address this gap by combining high performing algorithms with explainable artificial intelligence techniques, such as variable importance measures, Shapley value-based decompositions, and partial dependence plots, which help identify the financial ratios and risk drivers that most strongly influence predicted distress probabilities. Evidence from emerging markets suggests that such interpretable frameworks can highlight the dominant role of leverage, profitability, liquidity, and efficiency ratios while still achieving very high overall accuracy in financial distress forecasting (Ha et al., 2023).

Despite these advances, the review also reveals important limitations and gaps that constrain the practical deployment of machine learning based bankruptcy prediction in risk management. Many studies rely on relatively short sample periods or single country datasets, which raises questions about the stability of model performance across different business cycles, regulatory regimes, and structural breaks. Out of sample tests are often limited to random splits rather than true time based validation, making it harder to assess how models perform in changing macroeconomic conditions such as crises and recoveries. In addition, only a minority of papers explicitly address implementation issues such as data governance, model monitoring, and the integration of model outputs into credit processes, capital planning, or early warning frameworks. As a result, there is still limited evidence on how the documented gains in statistical performance translate into real world improvements in credit risk management, loss mitigation, and regulatory compliance.

5. Conclusion

The findings of this review show that machine learning is not just a fashionable alternative to traditional models, but a genuine step forward in corporate bankruptcy and financial distress prediction. Across the studies examined, ensemble models, deep learning architectures, and sequential methods generally outperform classical approaches in distinguishing distressed from healthy firms and in generating earlier warning signals. However, the results also make clear that these gains do not come automatically from using "more complex" algorithms. They depend on how models are designed and implemented: how class imbalance is handled, how rich and relevant the feature set is, how time is treated in the data, and how realistically the models are validated. In other words, the effectiveness of machine learning is best understood as the outcome of a full modelling strategy rather than of a single algorithmic choice.

These conclusions have several broader implications for research, practice, and regulation. For researchers, the evidence suggests that future work should move beyond simple algorithm comparisons and instead study configurations of techniques: combinations of feature engineering, resampling or cost-sensitive learning, and model architectures evaluated under clearly defined economic scenarios. There is also a clear case for more attention to interpretability, not only as a technical add-on but as a design requirement that links model outputs to managerial judgement and regulatory scrutiny. For practitioners and risk managers, the review supports a more strategic view of machine learning models as components of an integrated early-warning system. Models need to be backed by clear data quality standards, documented model risk management, and decision workflows that specify how predicted distress is translated into actions such as revising credit limits, restructuring exposures, or intensifying monitoring.

At the same time, the review points to important gaps that temper the overall optimism. Many studies still rely on single-country or sector-specific samples and relatively short time horizons, so the stability of model performance across business cycles, regulatory changes, and structural shocks remains only partially understood. Most papers focus on statistical performance metrics and say little about how improved predictions actually affect credit losses, capital allocation, or supervisory interventions in practice. This suggests a clear agenda for future research: to evaluate machine learning models not only on accuracy, but on their economic impact, robustness over time, and compatibility with governance and regulatory frameworks. By doing so, the field can move from showing that machine learning can predict bankruptcy well in controlled settings to demonstrating when, where, and how it delivers durable benefits for corporate risk management and financial stability.

References

Dasilas, A., & Rigani, A. (2024). Machine learning techniques in bankruptcy prediction: A systematic literature review. *Expert Systems with Applications, 255*, 124761.

Deng, S., Luo, Q., Zhu, Y., Ning, H., & Shimada, T. (2024). Financial risk forewarning with an interpretable ensemble learning approach: An empirical analysis based on Chinese listed companies. *Pacific-Basin Finance Journal, 85*, 102393.

Ha, H. H., Dang, N. H., & Tran, M. D. (2023). Financial distress forecasting with a machine learning approach. *Corporate Governance and Organizational Behavior Review, 7*(3), 90-104.

Jabeur, S. B., & Serret, V. (2023). Bankruptcy prediction using fuzzy convolutional neural networks. *Research in International Business and Finance, 64*, 101844.

Kim, H., Cho, H., & Ryu, D. (2022). Corporate bankruptcy prediction using machine learning methodologies with a focus on sequential data. *Computational Economics, 59*(3), 1231-1249.

Ling, Y., & Wang, P. P. (2024). Ensemble machine learning models in financial distress prediction: Evidence from China. *Journal of Mathematical Finance, 14*(2), 226-242.

Mahmoud, M. E., & Arifin, T. (2024). Systematic Literature Review of Advancements in Corporate Bankruptcy Prediction. *International Journal of Accounting, Management, Economics and Social Sciences (IJAMESC), 2*(6), 1913-1935.

Narvekar, A., & Guha, D. (2021). Bankruptcy prediction using machine learning and an application to the case of the COVID-19 recession. *Data Science in Finance and Economics, 1*(2), 180-195.

Pavlicko, M., Durica, M., & Mazanec, J. (2021). Ensemble model of the financial distress prediction in Visegrad group countries. *Mathematics, 9*(16), 1886.

Smiti, S., & Soui, M. (2020). Bankruptcy prediction using deep learning approach based on borderline SMOTE. *Information Systems Frontiers, 22*(5), 1067-1083.

Song, Y., Jiang, M., Li, S., & Zhao, S. (2024). Class-imbalanced financial distress prediction with machine learning: Incorporating financial, management, textual, and social responsibility features into index system. *Journal of Forecasting, 43*(3), 593-614.

Toudas, K., Archontakis, S., & Boufounou, P. (2024). Corporate bankruptcy prediction models: A comparative study for the construction sector in Greece. *Computation, 12*(1), 9.

Zhao, Q., Xu, W., & Ji, Y. (2023). Predicting financial distress of Chinese listed companies using machine learning: To what extent does textual disclosure matter?. *International Review of Financial Analysis, 89*, 102770.